Measuring the Cost of Misallocating Resources in a Dual Economy

Dietrich Vollrath*

Draft: June 15th, 2004

ABSTRACT: A dual economy is often presumed to exist in developing countries. Despite the prevalence of this idea in the economics literature, there are no clear estimates of the aggregate effect of this duality - meaning gaps in returns to factors of production between sectors - on income per capita. This paper provides for the first time macroeconomic estimates on the size of the deadweight losses associated with duality using a sample of countries in the time period 1970-1990 . The estimates indicate potentially large losses in output of up to 65% of GDP in developing countries due to the inefficient allocation of labor and capital to agriculture. The variation in allocative efficiency is able to explain up to one-half of the variation in TFP across countries, making it a significant source of potential growth in developing countries.

JEL Codes: O1, O4, Q1

Keywords: Resource allocation, Labor allocation, Agricultural Productivity, Dual Economy

*I'd like to thank Areendam Chanda, Carl-Johan Dalgaard, Oded Galor, Malhar Nabar, Omer Moav, Jonathan Temple, and David Weil for helpful comments and advice. In addition, the participants in the Brown Macro Lunch were especially helpful during the early stages of this research. All errors are, of course, my own.

Dept. of Economics, Box B, Brown University, Providence, RI 02906,
Dietrich_Vollrath@brown.edu

1 Introduction

The transformation of developing nations from primarily rural and agricultural to primarily urban and industrial led to one of the most enduring ideas in economics - the dual economy. The term itself is often attributed to Boeke (1953), but the concept is most strongly associated with Lewis (1954)[1]. Generally, the dual economy refers to the presence of two distinct sectors within a country: the backward, poor sector and the modern, prosperous sector. These sectors are identified in many ways within the development literature: rural versus urban, agriculture versus manufacturing, home versus factory production, or the absence or presence of markets for credit and risk. What all these definitions of the dual economy ultimately lead to, though, are differences in productivity between the two sectors.

This paper examines these gaps in both labor and capital productivity within the dual economy and the effect they have on aggregate productivity. Here the duality of the economy will be identified with the differences between the agricultural and non-agricultural sectors. Data from 48 countries over the period 1970-1990 shows that there are wide gaps between sectors in the marginal products of labor and capital. For labor, the size of these gaps is closely associated with income levels; the richer the country, the smaller the gap tends to be. This echoes the findings of Kuznets (1982), who found that the gap in labor productivity between agriculture and industry declined as countries got richer.

This macro level data accords well with the microeconomic theory and evidence of duality in wage rates between the rural (agricultural) and urban (industrial) sectors. Harris and Todaro (1970) explained the wage gap through the existence of uncertain employment in the urban sector, theorizing that people are equating expected wages rather than actual wages. Subsequent authors attributed the wage gap to employee turnover (Stiglitz 1974) and labor unions (Calvo 1978)[2]. Empirical research by Squire (1981) showed these wage gaps to be real phenomenon. Work by Todaro (1976), Yap (1977), and Lucas (1985) showed that wage differentials were significant in inducing internal migration between sectors in developing countries. Regardless of the source, the

[1] Running closely behind Lewis are the contributions of Jorgenson (1961) and Ranis and Fei (1961), who challenged and extended Lewis' model.

[2] See Rosenzweig (1988) for a more thorough discussion of the sources of the wage gap in developing countries.

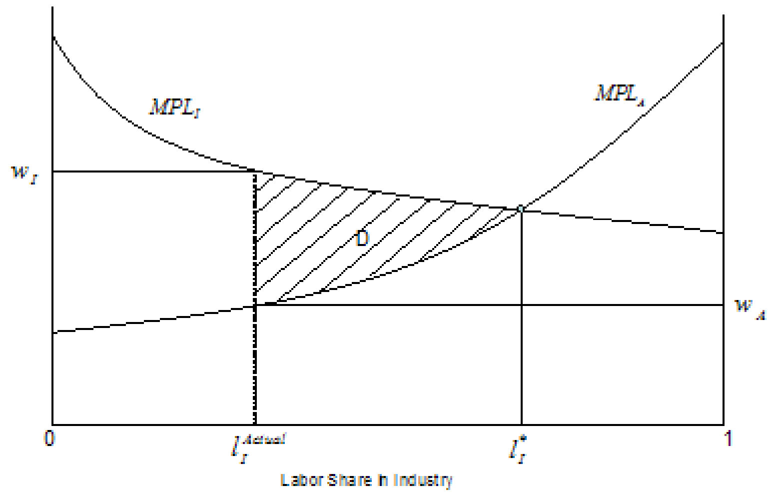

Figure 1: Deadweight Loss Due to Misallocation

evidence (both macro and micro) points to a gap in productivity between sectors within the dual economy.

The existence of these gaps imply that there is a deadweight loss within an economy. Figure 1 shows a standard diagram for understanding this loss. With the share of labor in industry indicated on the horizontal axis, the marginal product curves of the industrial and agricultural sectors are plotted from opposite sides of the diagram. Where these two intersect is the income-optimizing level share of labor in industry, l_I^*. If in fact the amount of labor in industry is only l_I^{Actual}, then there is a wage gap of size $w_I - w_A$ and a deadweight loss of output given by area D.

The essential question of this paper is how big is D? The limited empirical literature on this subject is mostly confined to estimates for single countries. Harberger (1959) estimates that in Chile the deadweight loss associated with labor market distortions was at maximum equal to 15% of GDP. Dougherty and Selowsky (1973) find a loss of only two percent for Colombia, although de Melo (1977) finds a loss between three and ten percent (depending on capital mobility) in

Colombia using a general equilibrium model. Floystad (1975) analyzes the Norweigan labor market and finds a deadweight loss of three percent of GDP due to gaps in marginal products of labor between manufacturing industries. For England during the Industrial Revolution, Williamson (1987) estimates a loss of only about one-half of one percent in national output. When he allows capital to be mobile between sectors as well the loss comes to about 3.3 percent of national output. His calculations were made assuming that England was an open economy and took the prices of goods as given.

More recently, Temple (2003) finds that the output loss to a stylized developing country due to Harris-Todaro type wage gaps is only on the order of 5%. His method is to build a simple two-sector model of the economy and include a wage gap defined by the level of urban unemployment. 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 paper goes beyond these previous studies by calculating the deadweight loss for a panel of countries in the post-war era, the first such attempt that I am aware of. Using sector-level data on both capital and labor as well as output we can calculate sector-specific TFP levels. Using these and the aggregate levels of capital and labor we can compute the maximum potential income for each country when marginal products are equalized and compare that to actual income. The ratio of actual to potential income - $Y/(Y+D)$ essentially - gives us the *allocative efficiency* at which economies are operating. The results show large differences both between countries and within countries across time in their allocative efficiency. The rich countries are indeed operating quite close to their income-maximizing allocations, while countries such as Kenya and Tanzania have incomes that are not even half of their potential (in other words D is actually larger than Y).

The finding that there are significant deadweight losses in some countries may seem to stand in contrast to previous research mentioned. This apparent inconsistency arises primarily because those papers focused on stylized versions of developing countires (Temple) or on single countries (all the others). The current results are not necessarily incompatible with these works, and in fact the empirical estimates are quite consistent with the earlier findings for Chile, Colombia and

Norway. What the present research indicates is that there is wide variation across countries in their allocative efficiency and that some individual countries may indeed have large deadweight losses.

The variation in efficiency suggests that it may play some role in shaping the distribution of income across countries. This ties the current work into the development accounting discussion associated most prominently with Hall and Jones (1999) and Klenow and Rodriguez-Clare (1997). Those papers establish that a large portion (50-70%) of the variation in income per capita across countries is due to variation in aggregate total factor productivity (TFP). More accurately, over half of the variation in income per capita is *unexplained* by variation in physical and human capital. Using the estimates in this paper we can perform a similar development accounting exercise and show that efficiency of resource allocation can explain about one-fifth of the variation in income per capita. In other words, efficiency can explain between one-third and one-half of the unexplained residual in a typical development accounting exercise.

Several authors have already noted how important sectoral allocations of resources are to understanding the variation in income per capita. Work by Gollin, Parente, and Rogerson (2002) and Restuccia, Yang, and Zhu (2003) explores the possibility that the combination of subsistence constraints and differences in agricultural TFP drive the income distribution. Restuccia (2004) and Graham and Temple (2003) use barriers to capital accumulation and multiple steady states, respectively, to create models in which the allocation of resources between sectors influences TFP. Their simulations show that these allocations can determine up to 50% of the variation in TFP between countries. Dalgaard and Chanda (2003) address the question more directly by doing a decomposition of aggregate TFP across countries. Their evidence suggests that one-third of the variation in aggregate TFP can be attributed to differences in the allocation of labor across sectors. In contrast to these studies Caselli (2003), as part of his examination of development accounting, finds that labor allocations have very little significance in explaining cross-country variation in incomes[3].

[3] Caselli's method is to construct counterfactual distributions of income which eliminate variation in productivity and leave only variation in factors and then compare this to actual income distributions. One aspect of this method that causes concern is that the counterfactuals are constructed using arbitrary levels (those of the U.S.) of productivity in the agricultural and non-agricultural sector. This eliminates variation in productivity but does not address the covariation between productivity and other elements of the production function. In particular, land per worker and productivity in agriculture are highly negatively correlated. If the counterfactual constructed holds land per worker

None of these papers distinguish in their analysis whether the allocation of resources across sectors maximizes income or not. Restuccia (2004) relies on assumption that the marginal product of labor is equalized between sectors, something which the evidence in this paper shows is not true. Graham and Temple (2003) and Dalgaard and Chanda (2003) include a Harris-Todaro style gap between wages in agriculture and industry in their modelling, but do not allow this parameter to vary across countries in their empirical work, eliminating this as a source of variation. In Gollin, Parente, and Rogerson (2002), the issue of wage equalization is bypassed completely by assuming a single optimizing agent in each economy. Caselli (2003) uses a method which is incapable of capturing the effects of allocative inefficiency. The counterfactual he constructs eliminates variation in sector-level productivity but leaves in place all the variation between countries in deadweight loss, resulting in low estimates of the impact of labor allocations on the income distribution.

The work by Restuccia, Yang, and Zhu (2003) is closest in spirit to the present paper. They allow for Harris-Todaro labor market distortions in an economy, estimating their size in each country by comparing the average product of labor in each sector. In their calibrations, they find that these gaps in average product are significant in explaining the distribution of income across countries. They do not identify, though, the actual deadweight losses associated with the dual nature of the economies they study.

There is of course a host of other research which explores the allocation of resources (labor, primarily) between sectors. Most of this work overlooks entirely the dual nature of the economy. Reviewing only relatively recent work, papers by Matsuyama (1992), Laitner (2000), and Kongasmut, Rebelo, and 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 and McDermott (1995) and Hansen and Prescott (2002) use the transition from agricultural to industrial workforces to capture the emergence of sustained growth, but again assume efficient allocations of labor between sectors. Kogel and Prskawetz (2001) construct a unified growth model in which agricultural workers are paid their average product, not their marginal, but again wages are assumed to be equal between sectors. Their model thus includes some deadweight

constant at the U.S. level as well, then the amount of variation in income explained rises by a significant amount.

loss due to this allocative inefficiency, but they do not explore this feature. In exlporing the sectoral composition of developed countries, Echevarria (1997) bypasses the issue completely by assuming a single optimizing agent in the economy.

The present work offers evidence that the quantitative effect of the deadweight losses due to duality play a large role in the development of economies - confirming the intuition of the development literature. Research which attempts to model the transformation of economies from agricultural to industrial would be improved by incorporating the idea of the dual economy. The evidence suggests that up to one-third of the present distribution of income may in fact be explained by the duality of the economic environment.

The paper proceeds as follows. Section 2 estimates the efficiency of resource allocation for a panel of countries over the period 1970-1990. Section 3 shows the importance of resource allocations in determining variation in income per capita and Section 4 concludes.

2 Estimating the Efficiency of Allocation

2.1 Set-Up

To evaluate the size of the inefficiency associated with labor (and capital) allocations across sectors, we first need to make some assumptions that will make this exercise empirically possible. The price level for each sector is assumed to be fixed within each country. This is equivalent to assuming each country is a small, open economy, but we do not require that prices are actually identical for *all* countries. The assumption of fixed prices is for computational simplicity, not a statement about the economic reality. Each country is also assumed to possess the same production function in each sector. The assumptions are restrictive, but are necessary to keep the exercise tractable from an empirical standpoint, as they allow us to ignore preferences and savings behavior. In the end we will arrive at an estimate for the deadweight loss due to misallocation of resources that may serve as a starting point for more refined analysis that takes into account openness to trade and changes in relatives prices.

To proceed we will define production functions for each sector and make assumptions regarding the parameters of these functions[4]. For our purposes here, we assume the economy is divided into two sectors: agriculture and industry[5]. The production functions are Cobb-Douglas as follows:

$$Y_A = A_A K_A^{\gamma} R^{\lambda} \left(L_A\right)^{1-\gamma-\lambda} \tag{1}$$

$$Y_I = A_I K_I^{\beta} \left(h_I L_I\right)^{1-\beta} \tag{2}$$

Where Y_i represents output, K_i is physical capital, R is land, L_i is labor, h_i is human capital and A_i is productivity in the sectors agriculture (A) and industry (I). The agricultural production function is consistent with a long literature on cross-country agricultural production functions begun by Hayami (1969) and Hayami and Ruttan (1970) and reviewed comprehensively in Mundlak (2000).

Equations (1) and (2) can be rewritten in per capita terms, with the share of each factor assigned to each sector clearly indicated:

$$\frac{Y_A}{L} = A_A \left(\frac{K}{L}\right)^{\gamma} \left(\frac{K_A}{K}\right)^{\gamma} \left(\frac{R}{L}\right)^{\lambda} \left(\frac{L_A}{L}\right)^{1-\gamma-\lambda} \tag{3}$$

$$\frac{Y_I}{L} = A_I \left(\frac{K}{L}\right)^{\beta} \left(\frac{K_I}{K}\right)^{\beta} \left(h_I\right)^{1-\beta} \left(\frac{L_I}{L}\right)^{1-\beta} \tag{4}$$

The elasticities on capital (γ) and land (λ) in agriculture, following Caselli (2003), are taken from Jorgenson and Gollop (1992), which are derived from factor payments in the U.S.. The elasticity on capital is 0.21, on land 0.19. This makes the labor share 0.60 in agriculture, which

[4] The approach taken here is not the only one possible to attack this question. Here we restrict the production functions in form and parameter and will allow the marginal returns of each factor to be calculated from sector specific data. Alternatively, we could make assumptions regarding the relationship of marginal products between sectors (such as a Harris-Todaro type wedge between wages due to urban unemployment) and then let the parameters of the production function be individually determined for each country by the observed data on output shares and factor shares. This is the approach used in Temple (2003), and limits the data necessary to proceed but requires assumptions regarding the level of unemployment in the urban sector. There does not appear to be anything that necessarily recommends one over the other.

[5] We 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.

is the same as that assumed for the industrial sector $(1-\beta)$, again following Caselli (2003). This obviously makes the capital share in industry equal to 0.4.

One thing to clearly note is that human capital is assumed to be absent from the agricultural sector. Evidence from Caselli and Coleman (2001) suggests that the human capital levels in agriculture are consistently lower than in any other area of the economy. Any variation in agricultural human capital will be absorbed into variation in A_A regardless. In addition, we will assume for the purposes of this paper that h_I is in fact simply equal to the average human capital per person, h, for the whole economy. These assumptions allow for a broader sample of countries to be included in the analysis and do not materially alter the results[6].

Output data is taken from the WDI database by the World Bank (2003), which gives output by sector at domestic price levels in 1995 US dollar terms. Data on total physical capital stocks is taken from Crego, Larson, Butzer, and Mundlak (1998). This data source includes a breakout of the amount of agricultural capital. Human capital is measured in a standard Mincerian manner, with returns to years of schooling taken from Psacharapoulos (1994)[7]. Average levels of schooling per person are taken from Barro and Lee (1996). Total population is taken from the FAOSTAT database of the Food and Agriculture Organization of the U.N. (FAO), 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]. The levels of A_A and A_I are easily calculated as residuals from equations (3) and (4) given the above data. The combination of all sources gives 206 country/time observation points[9].

The first step taken is to look at how actual marginal products of labor compare between sectors. Given the production functions for agriculture in (1) and industry in (2), the marginal product of labor is calculated in each sector for each country/time obsevation. In this case we want to use the

[6] The h_I term can be estimated, using data from Timmer (2000) on urban and rural years of education. This limits the number of observations further, and in the end offers little extra explanatory power. There is very little variation in the h_I/h ratio among countries despite great variation in the actual level of h.

[7] Specifically, these are 13% percent per year for the first four years of school, 10% for the second four years, and 8% for all schooling after eight years.

[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.

[9] There are 48 different countries represented, and five time periods: 1970,1975,1980,1985, and 1990. Not all countries have observations at each time period, giving a total of 206 observations.

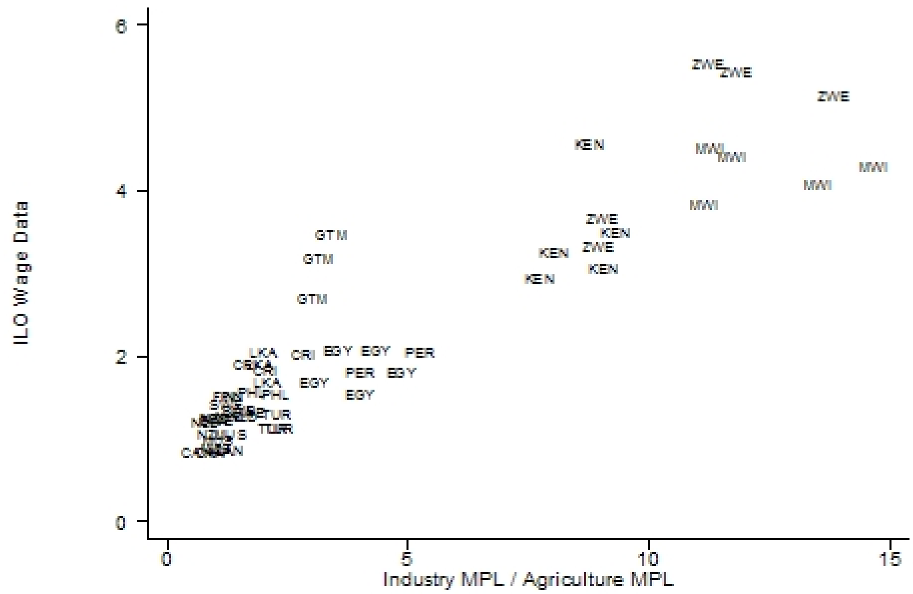

Figure 2: Comparison of Wage Ratio to Calculated Ratio of Marginal Products

domestic price data (not PPP adjusted) to calculate these marginal products because that is the relevant price for people within the economy. When we do this we find that most countries have a significant gap between the marginal products of labor. If we look at the ratio of the marginal product of labor in industry to that in agriculture, the average across the entire sample is 3.08. The range is from a low of 0.62 in Canada in 1990 to a high of 14.67 in Malawi in 1970. 183 of the 206 observations are greater than one, and 123 are greater than two.

To confirm that these marginal products of labor we have calculated do indeed reflect actual wage experiences, they are compared to (when available) data on actual wage ratios between sectors. Using wage index data from the International Labor Organization (2004) LABORSTA database the ratio of manufacturing to agicultural wages is calculated giving 54 country/year observations. Figure 2 plots this actual wage ratio from the ILO against the ratio of marginal products calculated from aggregate data.

As can be seen in the figure, the correlation of the measures is very high (0.92 and significant at

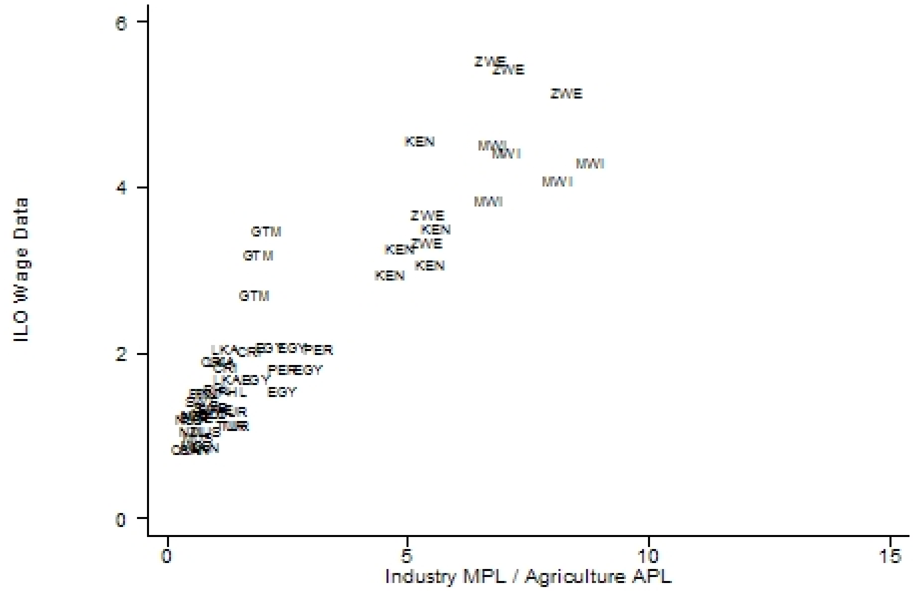

Figure 3: Comparison of Wage Ratio to Calculated Ratio - using Ag Average Product

less than one percent). The scale of the two measures is not identical, though, with the calculated ratio being much higher than the observed wage differentials. There are several possibilities for this discrepancy. First, the assumed elasticity of labor may not be identical in both sectors. If in fact the elasticity of labor in agriculture were relatively higher than in industry the calculated ratio of marginal products would decline. Second, home production by people in the agricultural sector, as discussed by Parente, Rogerson, and Wright (2000), is unmeasured and this may be falsely depresssing the calculated marginal product of labor in agriculture. Finally, agricultural workers may not in fact be paid their marginal products but rather their average product. Figure 3 is constructed similarly to Figure 2, only now using the ratio of marginal product in industry to the *average* product in agriculture. We see that the discrepancy in scale is greatly reduced. From these comparisons we conclude that our data is of a quality sufficient to pursue the objectives in this paper.

A parallel exercise can be taken with marginal products of capital. The results are very similar.

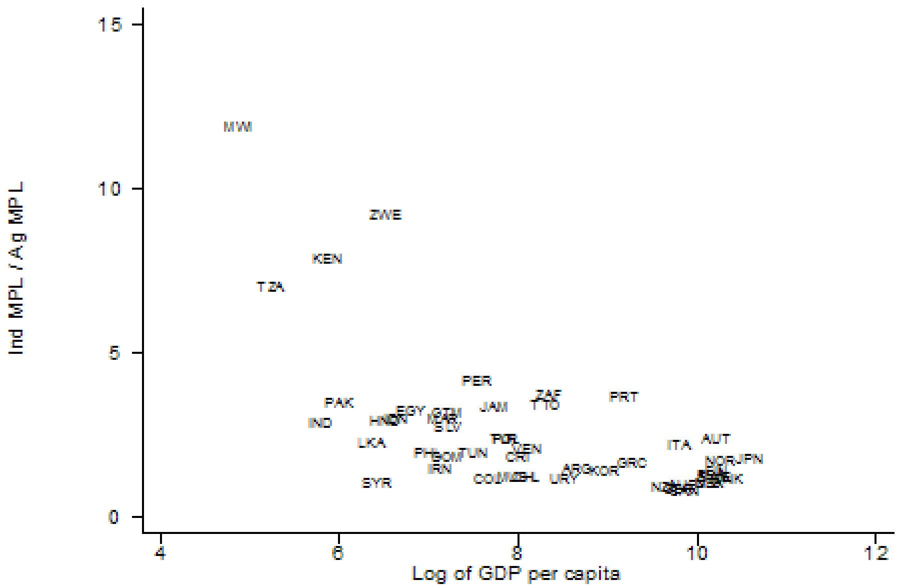

Figure 4: Ratio of Marginal Products of Labor versus Income Per Capita - 1990

The average ratio of marginal product of capital in industry to that in agriculture is 3.98. Of the 206 country/year observations, 187 show the ratio greater than one, and 148 are greater than two. No data that I am aware of reports the rates of return to capital by sector, so we have no way to compare the calculated marginal products to actual experienced returns.

Figures 4 and 5 show the relationship of these identified productivity gaps in labor and capital to income per capita. This first plots the ratio of the marginal product of labor in industry to that in agriculture against income per capita for the year 1990. There is evidence here of the inverse relationship identified by Kuznets (1982). Figure 5 makes a similar plot using marginal products of capital. Here, though, there is apparently a positive relationship of income with productivity gaps. These figures indicate that while development does not necessarily mean all factor prices converge between sectors, it does offer evidence of the wide variation in the gaps in productivity between sectors across countries.

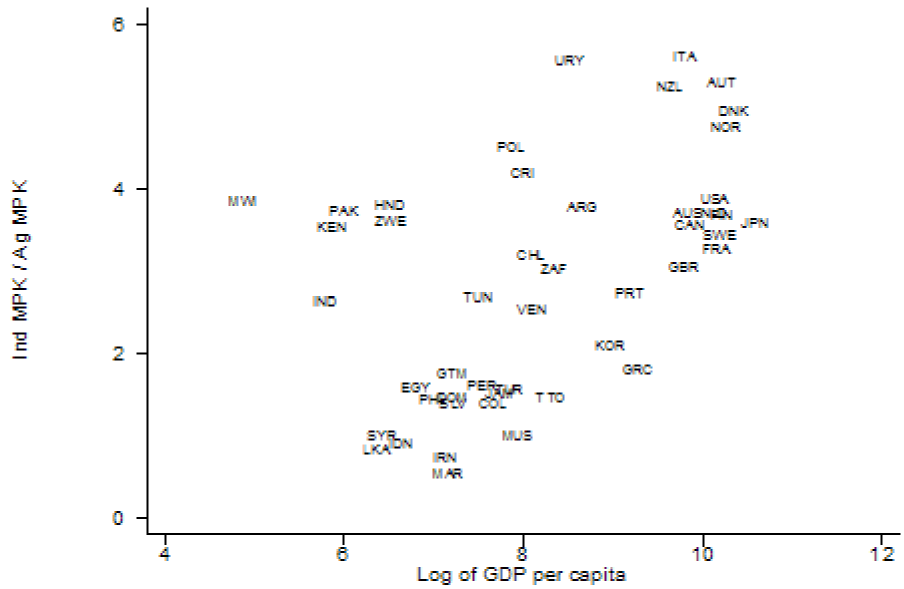

Figure 5: Ratio of Marginal Products of Capital versus Income per Capita - 1990

2.2 Calculating Efficiency

To calculate the scale of the deadweight loss, we need first to derive the income-maximizing allocation of labor and capital between the two sectors. This maximization only makes sense under the assumptions we laid out at the beginning of the section: namely that the TFP levels, total capital and total labor are all fixed. Note that the TFP levels capture within them the relative price levels in each sector, and that we have assumed (for now) that these prices remain fixed. The maximization is thus:

$$\max_{l_I,k_I}\left\{A_A\left(\frac{K}{L}\right)^{\gamma}\left(\frac{R}{L}\right)^{\lambda}(1-k_I)^{\gamma}(1-l_I)^{1-\gamma-\lambda}+A_I\left(\frac{K}{L}\right)^{\beta}(h_I)^{1-\beta}(k_I)^{\beta}(l_I)^{1-\beta}\right\} \tag{5}$$

where

$$
\begin{aligned}
l_I &= L_I/L \;\; \epsilon\,[0,1] \\
k_I &= K_I/K \;\; \epsilon\,[0,1]
\end{aligned}
$$

Using the fact that $1-\beta$ is assumed to be equal to $1-\gamma-\lambda$, we arrive at an intermediate solution for the share of labor that is:

$$l_I^* = \frac{1}{1+\left[\frac{A_A K^{\gamma}(1-k_I)^{\gamma} R^{\lambda}}{A_I K^{\beta} k_I^{\beta} h_I^{1-\beta}}\right]^{1/\beta}} \tag{6}$$

where the $*$ denotes the income-maximizing value. As can be seen, the value depends on the relative labor productivity in the two sectors, holding the capital shares constant. If we continue on with the derivation we can solve for the income-maximizing share of capital in industry, which is

$$k_I^* = 1 - \frac{1}{(K/L)}\left(\frac{A_A}{A_I}\frac{(R/L)^{\lambda}}{h^{1-\beta}}\right)^{1/(\beta-\gamma)}\left(\frac{\gamma}{\beta}\right)^{\beta/(\beta-\gamma)} \tag{7}$$

This shows again that increasing the capital stock moves resources towards industry, based solely on the differential in elasticities between the two sectors. Increasing productivity or the sector-specific resources (R and h) have the expected effects. The degree to which capital is allocated between sectors depends crucially on the difference $(\beta-\gamma)$.

Given the income-maximizing allocations of labor and capital shares, we can find the potential income in a country, holding constant the levels of K, R, h, A_I and A_A - call this potenial output $(Y/L)^*$ [10]. With the maximum income in hand, the allocative efficiency is just defined as:

$$E = \frac{(Y/L)^{Actual}}{(Y/L)^*} \tag{8}$$

[10] This output level should be viewed as individual to each country. That is, it is the output a single country could obtain if it allocated its resources to maximize income while the rest of the world remained at actual allocations. If the whole world were to re-allocate resources this would surely have an effect on relative prices and hence on A_I and A_A for any individual country.

2.3 Results

Table 1 shows the results of the allocative efficiency calculation for a selection of countries in the sample for 1990. Table 3, at the end of the paper, shows the results for all 206 country/year observations. The tables shows that allocative efficiency varies widely across countries. The club of rich countries has minimal losses on the order of between one and five percent of GDP. The developing countries of Central and South America are relatively efficienct, ranging from about 75% for Guatemala to about 96% in Colombia and Venezuela in 1990. Within Asia, the efficiencies lie between about 60 and 90 percent. This is slightly higher than the average found in the Middle-Eastern countries.

When we turn to the nations of Sub-Saharan Africa we find, perhaps not unsurprisingly, that they experience the largest losses due to inefficiency. Kenya, Malawi, and Zimbabwe all have E ranging between 38% and 53%. That is, these countries could all be between two or three times as rich as they are today by allocating labor and capital more efficiently between sectors of their economies. The numbers presented do not indicate that these countries *should* or *can* reallocate labor and capital into the industrial sector, only that they do fail to maximize their income given their total factors of production and productivities in the two sectors. Recall that these estimates tell us the cost of duality in each economy. The distortions existing between the agricultural and industrial sectors in Sub-Saharan Africa are costing these countries roughly half of their potential income.

A very noticeable aspect of the data in Table 3 is that E tends to rise over time almost without exception in the sample. The improvement over time is perhaps not surprising, given the large gaps between marginal products seen in the data. Among just the developing countries in the sample, efficiency rises, on average, 1.8 percentage points every 5 years. This may indicate that efficiency is simply a slow process of shifting resources out of agriculture, and that as new workers and capital are added the efficiency will rise naturally. Rich countries have higher efficiencies, perhaps, because they started this process earlier than poor countries.

The allocative efficiency measures are based on the income-maximizing shares of labor and

Country	E	l_A^{Actual}	k_A^{Actual}	l_A^*	k_A^*
Argentina	0.94	0.123	0.108	0.001	0.001
Canada	0.99	0.036	0.053	0.004	0.002
Colombia	0.98	0.266	0.151	0.055	0.029
Guatemala	0.74	0.562	0.234	0.002	0.001
India	0.69	0.595	0.356	0.002	0.001
Indonesia	0.80	0.509	0.110	0.005	0.003
Iran	0.98	0.329	0.089	0.078	0.042
Japan	0.96	0.072	0.046	0.000	0.000
Kenya	0.43	0.795	0.421	0.000	0.000
Malawi	0.38	0.822	0.389	0.000	0.000
Philippines	0.83	0.456	0.170	0.006	0.003
South Korea	0.94	0.161	0.081	0.003	0.001
Sri Lanka	0.84	0.492	0.111	0.011	0.006
Turkey	0.86	0.373	0.135	0.004	0.002
United Kingdom	0.99	0.022	0.028	0.003	0.002
Venezuela	0.94	0.142	0.073	0.001	0.000
Zimbabwe	0.53	0.682	0.241	0.000	0.000

Table 1: Efficient and Actual Allocations for Selected Countries in 1990

capital in agriculture, which are displayed for the selected countries in Table 1. The columns (2) and (3) show the actual share of labor or capital employed in agriculture, and the last two columns display the allocatively efficient shares. As can be seen, these efficient shares are extremely low. This indicates just how much less productive agriculture is than industry when measured using national accounts data. Except for a few outliers (Colombia and Iran, for example), the efficient allocation of labor and capital to agriculture is close to zero. Given the similarity of the efficient allocations across countries, it is then not surprising to see that the distribution of E finds rich countries like Japan and the U.K. with E close to one and Kenya and Malawi with E closer to only 0.40.

2.4 Robustness

The results presented are all for a very particular set of assumptions regarding the nature of the production functions. In addition, we maximized income over both capital and labor shares, but there may be good reason to think that the capital stock of each sector is not actually mobile between sectors - consider that a portion of measured agricultural capital consists of livestock. In this section we will consider several variations on the previous analysis to address the robustness of the results. For comparison, note that under the assumptions of the previous section the average efficiency in the entire sample of 206 country/year observations was 0.82 with a standard deviation of 0.17.

As a first check, let us assume that the capital stock as measured is in fact fixed in each sector. Alternatively, we could take the total capital stock and assume that it is already optimally allocated between sectors. In the case of this paper, these two assumptions are identical. This is because in order to perform the optimization we require levels of TFP in each sector, which are just calculated residuals. Given the output of each sector and the fixed elasticity of labor, any change in the allocation of capital is just offset completely by an inverse change in TFP levels in the sectors. Thus what we will really do is calculate labor allocations across sectors with no presumption on how capital is allocated. This is possible because of the fixed nature of the production functions. The average efficiency across the sample rises to 0.88, with a standard deviation of 0.13. There is a compression of the distribution of E towards the maximum value of one, as expected now that capital is presumed fixed.

Another possible concern could be that the assumed elasticities for labor are driving the results. First, we lower the labor elasticity in the production function, which should make the misallocation of labor less important to efficiency. The average E does indeed rise, but only by about three percent to 0.91 with a standard deviation of 0.11. Second, we create a difference in labor elasticity between the sectors, with agriculture's labor elasticity raised to 0.7 and industry's lowered to 0.5. Such a difference should raise the efficiency of allocation within countries because they are underallocating labor to a sector (industry) whose output is relatively insensitive to changes in labor force. We see again that average efficiency is raised, this time to an average of 0.92 with a standard deviation of 0.11. This type of check can be extended by widening the gap between agriculture and industrial labor elasticity even further, but it has not appreciable effect on the results.

In both cases in which we altered the elasticity of labor we have not optimized income over capital, but only over labor. Thus the average allocative efficiencies are likely lower than the values reported The biggest gain in efficiency was found when we assumed capital was fixed, and the changes in elasticities of labor had smaller effects on the results. The average allocative efficiency does rise under the new assumptions, but does not eliminate the large deadweight losses due to duality for developing countries. Consider that the highest value of E achieved for Kenya under any set of assumptions is 0.66, for Zimbabwe 0.69, and for Malawi 0.59.

2.5 Price Effects

To this point we have considered an economy in which the relative price of agricultural goods is fixed. This assumption made the income maximization possible, but is not realistic for most countries. In this section we extend the analysis to account for the fact that prices will adjust as labor is moved between sectors.

As labor 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 labor in agriculture beyond that observed just because of the declining work force. In Figure 6 this is illustrated more clearly as a shift upward of the MPL_A curve as the share of labor in industry is increased.

In this figure, the area defined by points (X, Y, Z) corresponds to the total area D in Figure 1 from the introduction. So far we have been calculating the size of D, but if prices are allowed to change than this area is no longer the correct measure of the deadweight loss. From Figure 6 we see that the area of loss actually shrinks to the area defined by (X, W, V) as P_A rises. Thus in a closed economy the shift in labor necessary to achieve an income-maximizing allocation will be, ceteris paribus, smaller than in the open economy.

To update our estimates of efficiency we have to account for two effects of shifting labor out of agriculture on prices, illustrated in Figure 7. First, as we move labor out of agriculture we reduce the supply 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 labor 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

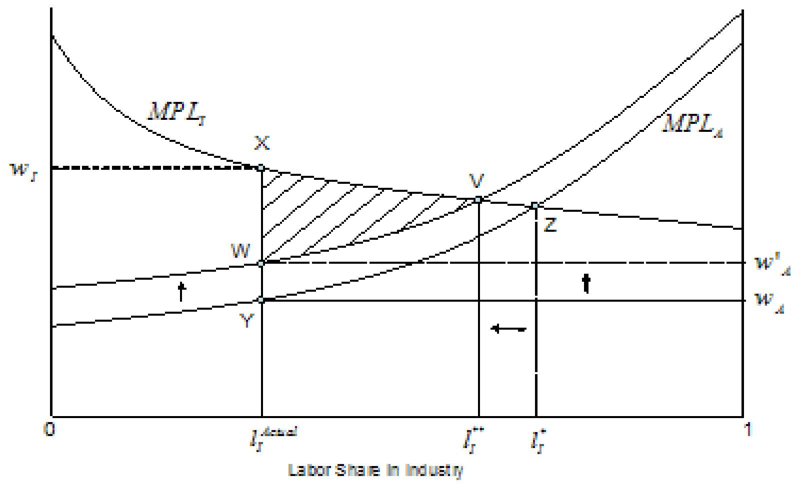

Figure 6: Deadweight Loss From Misallocation with Price Effects

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 labor 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 labor out of agriculture, the lower the estimated size of the deadweight loss will be (as the MPL_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, we make several simplifying assumptions regarding the structure of agricultural demand. First, we 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 means we do not have to obtain estimates of the original price level. Second, we assume that the values of ε_A and η_A are such that $\varepsilon_A = -\eta_A$. This assumption makes the price change easily calculated and in fact matches common

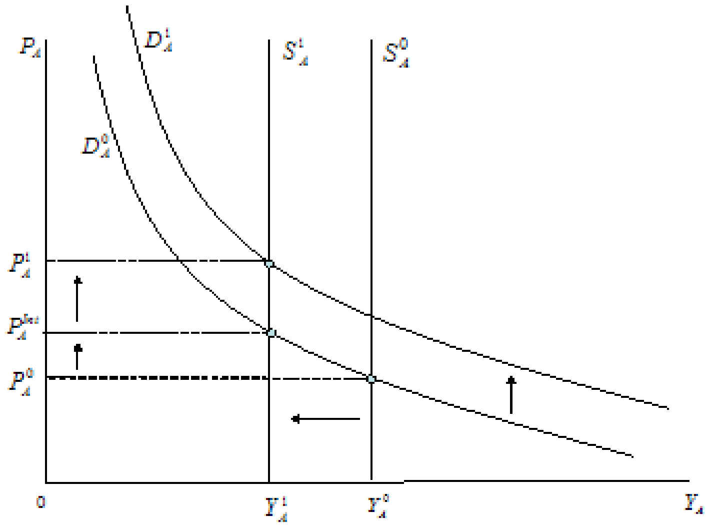

Figure 7: Effect of Shifting Labor on Price of Agricultural Goods

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.

With the elasticities in hand we can now calculate what change in the share of labor in agriculture would result in the equalization of the marginal product of labor across sectors. At this income-maximizing allocation of labor we can calculate the new output level and compare it to the actual output level. We must be careful in the comparison because the income-maximizing output level is valued using a different set of prices than the actual output level. Therefore we compute the value of output at the income-maximizing allocation of labor using the original, actual prices. We can then calculate efficiency as before in equation (8).

For these estimates we optimized income only over labor and used the original labor elasticity estimates. Table 2 shows the change in allocative efficiency for a selection of countries in 1990

Country	E - no price effects	E - w/ price effects
Argentina	0.98	0.99
Canada	1.00	1.00
Colombia	1.00	1.00
Guatemala	0.82	0.87
India	0.82	0.88
Indonesia	0.84	0.88
Iran	0.99	0.99
Japan	0.98	0.99
Kenya	0.54	0.66
Malawi	0.47	0.59
Philippines	0.89	0.93
South Korea	0.97	0.98
Sri Lanka	0.87	0.90
Turkey	0.91	0.93
United Kingdom	1.00	1.00
Venezuela	0.97	0.98
Zimbabwe	0.59	0.69
Sample Average	0.88	0.91
Sample SD	0.13	0.10

Table 2: Effect of Price Changes on Allocative Efficiency in 1990

What we see is that the estimated efficiency rises for every country. For those countries already at high levels of efficiency, the effect is small. If we examine, though, the countries which are estimated to have large deadweight losses and hence low E levels (Kenya, Malawi, and Zimbabwe) we find large increases from E due to the price effects. It seems that a large portion of any estimated gain in output due to shifting resources will be eaten up by a rising relative price of agricultural goods. Despite this, there still remain large deadweight losses (and low E) levels for these countries, such that they could nearly double their income per capita by efficiently allocating labor between sectors.

3 Efficiency and Variation in Income per Capita

The previous section established that the misallocation of resources is a significant factor in the low incomes of many developing countries. The size of the efficiency measures, E, is closely associated with the relative income level of the sample countries, and this suggests that efficiency might play a role in explaining the variation in income per capita among countries. In this section we explore how big a role E has in explaining variation in income per capita within a cross-section and over time.

3.1 Variation in Income across Countries

The manner in which we calculated efficiency lends itself to a simple analysis of the variance of income per capita across countries. We can calculate a counter-factual distribution of income in which we eliminate inefficiency in each country, effectively eliminating that as a source of variation in income per capita. We can compare the variance of this counter-factual distribution with the true distribution to see how much of the variation remains.

Call the actual log per capita income $\ln y^{Act}$ and the counterfactual log per capita income $\ln y^{Eff}$. The calculation of counterfactual income per capita is then very simply done as

$$y^{Eff} = \frac{y^{Act}}{E} \tag{9}$$

To do this calculation, we need to carefully consider our measure of output. Before, in determining the marginal products and the efficiency term E, we used domestically priced output data because those prices are relevant within the economy. To look across countries we want to use PPP-adjusted incomes to ensure comparability. These are taken from the Penn World Tables version 6.1 by Heston, Summers, and Aten (2002). Note that this method does not require us to have PPP-adjusted income figures for the industrial and agricultural sectors independently, a very limiting requirement. The only PPP-adjusted figures for the agricultural sector that I am aware of are in Prasada Rao (1993), and only for 1985, which would eliminate doing the analysis over time.

Because of the nature of the efficiency measure, when we eliminate variation in it, we are necessarily pushing the distribution of income to the right. Each country gets unambiguously richer when they are at $E = 1.00$. The greatest gains are of course from those countries with the lowest efficiency. In Figure 8 this can be clearly seen. This plots simple kernel density functions with a bandwith of 0.3 for both the actual income distribution and the counterfactual income

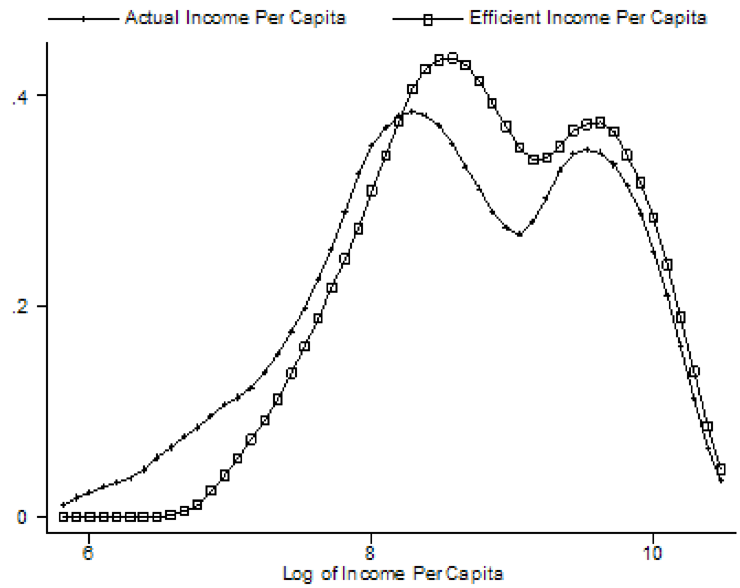

Figure 8: Kernel Densities for Actual and Efficient Income Distributions

distribution when we eliminate allocative inefficiency (calculated by maximizing income over both capital and labor) . As can be seen the density of the efficient distribution is more pushed up against the right side of the graph, and has a much smaller left-hand tail. Both densities retain a bimodal nature, with the efficient distribution seeming to exaggerate the first mode.

Figure 8 indicates that the variation in income per capita shrinks when inefficiencies are eliminated, but does not quantify the size of the effect. Therefore we consider the ratio of the variance in the counterfactual distribution to the variance of the actual distribution for the year 1990 - specifically $\frac{Var\left(\ln y^{Eff}\right)}{Var(\ln y^{Act})}$. For our baseline calculation - where E is calculated by optimizing over both labor and capital, this ratio is 0.64. In other words, the variation in allocative inefficiency can account for roughly one-third of the variation in income per capita in the entire sample.

If we instead restrict our calculations of E to optimizing only over labor, then the variance ratio rises to 0.77. Thus a large portion of the variation in income due to allocative inefficiency was due to capital misallocations. There still remains a significant 23% of variation in log income per capita explained by the deadweight loss due to the dual nature of the labor market.

In both of the previous two cases we have assumed that there were no price effects. If we use the calculated values of E in which we optimize over labor only, and allow for price changes, then the ratio $\frac{Var\left(\ln y^{Eff}\right)}{Var(\ln y^{Act})}$ is found to be 0.85. The percentage of income variation remaining is higher again, indicating that we are explaining less of the income distribution, but nonetheless allocative efficiency is responsible for 15% of the variation in income seen in this sample.

Recall that in calculating these efficiencies, we hold the actual levels of capital, land, and labor constant. Thus any variation in income per capita due to inefficiency is part of the unexplained residual, or TFP. Current research seems to allocate about 60% of the total variation in income per capita to variation in TFP. The current estimates indicate that between one-quarter and one-half of the variation in TFP is due to the misallocation of resources between sectors.

3.2 Variation in Income over Time

The previous section showed a significant influence of the efficiency of labor and capital allocations in creating variation in income per capita. This section will examine the role of these efficiencies in the development of income per capita over time. To do so we calculate the annual growth rate, in percents, over the period 1970-1990 for each component specificied in (8). The measure of efficiency used is the one calculated by maximizing over both labor and capital. There are only 29 countries for which we have data in both periods, and so we concentrate on those at this time.

Table 4 at the end of the paper shows the result of these calculations. Column (1) shows that five - all Central or South American - of the 29 countries had shrinking income per capita over this period. In each of these cases the maximum income per capita measure fell quickly over the period, overcoming gains in the other components of income per capita.

Efficiency growth was negative in only one case, Pakistan, and even in that country the negative growth rate was very small. As we noted earlier, efficiency seems to be improving over time across all countries. This is perhaps not surprising. The income-maximizing share of labor and capital in industry is relatively similar across countries - essentially all resources should be in industry. As more people, and presumably capital, move into urban areas they are bringing the economy closer to the efficient allocation of resources, as calculated under our restricted assumptions.

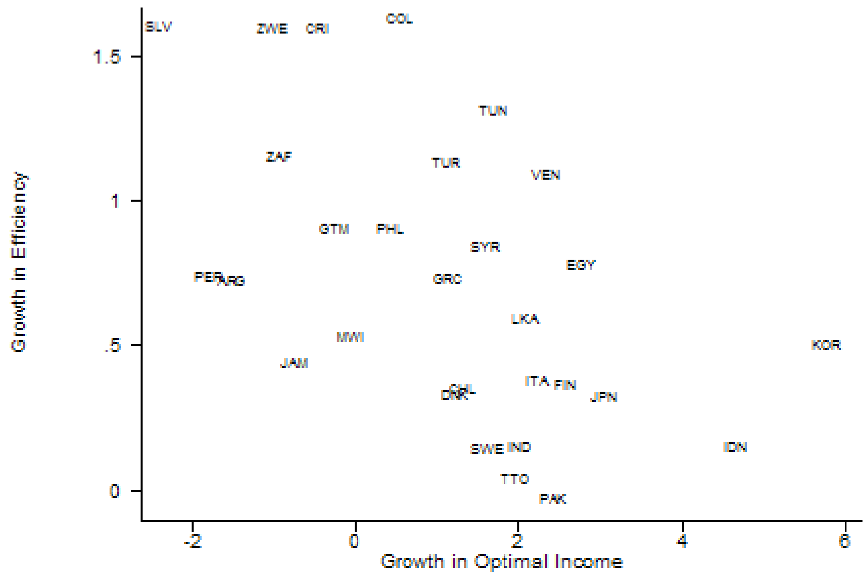

Figure 9: Percent Growth Rates of Efficiency and Potential Income - 1970-1990

This movement may not be entirely benign in its effects on the economy, though. It appears that there is some relationship between rising efficiency - more people and capital in industry - and falling maximal income per capita. Figure 9 plots the growth rate of E and $(Y/L)^*$ against each other and a negative relationship appears. The correlation of the two is -0.53 and is significant at less than one percent. Those countries in which efficiency was growing fastest also found themselves subject to deteriorating growth in their potential income per capita..

It seems unlikely that this is simply a coincidence, that those countries with larger flows of people and capital into industry happened to also have negative shocks. A more plausible explanation of the relationship may be that the industrial sector is not capable of absorbing people perfectly, and so while output remains stagnant, we are increasing the number of workers in that sector. This lowers the measured output per worker in the industrial sector, which would translate to a lower measured potential income. Thus improvements in income per capita due to efficiency may take hold over longer periods of time as industry adapts to the presence of the new labor. Further research is necessary to understand if there is an economically interesting relationship here or if this is simply a byproduct of measuring this activity at a high level of aggregation.

4 Conclusion

The nature of the dual economy - identified here with gaps in productivity between agriculture and industry - has been an important consideration in economic development research for many years. What is not commonly addressed in the literature, though, is the quantitative size of losses due to the dual economy. The answer to this question has implications for how we think about the process of development as well as how we promote it.

This paper provides for the first time macroeconomic estimates of the deadweight loss associated with the duality of economies for 48 countries across twenty years. These estimates allow us to see how efficiently - from an income-maximizing perspective - each economy is allocating their resources between agriculture and industry. The findings show that there are large deadweight losses for several countries, and that the size of the loss decreases with overall level of income. These results are robust to several specifications of the parameters of the production functions used as well as to assumptions regarding the flexibility of relative prices. The costs of the dual economy are real.

For several developing countries, the indications are that duality is economically crippling, leading to income per capita levels only half of what they could actually be. The implications are dramatic for the movement of labor within the economy. In Kenya, the estimates suggest that nearly 18 million out of the total of 24 million people would have to move from agriculture to industry to equalize marginal returns to labor. In the Philippines, the figure is 25 million moving to industry out of the total of 61 million. The size of these movements are vast, but the steady stream of people into the urban areas of these and other developing countries suggests that the economic forces estimated here have a solid basis in reality.

The same deadweight losses that imply such large potential movements of labor also may be able to explain some of the current distribution of income across countries. Depending on the assumptions chosen, the variance of log income per capita is reduced by between 15 and 36 percent when the losses are eliminated. This implies that these inefficiencies can explain between one-quarter and one-half of the unexplained residual (TFP) from a normal development accounting exercise. There is clearly some significance to the allocation of resources in explaining the income distribution.

Regardless of the reasons, the presence of these deadweight losses due to duality has implications for the study of growth and development. These losses are not necessarily related to the acquisition of new technology or capital, so they could theoretically be eliminated without any new investment or research. The identification of these inefficiencies in allocation offers a channel in addition to accumulation and technology through which economic growth and development can be promoted.

References

Barro, R., and J. Lee (1996): "International Measures of Schooling Years and Schooling Quality," American Economic Review Papers and Proceedings, 86(2), 218–223.

Boeke, J. (1953): Economics and Economic Policy of Dual Societies. Tjeenk Willnik, Haarlem.

Calvo, G. (1978): "Urban Development and Wage Determination in LDC's: Trade Unions in the Harris-Todaro Model," International Economic Review, 19, 65–81.

Caselli, F. (2003): "The Missing Input: Accounting for Cross-Country Income Differences," Working Paper.

Caselli, F., and W. J. Coleman (2001): "The U.S. Structural Transformation and Regional Convergence: A Reinterpretation," Journal of Political Economy, 109(31), 584–616.

Crego, A., D. Larson, R. Butzer, and Y. Mundlak (1998): "A New Database on Investment and Capital for Agriculture and Manufacturing," World Bank Working Paper.

Dalgaard, C.-J., and A. Chanda (2003): "Dual Economies and International Total Factor Productivity Differences," Working Paper.

DE MELO, J. A. P. (1977): "Distortions in the Factor Market: Some General Equilibrium Estimates," The Review of Economics and Statistics, 59(4), 398–405.

DOUGHERTY, C., AND M. SELOWSKY (1973): "Measuring the Effects of the Misallocation of Labor," The Review of Economics and Statistics, 55(3), 386–390.

ECHEVARRIA, C. (1997): "Changes in Sectoral Composition Associated with Economic Growth," International Economic Review, 38(2), 431–452.

FLOYSTAD, G. (1975): "Distortions in the Factor Market: An Empirical Investigation," The Review of Economics and Statistics, 57(2), 200–213.

FOOD AND AGRICULTURE ORGANIZATION OF THE U.N. (1999): "FAOSTAT Database," http://apps.fao.org/default.jsp.

GOLLIN, D., S. PARENTE, AND R. ROGERSON (2002): "The Role of Agriculture in Development," American Economic Review Papers and Proceedings.

GOODFRIEND, M., AND J. MCDERMOTT (1995): "Early Development," American Economic Review, 85(1), 116–133.

GRAHAM, B. S., AND J. TEMPLE (2003): "Rich Nations, Poor Nations: How Much can Multiple Equilibrium Explain?," Working Paper.

HALL, R. E., AND C. I. JONES (1999): "Why Do Some Countries Produce So Much More Output?," Quarterly Journal of Economics.

HANSEN, G., AND E. C. PRESCOTT (2002): "Malthus to Solow," American Economic Review, pp. 1205–1217.

HARBERGER, A. C. (1959): "Using the Resources at Hand More Effectively," American Economic Review, 49(2), 134–146.

HARRIS, J. R., AND M. TODARO (1970): "Migration, Unemployment and Development: A Two-Sector Analysis," American Economic Review, 60, 126–142.

Hayami, Y. (1969): "Sources of the Agricultural Productivity Gap among Selected Countries," American Journal of Agricultural Economics, 51, 565–575.

Hayami, Y., and V. W. Ruttan (1970): "Agricultural Productivity Differences among Countries," American Economic Review, 60(5), 895–911.

Heston, A., R. Summers, and B. Aten (2002): "Penn World Table Version 6.1," Center for International Comparisons at the University of Pennsylvania.

International Labor Organization (2004): "LABORSTA Database," http://laborsta.ilo.org/.

Jorgenson, D. W. (1961): "The Development of a Dual Economy," Economic Journal, 71(282), 309–334.

Jorgenson, D. W., and F. M. Gollop (1992): "Productivity Growth in U.S. Agriculture: A Postwar Perspective," American Journal of Agricultural Economics, 74(3), 745–750.

Klenow, P. J., and A. Rodriguez-Clare (1997): "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?," in NBER Macroeconomics Annual 1997, pp. 73–103. MIT Press.

Kogel, T., and A. Prskawetz (2001): "Agricultural Productivity Growth and Escape from the Malthusian Trap," Journal of Economic Growth, 6, 337–357.

Kongasmut, P., S. Rebelo, and D. Xie (2001): "Beyond Balanced Growth," Review of Economic Studies, 68(4), 869–882.

Kuznets, S. (1982): "The Pattern of Shift of Labor Force from Agriculture, 1950-70," in The Theory and Experience of Economic Development, ed. by M. Gersovitz, C. Diaz-Alejandro, G. Ranis, and M. Rosenzweig. Geogre Allen and Unwin, London.

Laitner, J. (2000): "Structural Change and Economic Growth," Review of Economic Studies, 67, 545–61.

Lewis, A. (1954): "Economic Development with Unlimited Supplies of Labor," Manchester School, 22, 139–91.

Lucas, R. E. B. (1985): "Migration Amongst the Batswana," Economic Journal, 95(378), 358–382.

Matsuyama, K. (1992): "Agricultural Productivity, Comparative Advantage, and Economic Growth," Journal of Economic Theory, 58, 317–334.

Mundlak, Y. (2000): Agriculture and Economic Growth: Theory and Measurement. Harvard University Press.

Parente, S. L., R. Rogerson, and R. Wright (2000): "Homework in Development Economics: Household Production and the Wealth of Nations," Journal of Political Economy, 108(4), 680–687.

Prasada Rao, D. S. (1993): "Intercountry Comparisons of Agricultural Output and Productivity," FAO Economic and Social Development Paper 112.

Psacharapoulos, G. (1994): "Returns to Investment in Education: A Global Update," World Development, 22(9), 1325–1343.

Ranis, G., and J. C. H. Fei (1961): "A Theory of Economic Development," American Economic Review, 51(4), 533–565.

Restuccia, D. (2004): "Barriers to Capital Accumulation and Aggregate Total Factor Productivity," International Economic Review, 45, 225–238.

Restuccia, D., D. T. Yang, and X. Zhu (2003): "Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis," Working Paper.

Rosenzweig, M. (1988): "Labor Markets in Low Income Countries," in Handbook of Development Economics, ed. by H. Chenery, and T. Srinivasan, pp. 713–762. North Holland, New York.

SQUIRE, L. (1981): Employment Policies in Developing Countries: A Survey of Issues and Evidence. Oxford University Press, London.

STIGLITZ, J. E. (1974): "Alternative Theories of Wage Determination and Unemployment in LDC's: The Labor Turnover Model," Quarterly Journal of Economics, 88(2), 194–227.

TEMPLE, J. (2003): "Dualism and Aggregate Productivity," University of Bristol Discussion Paper no. 02/532.

TIMMER, P. (2000): "Agriculture and Economic Development," in Handbook of Agricultural Economics, ed. by G. Rausser, and B. Gardner. North-Holland.

TODARO, M. P. (1976): Internal Migration in Developing Countries: A Review of Theory, Evidence, Methodology and Research. International Labour Office, Geneva.

WILLIAMSON, J. G. (1987): "Did English Factor Markets Fail During the Industrial Revolution?," Oxford Economic Papers, 39(4), 1–38.

WORLD BANK (2003): "World Development Indicators," http://devdata.worldbank.org/dataonline/.

YAP, L. (1977): "The Attraction of Cities: A Review of the Migration Literature," Journal of Development Economics, 4, 239–264.

	Allocative Efficiency, E, in year:				
Country	1970	1975	1980	1985	1990
Argentina	0.82			0.92	0.94
Australia		0.96	0.96	0.97	0.98
Austria		0.90	0.93	0.94	0.95
Canada		0.95	0.95	0.97	0.99
Chile	0.87	0.89	0.88	0.90	0.93
Colombia	0.71	0.76	0.83	0.93	0.98
Costa Rica	0.62	0.66	0.76	0.81	0.85
Denmark	0.91	0.93	0.94	0.95	0.97
Dominican Rep				0.86	0.92
Egypt	0.68	0.73	0.68	0.74	0.80
El Salvador	0.61	0.63	0.73	0.82	0.83
Finland	0.89	0.91	0.94	0.94	0.95
France		0.93	0.96	0.97	0.98
Greece	0.81	0.86	0.89	0.92	0.94
Guatemala	0.62	0.66	0.70	0.75	0.74
Honduras				0.67	0.73
India	0.67	0.63	0.66	0.65	0.69
Indonesia	0.78	0.82	0.85	0.84	0.80
Iran		0.77	0.89	0.92	0.98
Italy	0.88	0.90	0.92	0.93	0.94
Jamaica	0.81	0.82	0.83	0.87	0.89
Japan	0.91	0.93	0.94	0.96	0.96
Kenya		0.31	0.40	0.40	0.43
Malawi	0.35	0.35	0.39	0.37	0.38
Mauritius				0.99	0.99
Morocco			0.75	0.80	0.88
Netherlands		0.96	0.97	0.97	0.98
New Zealand		0.90	0.90	0.94	0.94
Norway		0.94	0.94	0.95	0.96
Pakistan	0.68	0.56	0.59	0.62	0.67
Peru	0.71	0.73	0.76	0.78	0.82
Philippines	0.70	0.71	0.76	0.83	0.83
Poland					0.85
Portugal		0.81	0.82	0.87	0.89
South Africa	0.71	0.79	0.85	0.86	0.89
South Korea	0.86	0.88	0.86	0.93	0.94
Sri Lanka	0.75	0.72	0.76	0.84	0.84
Sweden	0.95	0.96	0.96	0.97	0.98
Syria	0.85	0.92	0.98	1.00	1.00
Tanzania					0.18
Trinidad	0.94	0.96	0.96	0.94	0.95
Tunisia	0.68	0.77	0.80	0.85	0.89
Turkey	0.69	0.73	0.80	0.82	0.86
United Kingdom		0.98	0.99	0.99	0.99
United States		0.97	0.97	0.98	0.99
Uruguay			0.88	0.90	0.92
Venezuela	0.76	0.85	0.91	0.93	0.94
Zimbabwe	0.39	0.45	0.49	0.51	0.53

Table 3: Allocative Efficiency, E, for the full sample

Country	Growth Rate over 1970-1990 (1) $\ln \frac{Y}{L}$	(2) $\ln E$	(3) $\ln \left(\frac{Y}{L}\right)^*$
Argentina	-0.83	0.70	-1.53
Chile	1.65	0.33	1.32
Colombia	2.15	1.61	0.54
Costa Rica	1.10	1.57	-0.47
Denmark	1.52	0.31	1.21
Egypt	3.52	0.76	2.76
El Salvador	-0.83	1.58	-2.41
Finland	2.91	0.34	2.57
Greece	1.84	0.71	1.13
Guatemala	0.62	0.88	-0.26
India	2.15	0.13	2.02
Indonesia	4.78	0.13	4.65
Italy	2.60	0.36	2.24
Jamaica	-0.34	0.42	-0.76
Japan	3.34	0.30	3.04
Malawi	0.45	0.51	-0.06
Pakistan	2.36	-0.05	2.41
Peru	-1.08	0.72	-1.80
Philippines	1.31	0.88	0.43
South Africa	0.19	1.13	-0.94
South Korea	6.25	0.48	5.77
Sri Lanka	2.66	0.57	2.09
Sweden	1.73	0.12	1.61
Syria	2.40	0.82	1.58
Trinidad	1.97	0.02	1.95
Tunisia	2.98	1.29	1.69
Turkey	2.22	1.11	1.11
Venezuela	-1.26	1.07	2.33
Zimbabwe	0.56	1.57	-1.01
Sample Average	1.69	0.70	1.14

Table 4: Percent Growth Rates in Elements of Income