How Important are Dual Economy Effects for Aggregate Productivity?

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ABSTRACT: This paper brings together development accounting techniques and the dual economy model to address the role that factor markets have in creating variation in aggregate total factor productivity (TFP). Development accounting research has shown that much of the variation in income across countries can be attributed to differences in TFP. The dual economy model suggests that aggregate productivity is depressed by having too many factors to low productivity work in agriculture. Data show large differences in marginal products of similar factors within many developing countries, offering *prima facie* evidence of this misallocation. Using a simple two-sector decomposition of the economy, this article estimates the role of these misallocations in accounting for the cross-country income distribution. A key contribution is the ability to bring sector specific data on human and physical capital stocks to the analysis. Variation across countries in the degree of misallocation is shown to account for 30 – 40% of the variation in income per capita, and up to 80% of the variation in aggregate TFP.

JEL Codes: O1, O4, Q1

Keywords: Resource allocation; Labor allocation; Dual economy; Income distribution; Factor markets; TFP

a) I'd like to thank Francesco Caselli, Areendam Chanda, Carl-Johan Dalgaard, Jim Feyrer, Oded Galor, Doug Gollin, Vernon Henderson, Peter Howitt, Mike Jerzmanowksi, Omer Moav, Malhar Nabar, Jonathan Temple, David Weil, and an anonymous referee for helpful comments and advice. In addition, the participants at the Brown Macroeconomics Seminar, Northeast Universities Development Conference and Brown Macro Lunches were very helpful. All errors are, of course, my own.

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1 Introduction

One of the most persistent relationships in economic development is the inverse one between income and agriculture, seen here in figure 1. In the cross-section as well as over time, increases in income are associated with decreases in the relative size of the agricultural sector. The strength of this relationship is such that the decline of agriculture is often seen as a major hallmark of economic development.

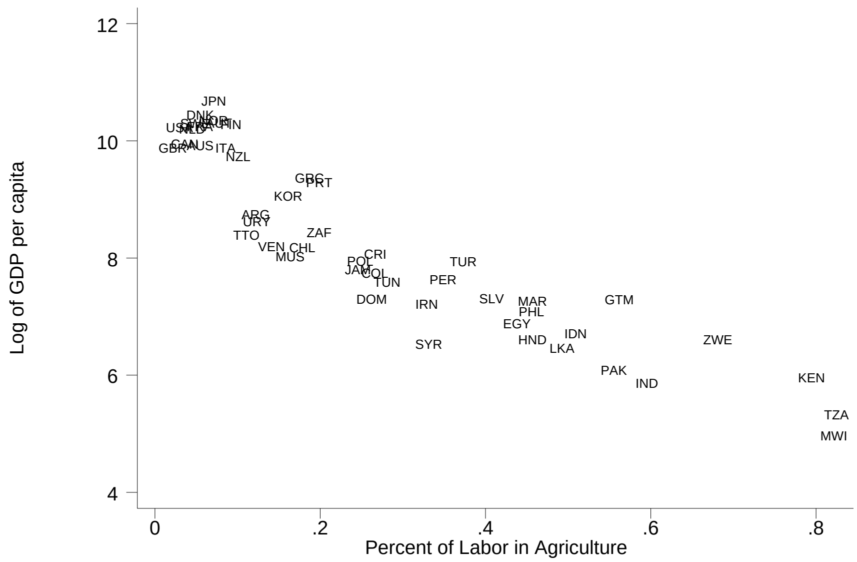

Figure 1: **Income per capita and Percent of Labor Force in Agriculture**
Note: GDP Data is from PWT 5.0 and agricultural labor share is from FAO.

The development accounting literature, typified by Hall & Jones (1999) and Klenow & Rodriguez-Clare (1997), has focused on the cross-country variation in income observed in figure 1. It is generally found that differences in total factor productivity (TFP) are the primary source of income variation. This literature, though, has not concentrated on the role of agriculture until very recently.

In contrast, the field of development economics since the contributions of Lewis (1954), Jorgenson (1961), and Ranis & Fei (1961) has been intimately concerned with agriculture and its connection

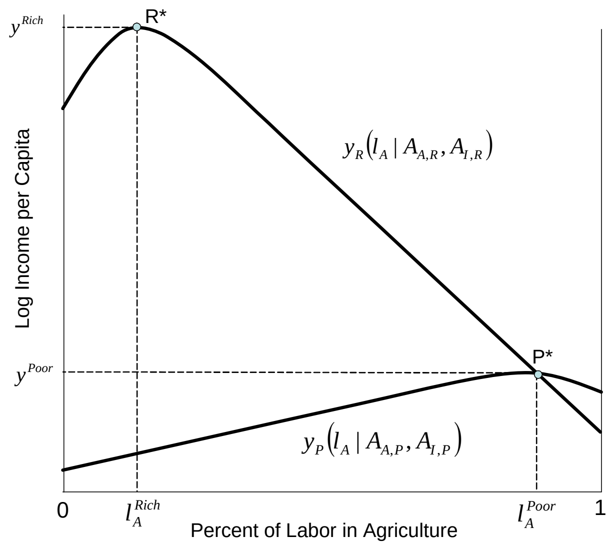

Figure 2: **Explanations for the Inverse Relationship of Income and Agric.**

to income levels. The dual economy theory suggests that, *prima facie*, factor market inefficiencies exist within the economy. This lowers overall productivity and income by allocating too many factors of production to the low productivity sector, typically agriculture.

This paper brings the dual economy model into the development accounting framework and quantifies the effect that factor market inefficiency has on income levels and TFP variation across countries. Simply put, how important are dual economy effects for aggregate productivity? The answer to this question is intimately related to the inverse relationship of agriculture and income in figure 1.

This can be seen more clearly in figure 2. In this diagram, points R^* and P^* represent the observations of a rich, low-agriculture country (R) and a poor, high-agriculture country (P). Each country is characterized by a two-sector economy (agriculture and industry) and their production functions are of the same form. For simplicity ignore any differences in capital endowments.

One possible answer is characterized by the neoclassical growth model, in which the operation of factor markets is bypassed completely by assuming there is only one sector.[1] According to this model, countries differ in the relative productivity of agriculture and industry. Thus R^* is the maximum point on $y_R(l_A|A_{A,R}, A_{I,R})$ and P^* is the maximum point on $y_P(l_A|A_{A,P}, A_{I,P})$. In country R, $A_{I,R}$ must be large relative $A_{A,R}$ and in P the opposite must be true: $A_{I,P}$ is small relative to $A_{A,P}$. This would account for the difference in labor shares in agriculture. To account for the income difference, though, it must *also* be the case that $A_{I,R}$ is large relative to $A_{I,P}$. Variation in income and the inverse relationship with agriculture is driven primarily by differences in sectoral productivity levels. The dual economy, if it exists, exerts a negligible effect on productivity and income differences, as the poor economy does equate marginal products between sectors.

The other possibility is that the inefficient factor markets in the dual economy have real, measurable effects.[2] In figure 2 this is would be the case if both countries R and P are operating on $y_R(l_A|A_{A,R}, A_{I,R})$, and again $A_{I,R}$ is large relative to $A_{A,R}$. What separates countries R and P, now, is that the rich country is maximizing income by equating marginal products between sectors, while P is poor because most of its people are in the low productivity agricultural sector. The differences in aggregate productivity and income between R and P are the result of factor market inefficiency, not differences in sector level productivity. This dual economy effect drives the inverse relationship of income and agriculture in this case.

In this paper I use development accounting techniques to demonstrate that the macroeconomic evidence overwhelmingly supports the second possibility, that factor market inefficiency is a source of variation in aggregate TFP.[3] Using data covering the period $1970-1990$ that includes sector-

[1] Included here as well are multi-sector growth models which explicitly incorporate factor markets, but generally do so under the assumption that these markets operate perfectly to equate marginal products across sectors. Reviewing only relatively recent work, papers by Matsuyama (1992), Laitner (2000), and Kongasmut, Rebelo & Xie (2001) all explore economic ramifications of the movement of labor between sectors, but do so assuming that wage rates are equalized across sectors. Unified growth models in Goodfriend & McDermott (1995) and Hansen & Prescott (2002) make use of the same assumptions, and Echevarria (1997) bypasses the issue by assuming a single optimizing agent in the economy. Kogel & Prskawetz (2001) construct a growth model in which agricultural workers are paid their average product, not their marginal, but do not explore the ramifications of this assumption.

[2] There is a variety of evidence suggesting real inefficiencies in factor markets within countries. Banerjee & Duflo (2005) review a host of studies indicating that rates of return to the same factor vary widely within countries. From a macroeconomic perspective, the structural transformation research exemplified by Chenery & Syrquin (1975) and Chenery, Robinson & Syrquin (1986) as well as recent work by Caselli & Coleman (2001) and Temple & Woessmann (2004) examines how the reallocation of factors within an economy contributes to income growth. None of these studies, though, show how important these effects are in creating variation in income between countries.

[3] There are, of course, other sources of inefficiency within economies. This paper does not deal with those sources explicity, and their effect will be captured within the residual TFP measures calculated by sector.

specific measures of physical capital and human capital I find that $30 - 40\%$ of the variation in income per capita across countries is due to variation in the efficiency of their factor markets. These dual economy effects also explain up to 80% of the variation in aggregate TFP in my sample. Differences in sector level TFP are negligible in creating income differences between countries. This holds despite the fact that agricultural TFP levels vary greatly by country. The relatively small size of agriculture in total output, though, keeps this variation from being very meaningful.

This paper is part of a growing literature examining the role of agriculture in the cross-country income distribution.[4] Work by Gollin, Parente & Rogerson (2002) and Restuccia, Yang & Zhu (2003) explores the possibility that the combination of subsistence constraints and differences in agricultural TFP drive the income distribution. Restuccia (2004) and Graham & Temple (2003) create models in which the allocation of resources between sectors influences total factor productivity (TFP), and hence income. Their simulations show that these allocations can determine up to 50% of the variation in TFP between countries. Chanda & Dalgaard (2003) address the question more directly by doing a decomposition of aggregate TFP across countries. Their evidence suggests that up to 85% of the variation in aggregate TFP can be attributed to differences in the allocation of resources across sectors. These papers, though, do not deal explicitly with the question of the efficiency of factor markets within countries. The work of Cordoba & Ripoll (2004) does examine the wage gap between sectors specifically as a determinant of aggregate TFP differences. They find, as does this paper, that conventional measures of human capital by sector cannot account for the wide gaps in marginal product between sectors. They then ask what human capital differences between sectors would have to exist to explain the gap in marginal product between sectors. Their results imply that the conventional measures of human capital underestimate greatly the gap in human capital between rich and poor nations.

In contrast to all of these studies Caselli (2005), as part of his examination of development accounting, finds that labor allocations have very little significance in explaining cross-country variation in incomes. My methodology allows for a comparison to his results, and I show that Caselli's results were likely driven by the way he was forced to deal with physical and human

[4] This literature can be seen more broadly as attempting to use development economics to create better theories of economic growth. See Temple (2005) and Ros (2000) for discussions of the issues involved.

capital allocations across sectors. Using more accurate data on these allocations will allow me to show how his work failed to identify the connection between factor market inefficiency and income levels across countries.

The paper proceeds as follows. Section 2 discusses the techniques to be used and compares them to previous studies. Section 3 outlines the technical parameters and data used, as well as offering some preliminary evidence on factor market efficiency. Section 4 performs the development accounting and Section 5 considers the relationship of factor markets to aggregate TFP. Section 6 concludes.

2 Factor Markets and Variation in Income

Before proceeding to the empirical section, it will be useful to consider a stylized description of the method to be used. Consider a situation in which all economies are composed of two sectors: agriculture (denoted A) and industry (denoted I). We can describe income in an economy i by the following simple function,

$$y_i = y\left(l_A | k_i, A_{Ai}, A_{Ii}\right) \tag{1}$$

where y^i is income per capita, l_{Ai} is the share of labor employed in agriculture, k_i is capital per person, and A_{Ai} and A_{Ii} are total factor productivities in the agricultural and industrial sectors, respectively. Note that for the purposes of this section we will ignore the allocation of capital between sectors.

Equation (1) says that income per capita is a function of l_A, given the level of capital and sector TFP's. I assume that the underlying production function in each sector ensures a unique value, call it l_A^*, which maximizes y_i. As Banerjee & Duflo (2005) point out, growth research at the aggregate level assumes that countries are actually at l_A^*, or in other words that their factor markets are operating efficiently. This section describes a method for estimating the actual efficiency of factor markets and how this efficiency is related to aggregate TFP.

The function in (1) is graphed in figure 3 under three different sets of factors and productivities.

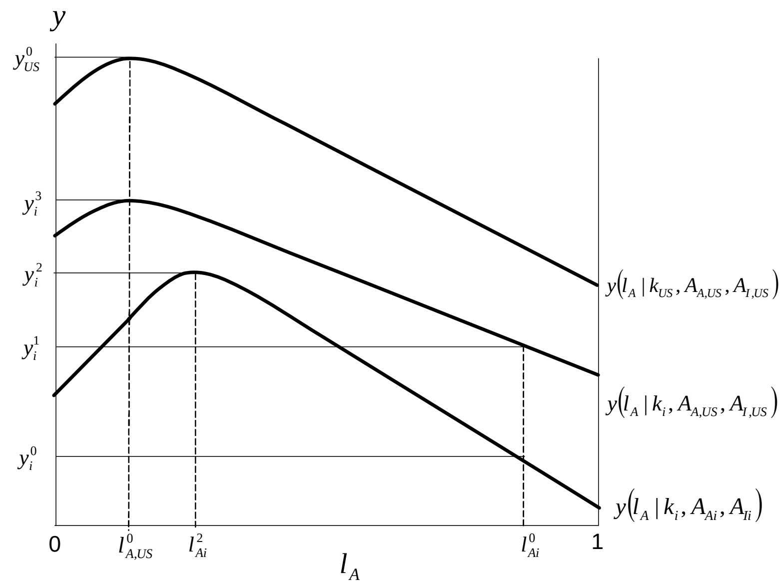

Figure 3: **Decomposing Income Differences**

The bottom-most function, $y\left(l_A|k_i, A_{Ai}, A_{Ii}\right)$, shows how y_i (plotted on the y-axis) is related to l_A (plotted on the x-axis) given its own endowment of capital and own sector level productivities. The middle function, $y\left(l_A|k_i, A_{A,US}, A_{I,US}\right)$, shows the relationship of y_i and l_A in the counterfactual situation where country i was given the levels of technology from the United States (which is presumed to be richer than country i), but where country i retains its own factor endowment, k_i. Finally, the upper-most function, $y\left(l_A|k_{US}, A_{A,US}, A_{I,US}\right)$, shows the relationship of income and labor allocation in the United States itself.

The initial position of country i on this diagram is at $\left(l_{Ai}^0, y_i^0\right)$. In other words, country i has a large allocation of labor in agriculture and a low income level. The income difference between the United States and country i is $\left(y_{US}^0 - y_i^0\right)$. The idea of development accounting is to break this difference down into its component parts, albeit over a large sample of countries. The basic concepts in the diagram, though, will follow through to evaluating variation in income amongst a sample of countries.

My approach will be to first look at the difference in income described by $\left(y_i^2 - y_i^0\right)$. This is the difference within country i between its maximized income given its endowments and its actual income. It measures the amount of income variation attributable to the efficiency with which factor markets allocate labor to agriculture. If factor markets are operating efficiently, then this difference should be at or close to zero. The actual value will obviously depend greatly on the shape I give to the function $y(\cdot)$, and much of the empirical section will be concerned with evaluating results under different assumptions regarding $y(\cdot)$.

The next step is to look at the difference $\left(y_i^3 - y_i^2\right)$. This shows the difference in income generated when we change the sector level productivites (A_A and A_I) for country i to those of the United States, *and* country i continues to maximize income over l_A. This gives us an idea of how much of income variation is due purely to sector TFP differences. As can be seen in the diagram, this does not mean that the allocation of labor is assumed to be constant, rather that the *efficiency* of the allocation is assumed to be constant.

Taken together the two differences, $\left(y_i^3 - y_i^2\right)$ and $\left(y_i^2 - y_i^0\right)$ comprise the amount of income variation attributable to *aggregate* TFP. To see this note that the only thing generating the remaining income difference $\left(y_{US}^0 - y_i^3\right)$ is the difference between k_{US} and k_i. We have eliminated everything but differences in factor endowments. The total income difference can be decomposed as follows.

$$\left(y_{US}^0 - y_i^0\right) = \overbrace{\left(y_{US}^0 - y_i^3\right)}^{\text{Factor Endowments}} + \overbrace{\underbrace{\left(y_i^3 - y_i^2\right)}_{\text{Sector Productivity}} + \underbrace{\left(y_i^2 - y_i^0\right)}_{\text{Factor Market Efficiency}}}^{\text{Aggregate TFP}} \tag{2}$$

Having outlined the decomposition strategy for two countries, the question becomes how to apply this methodology to a sample of countries. I will compare the variance of a counterfactual distribution of income to the actual variance of incomes across countries. The first step will be to calculate y_i^2 for each country in the sample, and then look at the following ratio

$$V = \frac{var\left(\ln y_i^2\right)}{var\left(\ln y_i^0\right)} \in [0, 1] \tag{3}$$

The ratio V tells us how much of the total variation in income across countries is *left* to explain after we have eliminated differences due to misallocation of factors.[5] So the smaller is V, the more of the cross-country variation in income we have accounted for by looking at misallocation. The empirical section of the paper will consider how different assumptions affect the calculation of y_i^2 and through this will change how important a place we give misallocation of resources in explaining income variation across countries.

3 Calculating Factor Market Efficiency

3.1 Set-Up

To perform the decomposition in (2) we need to move beyond the general function $y\left(l_A|k_i, A_{Ai}, A_{Ii}\right)$ and define more precisely how income is related to the allocation of not only labor but capital. Income per capita, y, is assumed to come from two sectors, agriculture and industry[6], and is defined simply as

$$y = \frac{Y_A}{L} + \frac{Y_I}{L} \tag{4}$$

where Y_j represents output in agriculture (A) and industry (I), L is total population. Output in each sector is described by the following Cobb-Douglas production functions

$$Y_{Ai} = A_{Ai} R_i^{\lambda} K_{Ai}^{\gamma} H_{Ai}^{1-\lambda-\gamma} \tag{5}$$

$$Y_{Ii} = A_{Ii} K_{Ii}^{\beta} H_{Ii}^{1-\beta} \tag{6}$$

[5] This method is similar to Caselli (2005), and the ratio V is analagous to his "success ratio". This method allows for a comparison with Caselli (2005), but I will come to very contrary conclusions regarding the importance of the allocation of resources in determining income levels. Caselli asks what the income difference is if we hold country i constant at the allocation l_{Ai}^0, but give it the sector productivity of the U.S. In Figure 3 this can be seen as the difference $\left(y_i^1 - y_i^0\right)$. The difference in our findings is due both to the different approach we take, as well as to the more accurate data on sector capital stocks that I utilize.

[6] I refer to the sectors as agriculture and industry for clarity. The industrial sector, in this paper, is more properly thought of as the non-agricultural sector. It includes all economic activity that is not specifically attributed to agriculture.

where K is physical capital, R is land, H is human capital, and A is productivity in each sector.[7] Human capital within a sector can be decomposed as follows: $H_{Ai} = h_{Ai}L_{Ai}$ and $H_{Ii} = h_{Ii}L_{Ii}$ where the lower case h_{Ai} and h_{Ii} refer to human capital per person in their respective sectors, and L_{Ai} and L_{Ii} refer to the total number of people in each sector. Total population, L_i, is the sum of L_{Ai} and L_{Ii}.

The agricultural production function is consistent with a long literature on cross-country agricultural production functions begun by Hayami (1969) and Hayami & Ruttan (1970) and reviewed comprehensively in Mundlak (2000). The industrial production function is assumed to be similar to the aggregate production function of an industrialized country, and so matches the standard formulation of aggregate output.

Given total capital as $K = K_A + K_I$ and total human capital as $H = H_A + H_I$, equations (5) and (6) can be rewritten in per capita terms

$$\frac{Y_{Ai}}{L_i} = A_{Ai}\left(\frac{R_i}{L_i}\right)^{\lambda}\left(\frac{K_i}{L_i}\right)^{\gamma}\left(\frac{H_i}{L_i}\right)^{1-\lambda-\gamma} k_{Ai}^{\gamma} q_{Ai}^{1-\lambda-\gamma} \tag{7}$$

$$\frac{Y_{Ii}}{L_i} = A_{Ii}\left(\frac{K_i}{L_i}\right)^{\beta}\left(\frac{H_i}{L_i}\right)^{1-\beta}(1-k_{Ai})^{\beta}(1-q_{Ai})^{1-\beta} \tag{8}$$

where

$$\begin{aligned} q_{Ai} &= H_{Ai}/H_i \in [0,1] \\ k_{Ai} &= K_{Ai}/K_i \in [0,1] \end{aligned}$$

The specific shape of the functions depends on the parameters. The elasticities on capital (γ) and land (λ) in agriculture, following Caselli (2005), are taken from Jorgenson & Gollop (1992), which are derived from factor payments in the U.S. The elasticity on capital is 0.21, on land 0.19.

[7] I will use the term "productivity" or "sectoral productivity" to refer to sector level total factor productivity (A_{Ai} and A_{Ii}) levels. This is to avoid confusion when referring to aggregate total factor productivity (which will be some combination of A_{Ai} and A_{Ii}).

This makes the labor share 0.60 in agriculture, which is the same as that assumed for the industrial sector $(1-\beta)$. This then makes the capital share in industry equal to 0.4. Perhaps contrary to expectations, the empirical results are not particularly sensitive to the choice of parameters in these functions. So for the remainder of this paper I take these parameters as given.

It is important to note that equations (7) and (8) concern themselves with the share of total human capital engaged in agriculture (H_{Ai}/H_i), as opposed to the share of total labor allocated to agriculture (L_{Ai}/L_i). This distinction is important because differences in the marginal product of labor between sectors may not reflect an inefficiency if human capital per worker differs by sector. If factor markets are operating correctly, then we would expect the marginal product of an *efficiency unit* of labor to be equalized across sectors, making the allocation of H_i the relevant issue.

3.2 Data Sources

Data on total output is at PPP, obtained from the Penn World Tables (PWT). The split of this output into Y_A and Y_I requires some calculations. Prasada Rao (1993) provides a measure of real value added in the agricultural sector for a cross-section of countries in 1985. However, his data is measured on a different scale than the PWT data, so that it requires some adjustment to the agricultural value added data before it is useful. The method is described fully in Caselli (2005), but the basic logic is as follows. For a large developed country like the U.S., output measured at PPP is nearly identical to output measured at domestic prices. The WDI database from World Bank (2003) provides domestically priced agricultural value added for the U.S. in 1985 $\left(Y_{A,US}^{WDI}\right)$, which is then assumed to be the same as PPP agricultural value added in the U.S. in 1985 $\left(Y_{A,US}^{PPP}\right)$. Comparing the WDI value added for the U.S. to Rao's value added for the U.S. $\left(Y_{A,US}^{RAO}\right)$ yields a simple conversion factor that tells us what to multiply the Rao PPP data by to obtain agricultural value added measured on the Penn World Tables scale for any country. To see this more clearly, the value of PPP agricultural value added for country i $\left(Y_{A,i}^{PPP}\right)$ is

$$Y_{A,i}^{PPP} = Y_{A,i}^{RAO}\frac{Y_{A,US}^{PPP}}{Y_{A,US}^{RAO}} \approx Y_{A,i}^{RAO}\frac{Y_{A,US}^{WDI}}{Y_{A,US}^{RAO}} \tag{9}$$

In the end we have a value of PPP agricultural value added for each country, and PPP industrial value added is simply total PPP output minus PPP agricultural value added. This method limits the sample to the year 1985, as this is the only year in which real agricultural value added is available.

Total population is taken from the FAOSTAT database of the Food and Agriculture Organization of the U.N., which in addition to totals includes a breakdown into agricultural and non-agricultural population based on economic activity, not simply rural versus urban residence[8]. By using data on agricultural population, this paper may be overstating the labor *effort* actually being employed in agriculture. This would understate the marginal product of labor in agriculture and suggest large inefficiencies that may not actually exist. So the current results must be viewed with this important caveat in mind.

One of the primary contributions of this article is the use of sector-specific data on both physical and human capital stocks. Most previous work has used aggregate stocks of both types of capital and then made assumptions about how they are distributed by sector. As will be discussed later, these assumptions lead to very different results than those obtained when using the actual sector level capital stock data.

Data on total physical capital stocks I take from Crego, Larson, Butzer & Mundlak (1998), which has a series on agricultural fixed capital for each country, as well as a series on total economy-wide fixed capital. The agricultural capital series includes not only what we normally conceive of as capital (e.g. machines, tools, etc.) but also livestock and agricultural buildings such as barns and storage units. This series is based on a domestically priced series of investment data, so there may be some questions regarding the comparability of the capital stock data across countries. However, as Hsieh & Klenow (2007) have documented, the price of investment goods does not vary greatly across countries, so that the domestically priced investment series are potentially comparable. Furthermore, the results do not appear to be driven by the differences in capital productivity between sectors, so the conclusions do not hinge on the domestically priced capital data.

[8] Total population in each sector is used throughout the paper to measure the labor force. There are no appreciable differences to the results if one uses only the economically active population in each sector as the relevant labor force.

Data on years of education by sector are obtained from Timmer (2000), who provides average years of education for people over 25 broken down by rural and urban residence. For the purposes of this article I apply the rural measure of education to all agricultural workers and the urban measure of education to all industrial workers. To translate this data into measures of human capital I employ a standard Mincerian technique. However, there is surprisingly little evidence available on the returns to education by sector. Data does seem to suggest that agriculture is less human capital intense than industry (see Caselli and Coleman 2001, for example), suggesting lower returns to education. Therefore I use the returns to years of education given by Psacharapoulos (1994) for the industrial sector only[9]. For the agricultural sector, I use values that are equal to one-half of the returns in the industrial sector. This choice is arbitrary, but in experimenting with various combinations of returns to rural education levels the effect on the results was negligible. One advantage of using agricultural returns that are one-half of industrial returns is that this leads to an near equalization of the marginal product of an efficiency unit of labor across sectors for most rich countries, where we would expect factors to be most mobile.

An additional issue is that sector level observations of years of education are not available for all countries, nor for all years. There is a regularity in the data, though, that can be used to interpolate years of education by sector for those missing observations. This regularity is that the ratio of rural to urban school years gradually climbs towards one as the total years of education increases.[10]. Appendix A describes in detail the interpolation technique, which is used to obtain data for 12 of the countries in the 1985 sample.

The amount of agricultural land, in hectares, is also obtained from the FAOSTAT database. Finally, the levels of A_A and A_I are calculated as residuals from equations (7) and (8) given data on output, the endowments, and allocations.[11]

[9] Those returns are 13.4% for each of the first four years of education, 10.1% for each of the next four years, and 6.8% for each year after the eighth.

[10] This fact is something exploited by Cordoba & Ripoll (2004) using UNESCO data to perform a similar interpolation process.

[11] An important difference with the work of Caselli (2005) arises here. He systematically overstates the value of A_A in rich countries because of the methods he uses to deal with physical and human capital distributions.

For physical capital, he assumes from the outset that capital is allocated efficiently across sectors in every country. This allows him to divide up an aggregate measure of total capital to agriculture and industry. Given that most output is produced in the non-agricultural sector, Caselli is therefore assuming that capital is heavily concentrated in industry. Caselli's method understates the allocation of capital in agriculture, particularily in poor countries where

The combination of different data sources yields a set of 42 countries for the year 1985. This sample ranges across the income scale, although it is tilted towards rich countries, including 10 from the EU as well as Australia, Canada, New Zealand, and the United States. There are three countries that are at the extreme lower end of the income scale (Kenya, Malawi, and Zimbabwe), and it will be shown that the exclusion of these countries does not materially impact the results.

3.3 Marginal Product Evidence

The microeconomic evidence surveyed by Banerjee & Duflo (2005) shows great heterogeneity in the rates of return to similar factors within a country. The macroeconomic data available in this paper offers the same evidence of misallocation of resources. Given the production functions for agriculture in (5) and industry in (6), I can calculate the marginal product of labor in each sector for each country. Most countries have a significant gap between the marginal products of labor across sectors. The ratio of marginal product of labor in industry to that of agriculture (MPL_I/MPL_A) ranges from a low of 1.67 in Australia to a high of 16.84 in Kenya. The ratio for all countries is found in table 3.[12]

As noted above, the more relevant measure for our purposes is the marginal product of a unit of human capital. The marginal product of H can be calculated for each sector, and the ratio of industry to agriculture (MPH_I/MPH_A) is obtained. This ratio ranges from 0.96 in Australia to 12.30 in Kenya, and values for all countries are available in table 3. The ratio MPH_I/MPH_A is lower in all cases than the ratio MPL_I/MPL_A, as expected, given that human capital per person is larger in the industrial sector than in the agricultural sector in each country. However, the fact

capital tends to be very inefficiently allocated.

A similar problem occurs with human capital. Lacking data on human capital by sector, Caselli assumes that there is *no* human capital in agriculture, and assumes that all the human capital in the economy (as measured by a standard Mincerian method) is spread over only the industrial labor force. This is understating the level of human capital in agriculture, and in particular this eliminates any variation between countries in human capital in agriculture.

The result of *understating* the variation in physical and human capital allocations to agriculture is to *overstate* the variation in agricultural productivity between countries. Thus he finds in his calculation that sector productivity levels are important for income variation. Referring back to Figure 3, his data methods have shifted up the $y\left(l_A|k_i, A_{A,US}, A_{I,US}\right)$ curve, raising his estimate of $\left(y_i^1 - y_i^0\right)$. Replicating Caselli's work, but using the actual sector allocations of human and physical capital causes his "success ratio" to rise appreciably, indicating that less of the income distribution can be explained by sector productivity.

[12] Given the structure of the production functions and the parameters chosen, the ratio of marginal product of labor between sectors is identical to the ratio of average product of labor between sectors.

that MPH_I/MPH_A deviates from a value of one indicates potential misallocation of human capital between sectors.[13] The evidence shows that MPH_I/MPH_A is far from one even in several highly developed countries (e.g. Austria and Italy). While we might expect these countries to have well functioning labor markets that equalize the marginal product of human capital across sectors, there are also many policies in place in these countries that deliberately act to retain labor in agriculture despite its relatively low productivity. On the other hand, these results could suggest that there are issues with the measurement of output, labor, or capital. This possibility should be kept in mind when drawing conclusions from the results of this paper.

4 Income Decomposition

The evidence of the preceding section suggests there may be misallocation of resources within economies, but does not address whether this misallocation contributes to the variation in income across countries. Returning to figure 3, I want to calculate y_i^2 for each country i (the maximum income over the share of resources in agriculture), so that we can evaluate V in (3). The basic maximization is:

$$y_i^2 = \max_{q_{Ai},k_{Ai}} y_i \tag{10}$$

Note that the maximization in (10) is over the share of human capital allocated to agriculture ($q_{Ai} = H_{Ai}/H_i$) as opposed to the share of the labor force allocated to agriculture (L_{Ai}/L_i). By focusing on the allocation of efficiency units of labor (H), the optimization in (10) allows for the possibility that wages *per person* by sector may vary because of differences in actual human capital by sector.

[13] As a check on the data that are used to obtain MPH_I/MPH_A I compare this ratio to (where available) data on the wage ratio between sectors. Using wage index data from the International Labor Organization (2004) LABORSTA database the ratio of manufacturing to agicultural wages (w_I/w_A) is calculated, giving only 14 matched observations. The correlation of the two ratios is 0.81, and significant at less than one percent. However, the scale of MPH_I/MPH_A is much larger than w_I/w_A. For example, the ratio of MPH_I/MPH_A in Kenya is 12.30, but the w_I/w_A ratio is only 3.18. Does this indicate that the MPH_I/MPH_A ratio is wrong? Not necessarily. The fact that wages do not deviate by as much as marginal product may indicate a distorted labor market in which wages do not equal marginal products. The relatively small size of the w_I/w_A ratio indicates a more efficient labor market only if one accepts that wages are exactly equal to marginal products. As we are interested in the determinants of aggregate productivity and income, though, MPH_I/MPH_A is the relevant measure.

Using (7) and (8) I can now expand (10) to

$$y_i^2 = \max_{q_{Ai},k_{Ai}} \left\{ \Omega_{Ai} k_{Ai}^{\gamma} q_{Ai}^{1-\gamma-\lambda} + \Omega_{Ii} \left(1 - k_{Ai}\right)^{\beta} \left(1 - q_{Ai}\right)^{1-\beta} \right\} \tag{11}$$

where

$$\Omega_{Ai} = A_{Ai} \left(\frac{R_i}{L_i}\right)^{\lambda} \left(\frac{K_i}{L_i}\right)^{\gamma} \left(\frac{H_i}{L_i}\right)^{1-\lambda-\gamma} \tag{12a}$$

$$\Omega_{Ii} = A_{Ii} \left(\frac{K_i}{L_i}\right)^{\beta} \left(\frac{H_i}{L_i}\right)^{1-\beta} \tag{12b}$$

There is a major assumption working within (11) that needs to be mentioned. Each country i is assumed to be a small open economy, so that relative prices are not affected by the allocation of human or physical capital within the country. This assumption will be relaxed in a subsequent section.

The first order conditions of the maximization show the standard result that marginal products of factors should be equal across different sectors.

$$\left(1 - \gamma - \lambda\right) \Omega_{Ai} k_{Ai}^{\gamma} q_{Ai}^{-\gamma-\lambda} = \left(1 - \beta\right) \Omega_{Ii} \left(1 - k_{Ai}\right)^{\beta} \left(1 - q_{Ai}\right)^{-\beta} \tag{13a}$$

$$\gamma \Omega_{Ai} k_{Ai}^{\gamma-1} q_{Ai}^{1-\gamma-\lambda} = \beta \Omega_{Ii} \left(1 - k_{Ai}\right)^{\beta-1} \left(1 - q_{Ai}\right)^{1-\beta} \tag{13b}$$

Given that $1 - \beta$ is assumed to be equal to $1 - \gamma - \lambda$, $(13a)$ can be solved for an intermediate solution for the share of human capital in agriculture.

$$q_{Ai}^{*} = \frac{1}{1 + \left[\frac{\Omega_{Ii}(1-k_{Ai})^{\beta}}{\Omega_{Ai} k_{Ai}^{\gamma}}\right]^{1/\beta}} \tag{14}$$

where the $*$ denotes the income-maximizing value. As can be seen, the value depends on the relative productivity in the two sectors, holding the capital shares constant. Given that we have assumed $\beta > \gamma$, any increase in the capital stock will imply a shift of human capital out of agriculture. If we continue on with the derivation by putting (14) into (13b) we can solve for the income-maximizing share of capital in industry, which is:

$$k^*_{Ai} = \left(\frac{\gamma}{\beta}\right)^{\beta/(\beta-\gamma)} \left(\frac{\Omega_{Ai}}{\Omega_{Ii}}\right)^{1/(\beta-\gamma)} \tag{15}$$

Given the income-maximizing allocations of labor and capital shares in (14) and (15) we can find y_i^2, which is the hypothetical potential income in each country holding constant the levels of K_i, H_i, R_i, A_{Ii} and A_{Ai}.

Recall from (3) that we wish to compare the variance of y_i^2 across all countries to the variance of initial income. This ratio V is recorded in Table 1 in the first row and first column, and is found to be 0.666. This indicates that one-third of the cross-country income distribution can be explained by differences in the efficiency of factor allocations within countries. The 66.6% of the variation in log income that remains can be attributed to variation in physical and human capital endowments as well as the sector productivity levels (A_A and A_I). The second column of Table 1 reports the ratio V_{NA}, which simply excludes the countries of Kenya, Malawi, and Zimbabwe from the calculation. As can be seen, this actually lowers the success ratio, implying that misallocations explain *more* of the distribution of income across countries when we ignore the poorest countries in the sample.

The effect of misallocation can be seen for individual countries in Table 3. The third column for each country shows how actual income per capita compares to the hypothetical maximum by looking at the ratio y_i^0/y_i^2. This can be interpreted as measuring the percentage of potential income (y_i^2) that a country is actually achieving given its endowments of capital, labor, and sector-specific productivities.

The club of rich countries show y_i^0/y_i^2 over 0.90 and mostly approaching 1.00, which is not surprising given their low share of labor and capital operating in agriculture. The developing countries of Central and South America are relatively efficient as well, with estimates ranging from 0.61 in Guatemala to 0.95 in Argentina. Within Asia, the ratios generally lie between 0.55 and

0.70, while the values for South Korea (0.84) and Japan (0.93) are much higher.

If we turn to the nations of Sub-Saharan Africa we find that they experience the largest losses due to factor market distortions. Malawi and Kenya both have y_i^0/y_i^2 of about 0.40, while Zimbabwe has a ratio of 0.49. The implication of these values is that income per capita could be two and a half times larger in Malawi and Kenya if physical and human capital were reallocated to the higher productivity industrial sector. While the current allocation of factors may be welfare optimizing given the actual conditions (e.g., imperfect or missing markets, institutional barriers to mobility), the current allocation is certainly not income maximizing. The factor market distortions existing between the agricultural and industrial sectors in Sub-Saharan Africa have very large effects on their measured productivity.

There is a limited empirical literature to which we can compare these results, mostly confined to estimates for single countries. Harberger (1959) estimates that in Chile the allocative efficiency (the equivalent of y_i^0/y_i^2) was at least 87%. Dougherty & Selowsky (1973) find an efficiency of 98% for Colombia, although de Melo (1977) finds a value between 91% and 97% (depending on capital mobility) for Colombia using a general equilibrium model. Floystad (1975) analyzes the Norwegian labor market and finds an allocative efficiency of 97% due to gaps in marginal products of labor between manufacturing industries. For England during the Industrial Revolution, Williamson (1987) estimates an allocative efficiency of essentially 100%, looking only at labor. When he allows capital to be mobile between sectors as well the efficiency falls to 96%. His calculations were made assuming that England was an open economy and took the prices of goods as given[14].

In a broader setting, Temple (2003) finds that the allocative efficiency in a stylized developing country due to wage gaps is on the order of 95%. His method is to build a simple two-sector model of

[14] In a related line of inquiry, researchers have examined internal migration restrictions in China to understand their effect on economic development. Yang & Zhou (1999) calculate that the marginal product of labor in urban, state industries in 1992 was nearly eight times that in rural industry, and more than 16 times the marginal product of labor in agriculture. They do not provide estimates of the deadweight loss to the economy these disparities created. Yang (2004) finds that prior to the reform period beginning in 1986 capital and labor were inefficiently over-allocated to agriculture. As reforms took place, rural households shifted their resources to more productive non-agricultural activities. Interestingly, Yang finds that schooling plays a significant role in the pace at which rural households transitioned their resources out of agriculture. Finally, Au & Henderson (2006) find that internal migration restrictions have led to insufficient agglomerations of capital and labor in cities and townships. This creates a further deadweight loss to GDP over and above that caused by the simple misallocation of resources between sectors.

the economy and include a Harris-Todaro wage gap. For a stylized version of a developing country, he can calculate the potential output in two stages: first by eliminating the wage gap between sectors and second by eliminating the unemployment. Most of the loss in output is apparently due to unemployment, not the existence of the wage gap.

The current results are not necessarily incompatible with these works, and in fact the empirical estimates are consistent with the earlier findings for Chile and Norway. The previous work on Colombia indicates much higher efficiency than found in this paper. However, Dougherty & Selowsky (1973) looks only at efficiency *within* the industrial sector, while de Melo (1977) assumes that there is no distortion between rural and urban areas and focuses on distortions within broader sectors. By including the possibility of inefficiency between the agricultural and industrial sectors, this paper has found a larger effect than the previous work.

4.1 Sector-Specific Capital

In the previous section it was found that inefficiency in the allocation of physical and human capital could explain approximately one-third of the cross-country income distribution. However, this result does not offer any evidence as to how important the allocations of physical and human capital are separately. In this section I fix the capital stock at its actual level in each sector. This will allow us to see how important the misallocation of human capital is by itself. The maximization in (11) is changed to be an optimization over only q_{Ai}, and the share of capital found in agriculture is fixed at $\bar{k}_{Ai}$.

$$y_i^2 = \max_{q_{Ai}} \left\{ \Omega_{Ai} \left(\bar{k}_{Ai}\right)^{\gamma} \left(q_{Ai}\right)^{1-\gamma-\lambda} + \Omega_{Ii} \left(1-\bar{k}_{Ai}\right)^{\beta} \left(1-q_{Ai}\right)^{1-\beta} \right\} \tag{16}$$

For each country I again calculate y_i^2 and use these values to create the ratio V. Row (2) of Table 1 shows the results of this procedure. V rises, as expected, but the increase is rather small, going up by 0.016. Even holding the allocation of physical capital constant, the misallocation of human capital across sectors is still capable of explaining 30% of the cross-country income distribution. This conclusion follows as well when the sample is reduced by excluding Kenya,

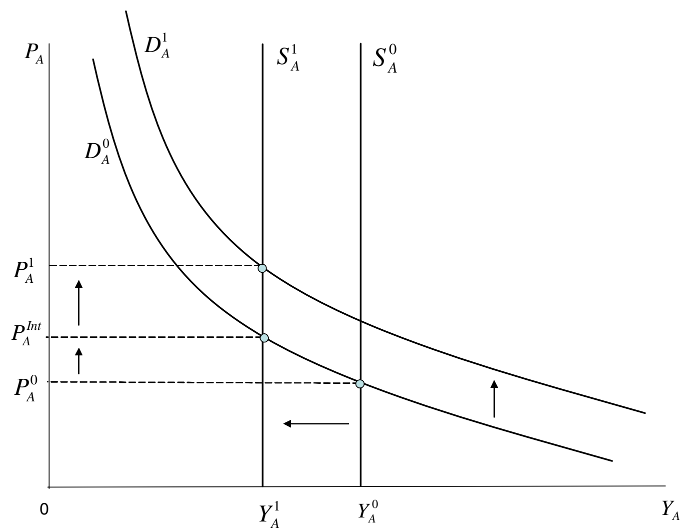

Figure 4: **Price Change Due to Change in Agricultural Labor Supply**

Malawi, and Zimbabwe, as can be seen in the second column of Table 1.

4.2 Demand Effects

To this point we have considered small open economies in which price levels were fixed. This assumption made the income maximization easier, but is not necessarily realistic for most countries. In this section I endogenize the relative price of agricultural goods by introducing some simple demand effects to the calculation of the hypothetical potential income.

As labor (more precisely, human capital) moves from the agricultural sector to the industrial sector, the supply of agricultural goods falls and so we would expect the relative price of them (P_A) to rise. This increase in P_A acts to increase the value of the marginal product of human capital in agriculture beyond that observed just because of the declining work force. The exact size of the effect depends on how sensitive P_A is to supply.

In calculating the size of this effect I have to account for two effects on prices of shifting human capital out of agriculture, illustrated in figure 4. First, as human capital moves out of agriculture the supply falls from Y_A^0 to Y_A^1. Holding the demand curve D_A^0 constant, this induces a price increase from P_A^0 to P_A^{Int}. The size of this move will depend on the price elasticity of demand for agricultural goods, which we denote ε_A. As we have seen above, moving human capital out of agriculture and into industry not only shifts the output mix but also increases overall incomes. This in turn will push out the demand curve from D_A^0 to D_A^1, raising prices from P_A^{Int} to P_A^1. The size of this shift will depend on the income elasticity of agricultural goods, denoted η_A.

Note that we are assuming the supply is inelastic at the level determined by the choice of human capital in agriculture. This allows for a simpler analysis, but also leads us to overestimate the change in price. The larger the price change that occurs due to a shift in human capital out of agriculture, the lower the estimated size of the potential income (as the MPH_A curve will shift up faster). This biases the subsequent analysis against finding large losses and hence will tend to push all the efficiency estimates closer to one, which works against the general theme of this paper that efficiency plays a significant role in the distribution of income.

To estimate the price effects, I make several simplifying assumptions regarding the structure of agricultural demand. First, I assume that both the price and income elasticities are constant. Thus any changes in P_A are independent of the level of P_A and this means I do not have to obtain estimates of the original price level. Second, I assume that the values of ε_A and η_A are such that $\varepsilon_A = -\eta_A$. This assumption makes the price changes easy to calculate and in fact matches common assumptions made about these values - see Williamson (1987). The actual values chosen for the elasticities are $\varepsilon_A = -0.6$ and $\eta_A = 0.6$. Thus the demand for agricultural goods is inelastic to price and has an income elasticity less than one, both of which mesh with general intuition and match those chosen in Williamson (1987) when doing a similar exercise.

The elasticities allow me to calculate the price P_A that must prevail at any allocation of human capital to agriculture, q_A, such that the quantity of agricultural goods demanded equals the quantity being supplied. The price of agricultural goods is thus a function of q_A, given ε_A and η_A:

$$P_A = p\left(q_A|\varepsilon_A, \eta_A\right) \tag{17}$$

For the purposes of this section I continue with the assumption that capital is fixed in each sector, as in the maximization in (16). Using (17) I can now analyze the following.

$$q_{Ai}^{*} = \arg\max_{q_{Ai}} \left\{ P_A \Omega_{Ai} \left(\bar{k}_{Ai}\right)^{\gamma} \left(q_{Ai}\right)^{1-\gamma-\lambda} + \Omega_{Ii} \left(1 - \bar{k}_{Ai}\right)^{\beta} \left(1 - q_{Ai}\right)^{1-\beta} \right\} \tag{18}$$

Note that in (18) I am looking for the optimal value of q_{Ai}^{*}, not the maximized value of y_i^2. This is because to compare y_i^2 in this calculation to the previous calculations, it must be valued at a similar set of prices. Therefore y_i^2 is calculated at the original set of prices as follows:

$$y_i^2 = \Omega_{Ai} \left(\bar{k}_{Ai}\right)^{\gamma} \left(q_{Ai}^{*}\right)^{1-\gamma-\lambda} + \Omega_{Ii} \left(1 - \bar{k}_{Ai}\right)^{\beta} \left(1 - q_{Ai}^{*}\right)^{1-\beta} \tag{19}$$

With (19) I can now calculate the values of V for the sample. These results are reported in row (3) of Table 1. The value of V increases, but by only two percentage points. It remains that roughly thirty percent of the income distribution has been accounted for solely by the misallocation of human capital, even including price effects that operate to minimize this number. Again, this result is not reversed by the exclusion of Kenya, Malawi, and Zimbabwe from the analysis, as can be seen by the value of V_{NA} in row (3).

4.3 Domestic Price Data

To this point I have been performing calculations using PPP valued output data by sector, which limited the analysis to the year 1985. This was done to ensure comparability of y_i^2 across countries. This had indicated that both human and physical capital appear misallocated between agriculture and industry. One possible reason for this is that the domestic relative price of agricultural goods is much greater than the PPP relative price of agricultural goods, so that allocations of human and physical capital across sectors are efficient from the domestic perspective.

To address this possibility, I redo the previous analysis with domestically priced output data by sector. Using this data I can create a domestically priced value for sector productivity levels A_A and A_I, and then calculate y_i^2 under various assumptions. With y_i^2 I can then calculate V again. If V approaches one, this would indicate that factors are efficiently allocated across sectors when output is valued at domestic prices. Thus domestic price distortions could be a major cause of the observed real misallocation of human and physical capital. However, if the V ratio does not change much, this would indicate that domestic prices are not distorted enough to explain the misallocation.

Table 2 reports the ratios V and V_{NA} in the case where y_i^2 is calculated by optimizing over q_{Ai}, holding $\bar{k}_{Ai}$ constant, and allowing for price effects as in the previous section. The values are reported not only for 1985, but for four other years as well, because by using domestically priced output data I can expand the available years.[15] Looking at the year 1985, the ratio V is now 0.707, while the comparable ratio when I used PPP valued output was 0.701 (see table 1). V has risen by less than a percentage point, indicating that domestic price distortions play a small role in explaining the apparent misallocation of factors.

Examining the other years of data available in table 2, one can see that the ratio V for 1985 is relatively high, and that the share of the income distribution explained by factor misallocations is closer 40% in 1970, 1975, and 1980. The ratio V_{NA} is also reported for all years, and this shows a similar result to before. When we exclude the outlying countries of Kenya, Malawi, and Zimbabwe, factor market efficiency actually explains more of the income distribution than when they are included.

Without comparable PPP numbers for the other years, we cannot make a definitive statement, but it appears that domestic price distortions are not the primary cause of the observed inefficiency in factor markets.

5 Factor Markets and Aggregate TFP

To this point we have established that misallocations of capital and labor can account for a large portion of the income distribution. Recall from (2) that this portion is a subset of the portion attributable to variation in aggregate TFP. The question in this section is: how big a subset of aggregate TFP does factor market efficiency account for?

[15] The number of observations are: 29 for 1970, 39 for 1975, 42 for 1980, 42 for 1985, and 46 for 1990.

To answer this question will require determining the level of y_i^3 from figure 3, which is the income a country would have if it 1) had the sector level productivity of the United States and 2) maximized its income over the allocation of factors to agriculture.[16] We can then calculate a new ratio using y_i^3, and this will indicate how much of the income distribution is explained by aggregate TFP in total.

$$W = \frac{var\left(\ln y_i^3\right)}{var\left(\ln y_i^0\right)} \in [0,1] \tag{20}$$

We expect that $W < V$ for a comparable sample, because we are now eliminating an additional source of variation in income between countries. Comparing W to the previous values of V will show how much more of the income distribution is being explained by differences in sector productivity levels across countries.

To calculate y_i^3, I need to only slightly modify the original maximization in (11). The maximization is now:

$$y_i^3 = \max_{q_{Ai},k_{Ai}} \left\{ \Omega_{Ai}^{US} \left(k_{Ai}\right)^{\gamma} \left(q_{Ai}\right)^{1-\gamma-\lambda} + \Omega_{Ii}^{US} \left(1-k_{Ai}\right)^{\beta} \left(1-q_{Ai}\right)^{1-\beta} \right\} \tag{21}$$

where

$$\Omega_{Ai}^{US} = A_{A,US} \left(\frac{R_i}{L_i}\right)^{\lambda} \left(\frac{K_i}{L_i}\right)^{\gamma} \left(\frac{H_i}{L_i}\right)^{1-\lambda-\gamma} \tag{22}$$

$$\Omega_{Ii}^{US} = A_{I,US} \left(\frac{K_i}{L_i}\right)^{\beta} \left(\frac{H_i}{L_i}\right)^{1-\beta} \tag{23}$$

This maximization can be modified as before to hold the capital share in agriculture fixed and

[16] The use of the United States as the reference country is not essential because I am examining income levels when allocations are optimized for the reference levels of $A_{A,US}$ and $A_{I,US}$ Any set of levels of sector productivity could be used for this purpose, and I chose the U.S. as a reference only to be consistent with previous work.

This, though, is in contrast to the work of Caselli (2005). Using the data from my sample, I replicated Caselli's methodology (i.e. leave q_{Ai} and k_{Ai} as they are and giving each country $A_{A,US}$ and $A_{I,US}$) and found that the share of the income distribution explained in this manner depends crucially on the choice of reference country. In my sample, Caselli's success ratio of $var\left(\ln y_i^1\right)/var\left(\ln y_i^0\right)$ is 0.68 when the U.S. is used. However, the ratio is 0.78 if Japan is the reference country. As mentioned previously, these ratios rise appreciably when the actual sector allocations of human and physical capital are used (to 0.76 with the U.S. as the reference and to 0.96 with Japan).

to include changes in relative prices between sectors. Results can be found in Table 1 in the final two columns. As can be seen, W is lower than the respective values of V, as expected. However, the difference between V and W is not terribly large, suggesting that eliminating variation in sector productivity levels has not explained much of the variation in income per capita across countries. In other words, once we have eliminated the misallocations of factors of production, there is not much left for sectoral productivity to explain.

The values of W indicate that 40% of the variation in income per capita can be explained by aggregate TFP, a number smaller than found in larger samples. So some caution should be attached to these findings, as some part may be played by the choice of countries for the sample. With this caveat in mind, the results here indicate that a very large portion of variation in aggregate TFP is due to inefficiency in factor markets, and not to variation in sector productivity levels. The comparison of V with W in Table 1 indicates that about 80% of the variation in aggregate TFP is accounted for by variation in the efficiency of factor markets alone. This result holds as well when the potential outliers of Kenya, Malawi, and Zimbabwe are excluded.

The implications of these results are significant for the study of cross-country income differences. Factors, both in endowments and in allocation, take on a driving role in determining income level differences. Technology, as embodied in the levels of sectoral productivity, A_I and A_A, varies much less than does aggregate TFP. A theory of aggregate TFP variation should not exclude a consideration of technology, but it appears it would fail to match the evidence if it does not consider the operation of factor markets and the efficiency with which they allocate resources to different uses within the economy.

6 Conclusion

Recent research into the distribution of income across countries has begun to look more closely at the composition of the economy, in particular the division of the economy between agriculture and non-agriculture. This work, though, has largely remained silent on the efficiency of this division, often assuming that factor markets are operating to equate marginal products between sectors. In contrast, the dual economy model has long pointed to evidence showing that similar factors receive widely varying returns within developing countries. This work, though, has not addressed whether these observed inefficiencies have appreciable aggregate impacts.

This paper is an attempt to bridge the two areas by examining the effect of factor market efficiency on aggregate productivity and income. I focus here only on the allocation of resources between agriculture and non-agriculture. The evidence shows that differences in factor market efficiency can explain nearly 80% of the variation in aggregate TFP between countries, and between 30-40% of the variation in income per capita. Most strikingly, productivity levels within the agricultural and non-agricultural sector appear to have very little impact on the relative incomes of rich and poor countries. The analysis is based upon the best available data on sector-level inputs and output across sectors, but this data is not perfect and better measures or a broader set of countries might diminish the magnitude of the results found here.

This finding, though, should not be confused with a prescription for deliberately moving capital and people out of agriculture. The results suggest that if distortionary policies were removed, labor and capital would likely flow to industry and raise aggregate income. Whether this would result in an improvement in welfare within an economy is something beyond the ability of this paper to answer.

Lastly, the results warn against equating TFP with technology, and suggests that theoretical studies of TFP would benefit from a consideration of the operation of factor markets. This paper was able to establish the importance of these factor market inefficiencies, but leaves open the question of why inefficiencies exist and persist within countries. The estimates here show that policies that would enhance the mobility of capital and labor within countries could have a significant impact on income levels, even without changes in technology employed.

Appendix - Interpolating Schooling Data

Years of schooling broken down by rural and urban populations is available in Timmer (2000), and is derived from the data sources used by Barro & Lee (1996). This data is available for most countries in the sample for the years 1970, 1975, 1980, and 1985. This data displays a very strong relationship between rural and urban schooling years that I use to interpolate the schooling data for all countries in 1990.and for missing observations in previous years.

The relationship I rely on is that rural school years appear to converge towards urban school years as overall schooling levels increase. This relationship exists until overall years of education is greater than 6.6. For every country with total years of education per person over 6.6, urban and rural school years are the same.

Calling urban school years in country i at time t E_{Uit} and rural school years E_{Rit} I perform a simple OLS regression on the 77 country/year observations which have total years of education of less than 6.6 years. The results are as follows, with t-statistics for the coefficients listed in parentheses under the equation.

$$E_{Rit} = \underset{(16.18)}{1.071} E_{Uit} - \underset{(5.17)}{1.518},\ R^2 = 0.78,\ n = 77 \tag{24}$$

In addition to this relationship, I know that overall years of education are simply the average of the rural and urban years, weighted by the size of the population in each area.

$$E_{Tit} = l_{Ait} E_{Rit} + (1 - l_{Ait}) E_{Uit} \tag{25}$$

where E_{Tit} is total years of education per person in country i at time t, and l_{Ait} is the share of population in rural areas. I can solve (24) and (25) together to find expressions for E_{Rit} and E_{Uit} as functions of total education and the rural population share. Total years of education is available from Barro & Lee (1996) for the missing country/year observations, which includes all countries in 1990. Rural population share is obtained from the FAOSTAT database. I can then interpolate values for E_{Rit} and E_{Uit} in all country/year observations where overall years of education is less than 6.6. For all countries in which total years of education is greater than 6.6 I assign the total years of education to both the rural and urban sectors.

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Case	y_i^2 maximized over	Price Effects	(1) V	(2) V_{NA}	(3) W	(4) W_{NA}
(1)	q_{Ai}, k_{Ai}	No	0.666	0.602	0.623	0.534
(2)	q_{Ai}	No	0.681	0.614	0.633	0.542
(3)	q_{Ai}	Yes	0.701	0.631	0.633	0.543
	Number of countries		42	39	42	39

Notes:
$V = var\left(\ln y_i^2\right)/var\left(\ln y_i^0\right)$
$W = var\left(\ln y_i^3\right)/var\left(\ln y_i^0\right)$
V_{NA} and W_{NA} exclude Kenya, Malawi, and Zimbabwe

Table 1: Variance Ratios, 1985

Year	V	V_{NA}
1970	0.622	0.551
1975	0.604	0.550
1980	0.616	0.550
1985	0.707	0.632
1990	0.686	0.613

Notes:
$V = var\left(\ln y_i^2\right)/var\left(\ln y_i^0\right)$
y_i^2 maximized over q_{Ai}
including price effects
V_{NA}excludes Kenya, Malawi,
and Zimbabwe

Table 2: Variance Ratios using Domestic Prices

Country	$\frac{MPL_I}{MPL_A}$	$\frac{MPH_I}{MPH_A}$	y_i^0/y_i^2	**Country**	$\frac{MPL_I}{MPL_A}$	$\frac{MPH_I}{MPH_A}$	y_i^0/y_i^2
Argentina	2.81	1.87	0.95	Malawi	13.72	8.36	0.40
Australia	1.67	0.96	0.98	Netherlands	2.05	1.26	0.97
Austria	4.27	2.64	0.94	New Zealand	1.83	0.99	0.98
Canada	2.00	1.13	0.96	Norway	3.37	2.07	0.93
Chile	2.10	1.39	0.85	Pakistan	4.70	3.72	0.63
Colombia	2.03	1.48	0.80	Peru	7.44	4.59	0.76
Costa Rica	4.23	2.83	0.81	Philippines	3.91	2.44	0.69
Denmark	2.90	1.71	0.96	Portugal	5.21	3.70	0.84
Dominican Rep.	2.83	2.00	0.84	South Africa	9.37	6.29	0.84
Egypt	4.55	3.29	0.69	South Korea	2.65	1.65	0.84
El Salvador	4.53	3.21	0.72	Sri Lanka	2.73	1.80	0.69
Finland	2.32	1.46	0.91	Sweden	2.70	1.60	0.96
France	2.41	1.56	0.94	Syria	1.74	1.27	0.77
Greece	2.91	1.92	0.87	Tunisia	2.88	2.21	0.77
Guatemala	3.78	2.58	0.61	Turkey	3.03	2.31	0.72
Honduras	6.26	4.25	0.66	United Kingdom	1.89	1.16	0.99
India	3.21	2.11	0.56	United States	2.26	1.20	0.99
Indonesia	3.32	2.37	0.69	Uruguay	1.81	1.15	0.97
Iran	3.70	2.75	0.78	Venezuela	3.86	2.35	0.91
Italy	3.89	2.72	0.93	Zimbabwe	11.91	8.40	0.49
Japan	3.31	2.02	0.93				
Kenya	16.84	12.30	0.40				

Note: Method of calculation described in text.

Table 3: Selected Ratios for Sample, 1985