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Sector-Specific Capital, Labor Market Distortions and Cross-Country Income Differences: A Two-Sector General Equilibrium Approach*

Asad Karim Khan Priyo

Abstract

This paper highlights the significance of labor market distortions in explaining cross-country income differences using a two-sector general equilibrium model that incorporates modern intermediate inputs used in agriculture together with sector-specific human and physical capital. Using the best available information, I construct new sectoral data on quality-adjusted human capital and PPP-adjusted physical capital. Although both types of capital - physical capital in particular - play important roles, using a sample of 43 countries, I find that in terms of capturing the observed disparities, either in relative labor productivity in agriculture or aggregate output per worker between the rich and the poor countries, the role of labor market distortions outweighs the role of either sectoral human or physical capital.

KEYWORDS: sectoral human capital, sectoral physical capital, labor market distortions, agricultural productivity, income differences, two-sector model

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1. Introduction

Over the years, using one-sector neo-classical growth models, various researchers have tried to determine why some countries in this world are rich while others are poor (e.g., Mankiw et al., 1992; King and Levine, 1994; Chari et al., 1996; Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999). However, as Caselli (2005) points out, in a simple one-sector model with two factors of production, a large fraction of the wide cross-country disparity in aggregate output per worker remains unexplained. Prescott (1998) suggests that in a one-sector growth framework, differences in capital per worker, even after including intangible capital, cannot explain the large differences in output per worker. One of the inadequacies of using the one-sector growth model for the purpose of explaining international productivity differences is that it considers only the aggregate-level differences and ignores the differences that may exist at the sectoral levels.

Several authors (e.g., Gollin et al., 2004; Restuccia et al., 2008), based on existing data, document that cross-country differences in labor productivity are much larger in agriculture than in non-agriculture; and in spite of having very low productivity, poor countries, in comparison to the rich ones tend to allocate a much larger share of their employment in agriculture. Such observations give rise to the following important questions: what are the factors that explain (i) the inverse relationship between aggregate labor productivity and employment share in agriculture and (ii) the large discrepancies in relative productivity in agriculture (ratio of labor productivity in agriculture to non-agriculture) across countries? A two-sector growth model that incorporates both agriculture and non-agriculture with a view to answering these questions is undoubtedly crucial in explaining the large cross-country income differences observed in data.

In a recent study, utilizing a two-sector general equilibrium model, Restuccia et al. (2008) address these questions and attribute the international differences in relative agricultural productivity to cross-country variations in economy-wide productivity, costs of modern intermediate inputs used in agriculture and labor market distortions.[1] They, however, do not control for sectoral differences in human or physical capital. If cross-country differences in human and physical capital per worker in agriculture are larger than the differences in non-agriculture, then their inclusion in the model should be significant in capturing the observed sectoral patterns. Furthermore, in that case, if sectoral human and physical capital are not included, the model would potentially

[1] Modern intermediate inputs imply factors produced in the non-agricultural sector e.g. chemical fertilizers, pesticides, machine services, processed seeds, fuel and energy that are used in agricultural production. Labor market distortions on the other hand are measured as the sectoral wage gap i.e. ratio of non-agricultural wage per worker to agricultural wage per worker.

over predict the importance of labor market distortions in accounting for the productivity differences.

In this paper, I extend the two-sector general equilibrium model employed by Restuccia et al. (2008) by incorporating sector-specific human and physical capital in the production technologies and quantitatively assess the contribution of sectoral human capital, sectoral physical capital and labor market distortions in explaining cross-country income differences. To be more precise, in addition to the questions mentioned above, in this paper, I also address the following questions: (iii) how much do cross-country variation in sectoral human capital, sectoral physical capital and labor market distortions add to the explanatory power of the model, both separately and together, in explaining the observed disparities in relative labor productivity in agriculture and in turn aggregate labor productivity between the rich and the poor countries and (iv) which of these three factors plays the most important role?

This paper illustrates that although differences in economy-wide productivity, costs of modern intermediate inputs as well as sectoral human and physical capital play important roles, they are not enough to account for the large cross-country discrepancies observed in relative productivity in agriculture and, as a result, aggregate output per worker. I demonstrate that even after controlling for sectoral differences in human and physical capital, labor market distortions continue to play an important role in explaining cross-country income differences. One of the major implications of this paper is that, in terms of capturing the observed disparities either in relative labor productivity in agriculture or aggregate output per worker between the rich and the poor countries, the role of labor market distortions outweighs the role of either sectoral human or physical capital.[2]

Calibrating the model parameters to the US data for 1985, this paper generates predictions for employment share, gross output per worker and GDP per worker in agriculture, GDP per worker in non-agriculture and aggregate labor productivity for all the countries in my sample. The baseline model that includes quality-adjusted sector-specific human capital, PPP-adjusted sector-specific physical capital and variation in labor market distortions does an excellent job of capturing the sectoral characteristics as well as the aggregate data; e.g. the model explains 101% of the observed difference in employment share in agriculture, 34% of the difference in GDP per worker in agriculture and 60% of the difference in aggregate labor productivity between the richest 10% and the poorest 10% of the countries in my sample.

[2] Restuccia et al. (2008) interpret the labor market distortions as the cost of reallocating labor from agriculture to non-agriculture whereas in the presence of human capital in the model, following Caselli and Coleman (2001), I interpret the distortions as the cost of acquiring the additional skills necessary to work in the non-agricultural sector.

The inclusion of sector-specific human and physical capital improves the prediction power of the model. Prediction power of the model improves by more when only sectoral physical capital is added, in comparison to the addition of only sectoral human capital. The version of the model without human and physical capital (identical to Restuccia et al., 2008) explains 41% of the observed difference in aggregate labor productivity between the richest 10% and the poorest 10% of the countries in my sample. The prediction improves to 46% when only human capital is added and to 55% when only physical capital is added. Finally, when both are included in the analysis, the model accounts for 60% of the observed difference.

For the purpose of this study, I need country-specific data on aggregate GDP, agriculture, population and returns to schooling, and country-wise, sector-specific data on physical capital and average schooling years. My sample of countries is determined on the basis of the availability of all the necessary data. Data on sector-specific physical capital and schooling years are scarce. I construct new sectoral data on quality-adjusted human capital and PPP-adjusted physical capital using the best available information. Based on the availability of all the necessary data, my sample includes a total of 43 countries.[3]

In addition to Restuccia et al. (2008), a number of recent studies have also utilized two-sector growth frameworks that incorporate agriculture in the analysis of international productivity differences (e.g., Gollin et al., 2004, Cordoba and Ripoll, 2006; Gollin et al. 2007; Chanda and Dalgaard, 2008; Vollrath, 2009; Lagakos and Waugh, 2010). Gollin et al. (2004) highlight the role of home production in explaining cross-country productivity differences whereas in a later study, they (Gollin et al., 2007) make a case that low agricultural productivity may slow down the initiation of a country's industrialization process. Lagakos and Waugh (2010) on the other hand suggest that lower measured productivity in agriculture in poor countries primarily results from aggregate factors such as weak institutions or poor social infrastructure. Studies that relate more closely to my work are those of Cordoba and Ripoll (2006), Chanda and Dalgaard (2008) and Vollrath (2009) - all of whom have used sector-specific human and/or physical capital data in quantitatively analyzing international productivity differences.[4] The following two paragraphs discuss how this paper differs from theirs.

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[3] The sample is fairly representative and consists of rich countries such as the United States, Canada, Australia and Norway, as well as poor countries such as Zimbabwe, India, Kenya and Tanzania. The sample of 43countries in this paper demonstrates the same sectoral patterns that can be observed in a larger sample of countries e.g. the sample of 86 countries in Restuccia et al. (2008). The sectoral patterns for my sample of 43 countries are explained in detail in section 2.2.

[4] Chanda and Dalgaard (2008) and Vollrath (2009) include both sector-specific human and physical capital, whereas Cordoba and Ripoll (2006) include only sector-specific human capital in their analysis.

Cordoba and Ripoll (2006) fix the level of distortions at a low level for all the countries and attempt to determine how much human capital differences between sectors would need to exist in order to explain the large gap in sectoral productivities and conclude that most of the income dispersion across countries is particularly due to differences in quality of human capital in rural areas. Their approach may overestimate the importance of human capital by attributing most of the difference in sectoral labor productivity to quality difference in rural human capital, a large part of which can, in fact, arise from distortions.[5] Chanda and Dalgaard (2008) set out to explain cross-country differences in aggregate Total Factor Productivity (TFP), rather than aggregate labor productivity, and focus on channels such as institutions, trade and geography through which variation in sectoral efficiencies affect TFP. Their accounting analysis attributes 85% of the cross-country differences in aggregate TFP to variation in relative efficiency across sectors. However, their accounting approach cannot differentiate between technological and non-technological sources of relative efficiency and therefore is not suited to answer the questions posed in this paper.

Vollrath (2009) demonstrates that 30–40% of the variation in per capita income and up to 80% of the variation in aggregate TFP can be attributed to cross-country variation in the degree of misallocation of human and physical capital. The framework employed by Vollrath (2009) neither includes a household sector nor considers modern intermediate inputs in agricultural production. Given Cobb-Douglas production functions, the non-inclusion of a household sector in the model implies that agricultural and non-agricultural goods are essentially treated as perfect substitutes, an assumption which may overestimate the degree of sectoral misallocation. In the general equilibrium model that I employ in this paper on the other hand, representative household treats the two goods as imperfect substitutes and have non-homothetic preferences with a subsistence requirement for the consumption of the agricultural good, which forces poor countries to allocate a greater share of employment in agriculture. Not considering modern intermediate inputs in agricultural production implies that the model misses out on capturing the effects of cross-country variation in costs of these inputs in explaining international productivity differences that this paper captures. Therefore, his approach relative to the approach taken in this paper potentially overestimates the importance of sectoral distortions by attributing the fraction of cross-country income differences that may have actually resulted from the general equilibrium effects or differences in cost of intermediate inputs to sectoral misallocation of resources.

[5] In this paper, I show that even after adjusting for quality, sectoral human capital is not as important as either physical capital or labor market distortions in explaining international productivity differences.

The rest of this paper is organized as follows. Section 2 discusses the sources of data, presents a data summary and demonstrates how the data for sector-specific human and physical capital are constructed. Section 3 presents the theoretical framework of this paper. Section 4 discusses how the labor market distortions and economy-wide productivities are measured, explains the calibration process and presents the quantitative analysis highlighting the effects of sector-specific human capital, sector-specific physical capital and labor market distortions. Section 5 concludes.

2. Data

In this section, I discuss the sources of data, provide a data summary and demonstrate how I construct the data for sector-specific human and physical capital.

2.1 Sources of Data

I use data for 1985 because of their availability. Additionally, the use of these data allows the results of this paper to be directly comparable with those of the paper by Restuccia et al. (2008) who also employ 1985 data. I obtain all the necessary data except data on total employment, sector-specific physical and human capital from the web link of the paper by Restuccia et al. (2008).[6] Restuccia et al. (2008) collect the data on aggregate GDP from the Penn World Tables (PWT 5.6) and the data on agriculture from the Food and Agricultural Organization (FAO) of the United Nations (see Prasada Rao, 1993).[7] I compute

[6] http://www.economics.utoronto.ca/diegor/research/research.html

[7] Data on PPP for modern intermediate inputs are not available for any year other than 1985. Prasada Rao (1993) reports this information only for 1985 utilizing data reported by the Food and Agricultural Organization (FAO) of the United Nations. This information is necessary in order to measure the PPP-adjusted relative price of modern intermediate inputs, which is a vital component of the two sector model presented in this paper. It would be possible to compute PPP-adjusted intermediate input costs if data on gross agricultural output in domestic prices were available. Unfortunately, the updated versions of FAO dataset neither report gross or net agricultural output in domestic prices at the aggregate level. Although it is possible to obtain a measure of net agricultural output (GDP) in domestic prices by combining information from Penn World Tables (PWT) and the World Bank, there is a problem in measuring gross agricultural output in domestic prices. FAO does report gross agricultural production value in domestic prices for individual agricultural products. One way to obtain the aggregate value in domestic prices would be to add up these reported values of the individual agricultural products for every country. However, following this method, it turns out that for many of the countries, gross agricultural output in domestic prices (computed using available data from FAO) is less than net agricultural output in domestic prices (measured by combining available information from PWT and the World Bank), which may imply that there is a discrepancy between the set of agricultural products that the World Bank uses to compute the percentage of agricultural value added in total GDP in domestic prices and the set of agricultural products for which FAO reports value of gross production in domestic prices. This is

data on total employment using information available in PWT 5.6. The data sources used for construction of sectoral physical and human capital series are detailed in sections 2.3 and 2.4.

2.2 Data Summary

Table 1, Figure 1 and Figure 2 summarize all the data other than data on sectoral human and physical capital, as they are discussed separately. All the data in Table 1, with the exception of data on total employment (L), are obtained from Restuccia et al. (2008). Total employment (L) is calculated on the basis of PWT 5.6 data as follows: PWT 5.6 reports real GDP per worker (Y/L), real GDP per capita - Laspeyres index (Y/N) and total population (N). L is calculated by dividing Y/N by Y/L and multiplying the resulting employment-to-population ratio (L/N) by N.

In my sample of 43 countries, in 1985, GDP per worker in the richest country is 34.6 times that of the poorest one. In the agricultural sector, this productivity disparity between the richest and the poorest country is 82.2 times; however, in non-agriculture, this difference is only 7.2 times. Simultaneously, the poorest country's share of employment in agriculture is 84%, as opposed to 3% for the richest country. The same sectoral pattern can be observed if we move on to differences between greater number of rich and poor countries. For example, if I consider the richest 10% and the poorest 10% of the countries in my sample (the four richest and the four poorest countries), in the richest 10% of the countries, GDP per worker is 13.7 times that of the poorest 10%; the difference is 48.3 times in agriculture and only 3.5 times in non-agriculture. The employment share in agriculture is 78% in the poorest 10% of the countries in my sample, compared to only 5% for the richest 10%. The richest 10% of the countries in my sample are the United States, Canada, Australia and Norway whereas the poorest 10% are Zimbabwe, India, Kenya and Tanzania.

Figure 1 presents the relationship between GDP per worker and employment share in agriculture and Figure 2 presents country-wise data on GDP per worker in non-agriculture and GDP per worker in agriculture.

why I use 1985 FAO data reported by Prasada Rao (1993) for my analysis. At the same time, I employ PWT 5.6 data since it is the only version of the dataset that uses 1985 as the base year and therefore can be used in conjunction with the FAO data, which also uses 1985 as the base year.

Table 1
Data Summary[a]

Country	GDP/L	GDP_n/L_n	GDP_a/L_a	Y_a/L_a	X/Y_a	L_a/L	Z/L	L
United States	33,783	34,206	19,330	31,877	0.39	0.03	1.62	136,128,757
Canada	31,147	32,006	11,609	21,072	0.45	0.04	3.65	12,595,023
Australia	28,960	29,503	20,227	28,642	0.29	0.06	6.39	7,390,916
Norway	28,749	30,537	3,488	6,348	0.45	0.07	0.42	2,043,203
Netherlands	28,563	29,155	15,994	24,321	0.34	0.04	0.15	5,854,539
Italy	27,189	29,290	6,474	8,037	0.19	0.09	0.53	22,714,330
France	27,064	28,336	9,215	14,945	0.38	0.07	0.77	24,881,947
Sweden	26,504	27,503	6,128	10,907	0.44	0.05	0.69	4,237,694
New Zealand	26,039	25,961	26,743	37,810	0.29	0.10	0.36	1,437,901
Denmark	23,861	24,638	11,393	20,233	0.44	0.06	0.94	2,779,576
Finland	23,700	25,882	3,685	5,861	0.37	0.10	0.97	2,492,574
United Kingdom	22,981	23,280	10,196	17,652	0.42	0.02	0.25	27,684,455
Israel	21,953	22,764	6,924	13,545	0.49	0.05	0.26	1,602,343
Ireland	19,197	20,976	9,665	12,889	0.25	0.16	0.77	1,341,538
Japan	18,820	20,095	1,160	2,254	0.49	0.07	0.06	75,525,788
Venezuela	18,362	20,855	2,121	2,898	0.27	0.13	0.64	5,789,365
Syria	17,166	23,069	1,649	2,787	0.41	0.28	2.18	2,555,955
Greece	16,270	21,373	2,853	4,270	0.33	0.28	1.04	3,800,198
Iraq	15,855	20,649	1,070	1,419	0.25	0.24	1.28	4,105,357
Argentina	14,955	15,743	9,025	12,581	0.28	0.12	2.52	10,797,877
Iran	13,847	19,289	1,043	1,468	0.29	0.30	1.07	13,540,123
Portugal	11,343	13,865	1,174	1,679	0.30	0.20	0.70	4,539,892
Korea Republic	10,361	14,684	579	784	0.26	0.31	0.13	16,608,330
Uruguay	10,216	10,895	6,202	8,339	0.26	0.14	1.13	1,168,633
South Africa	9,930	11,507	2,132	2,972	0.28	0.17	1.25	11,239,601
Colombia	9,276	12,630	1,306	1,759	0.26	0.30	0.55	9,432,903
Costa Rica	9,148	11,826	1,936	2,950	0.34	0.27	0.57	919,559
Peru	8,141	12,666	659	849	0.22	0.38	0.60	6,107,038
Guatemala	7,358	15,191	678	853	0.21	0.54	0.81	2,261,847
Egypt	7,142	12,024	744	963	0.23	0.43	0.20	12,718,564
Turkey	7,091	14,342	722	978	0.26	0.53	1.26	21,829,299
Dominican Republic	7,082	11,467	1,010	1,284	0.21	0.42	0.75	1,912,479
Morocco	6,427	10,379	623	857	0.27	0.41	0.46	6,714,068
Sri Lanka	5,597	11,347	455	573	0.21	0.53	0.32	5,786,433
El Salvador	5,547	8,398	830	960	0.14	0.38	0.47	1,564,289
Honduras	4,652	10,241	672	807	0.17	0.58	1.36	1,306,797
Indonesia	4,332	8,746	399	488	0.18	0.53	0.33	62,135,835
Pakistan	4,249	8,229	520	659	0.21	0.52	0.67	28,566,524
Philippines	4,229	7,608	666	770	0.14	0.49	0.39	19,944,999
Zimbabwe	3,261	12,212	361	453	0.20	0.76	0.88	3,134,528
India	2,719	7,726	282	339	0.17	0.67	0.57	295,477,878
Kenya	2,014	11,232	253	297	0.15	0.84	0.30	7,979,818
Tanzania	975	4,767	235	269	0.12	0.84	0.30	10,265,798

Notations: GDP/L = GDP per worker, GDP_n/L_n = GDP per worker in the non-agricultural sector; GDP_a/L_a = GDP per worker in the agricultural sector; Y_a/L_a = Gross output per worker in the agricultural sector; X/Y_a = Intermediate input to gross agricultural output ratio; L_a/L = Share of employment in agriculture; Z/L = Land-to-employment ratio, L = Total Employment (see the theoretical framework in section 3 for detailed explanations of the notations)

[a] The numbers in this table are rounded up/down.

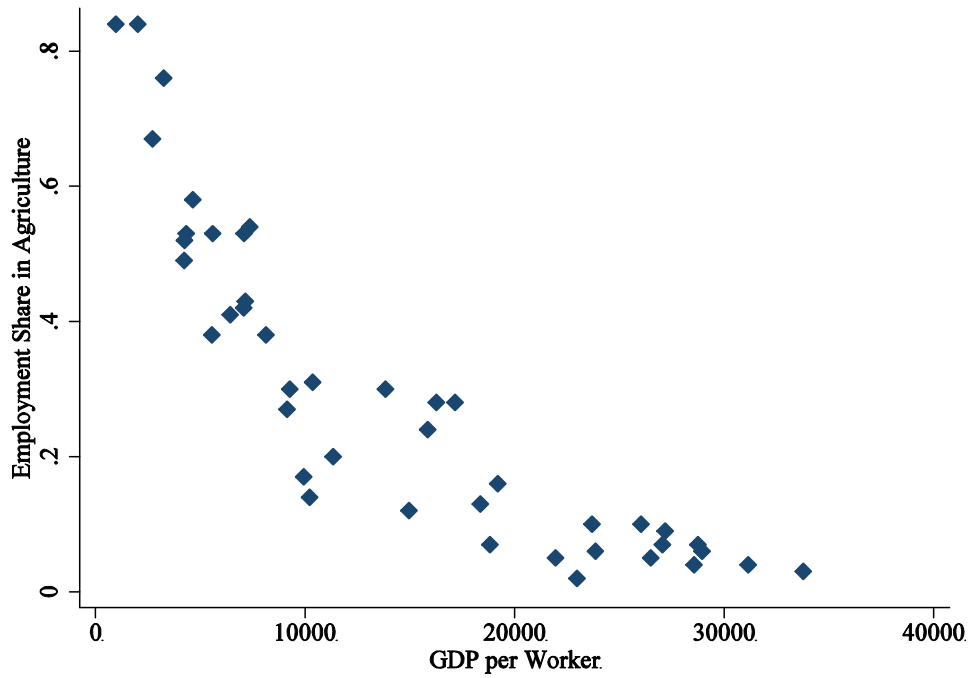

Figure 1: GDP per Worker and Employment Share in Agriculture

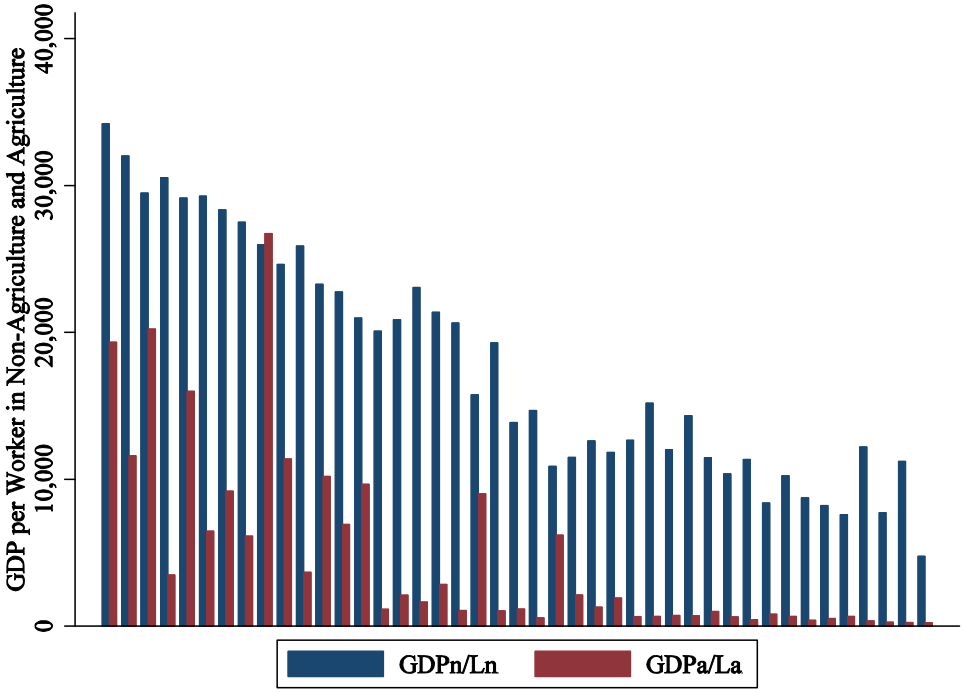

Figure 2: GDP per Worker in Non-agriculture and Agriculture. The *X* axis lists the countries from the richest to the poorest.

Figure 1 clearly depicts the inverse relationship between GDP per worker and employment share in agriculture. The poorest countries have the highest employment shares in agriculture; as we move towards the richer countries, the employment shares tend to drop drastically. Figure 2 demonstrates that poor countries have a lower GDP in both sectors, but the difference is much more pronounced in the agricultural sector.

2.3 Construction of Sector-Specific Physical Capital Data

Cross-country data on sector-specific physical capital are rare. However, certain available evidence (e.g., Crego et al., 2000; Chanda and Dalgaard, 2008; Vollrath, 2009) reveals that cross-country variations in capital per worker in agriculture are larger than the variations in non-agriculture. This supports the argument that the inclusion of sector-specific physical capital should play an important role in explaining the cross-country differences in agricultural labor productivity and, in turn, aggregate labor productivity. Chanda and Dalgaard (2008) and Vollrath (2009) use sector-specific capital data directly from the work of Crego et al. (2000). However, the data reported by Crego et al. (2000) are not PPP-adjusted and therefore entail serious issues with respect to international comparability. In fact, the PPP-unadjusted sector-specific capital data reported by Crego et al. (2000) overestimate the difference in sectoral physical capital per worker between the rich and the poor countries, which I explain later in this section.

For all the countries in my sample, Crego et al. (2000) report fixed investments in 1990 domestic prices in local currency units for both the agricultural sector and the entire economy. Their data set covers the period between 1948 and 1992. For each country and each year, they also report the domestic deflators (both for agriculture and the entire economy) they use to obtain their numbers.[8] I use available information from their work and construct a PPP-adjusted measure of sector-specific physical capital by using the following method.

To construct PPP-adjusted physical capital for the agricultural sector, first, for each country and each year for which information is available, I multiply investments in agriculture in 1990 domestic prices by the relevant deflator and obtain investments in agriculture in current domestic prices. These figures are in local currency units. In order to convert the local currency units into U.S. dollars, I multiply these figures by the ratio of U.S. PPP for investments to the country's PPP for investments for each year. I collect the required data on investment prices

[8] They use country specific investment deflators if available; otherwise they use economy-wide GDP deflators.

from PWT 5.6.[9] Finally, I divide the resulting figure by the relevant U.S. deflator (1985=100) to obtain investments in agriculture in 1985 U.S. prices for each country and each year.[10] To generate economy-wide PPP-adjusted physical capital for each country and each year, I utilize information on economy-wide investments in 1990 domestic prices and deflators reported by Crego et al. (2000) and follow the same technique.

I employ the perpetual inventory method explained by Caselli (2005) on the PPP-adjusted investments in agriculture and the entire economy, respectively, to construct PPP-adjusted physical capital in agriculture and the entire economy.[11] I compute non-agricultural physical capital by deducting agricultural physical capital from economy-wide physical capital. I generate PPP-adjusted data on sectoral physical capital for the entire period for which information is available for each country in my sample. For the purpose of this paper, I use the generated PPP-adjusted value for sector-specific physical capital for 1985.

Table 2 reports country-wise physical capital per worker in non-agriculture and agriculture whereas Figure 3 presents the relationship between GDP per worker and the ratio of non-agricultural to agricultural physical capital per worker. From the table and the figure, it is obvious that even after adjusting for PPP, there is a considerable difference in capital per worker between the rich and the poor countries and the difference is far larger in the agricultural sector e.g. capital per worker in non-agriculture in the richest 10% of the countries in my sample is 6.6 times that of the poorest 10% whereas capital per worker in agriculture in the richest 10% of the countries is a staggering 204.5 times that of their poorest counterparts. Such evidence makes an extremely strong case for

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[9] For each country and each year, PWT 5.6 reports PPP_{inv} / XR as well as XR, where PPP_{inv} denotes the PPP for investments while XR stands for the nominal exchange rate per U.S. dollar. I multiply PPP_{inv} / XR by XR to obtain PPP_{inv} for each country for each year.

[10] Crego et al. (2000) report 1990 U.S. deflators where deflator for 1990 is equal to 100. Since all the data in my paper are reported in 1985 prices, I convert the 1990 U.S. deflators to 1985 U.S. deflators by simply normalizing the 1985 deflator to 100. It should be alright to use this method since relative prices in 1985 should not be too different from relative prices in 1990.

[11] Following Caselli (2005), I utilize the following perpetual inventory equation: $K_t = I_t + (1 - \delta) K_{t-1}$, where K_t is aggregate capital stock, I_t is investment and δ is depreciation rate (following Caselli, 2005, δ is set to 0.06). The initial capital stock K_0 is calculated as $I_0 / (g + \delta)$, where I_0 is the investment in the first year with available data. If the first year with available data is 1960 or before, then g is the average geometric growth rate for investment between the first year with available data and 1970. If, on the other hand, the first year for which information is available is 1961 or later, then g is the average geometric growth rate for investment between the first year and the 10th year after the first year with available data.

including sector-specific physical capital in the analysis; and as we discover in Section 4, the inclusion of sector-specific physical capital indeed plays an important role in explaining cross-country income differences (see Table 5 in Section 4).

Table 2
PPP-Adjusted Sector-Specific Physical Capital per Worker[a]

Country	Capital per Worker in Non-agriculture	Capital per Worker in Agriculture
United States	64,125	82,960
Canada	56,095	111,745
Australia	75,101	85,248
Norway	79,884	92,886
Netherlands	65,634	92,133
Italy	57,261	49,496
France	70,320	52,222
Sweden	62,506	80,597
New Zealand	65,156	67,114
Denmark	55,959	82,446
Finland	82,643	86,327
United Kingdom	41,832	58,925
Israel	45,521	49,619
Ireland	46,638	38,981
Japan	52,337	41,691
Venezuela	31,169	15,809
Syria	27,934	8,496
Greece	42,331	12,002
Iraq	27,259	11,471
Argentina	23,280	29,837
Iran	33,351	5,152
Portugal	24,903	7,187
Korea Republic	22,774	4,729
Uruguay	21,464	4,590
South Africa	21,410	7,566
Colombia	15,299	2,527
Costa Rica	16,258	6,555
Peru	21,377	1,895
Guatemala	11,836	1,338
Egypt	3,541	609
Turkey	28,349	2,939
Dominican Republic	17,256	1,199
Morocco	8,790	463
Sri Lanka	9,554	227
El Salvador	7,939	597
Honduras	11,782	1,323
Indonesia	12,630	382
Pakistan	8,228	2,109
Philippines	5,689	379
Zimbabwe	17,574	755
India	6,139	664
Kenya	12,864	292
Tanzania	5,060	111

[a] The numbers are rounded up/down.

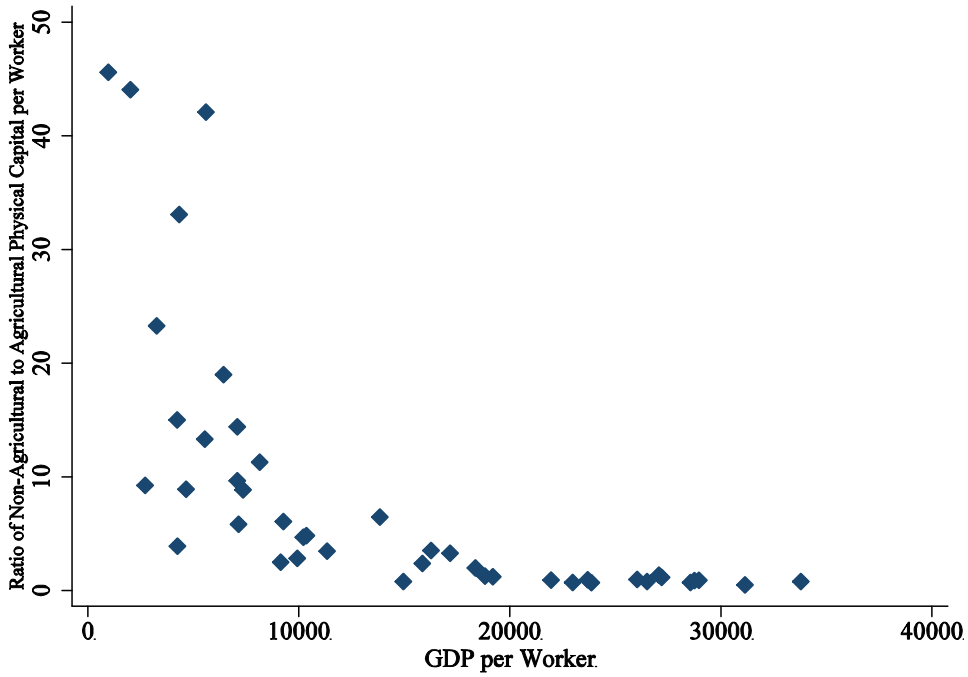

Figure 3: GDP per Worker and the Ratio of Non-Agricultural to Agricultural Physical Capital per Worker

Instead of using the constructed PPP-adjusted measure, if I directly use the PPP-unadjusted sectoral capital data reported by Crego et al. (2000) in calculating the sectoral capital per worker, the differences in both the sectors between the richest and the poorest countries significantly increase. Based on the PPP-unadjusted measure of sectoral physical capital, capital per worker in non-agriculture in the richest 10% of the countries in my sample is 8.6 times that of the poorest 10% whereas in agriculture, capital per worker in the richest 10% of the countries is 293.5 times that of their poorest counterparts (compared to 6.6 times in non-agriculture and 204.5 times in agriculture when using the PPP-adjusted measure).[12] This clearly indicates that a significant difference exists between the two measures and the PPP-unadjusted measure would overestimate the importance of sectoral physical capital in explaining international productivity differences.[13]

[12] Table C.1 in Appendix C reports sectoral capital per worker for all the countries in my sample when the PPP-unadjusted measure is used.

[13] It should however be noted that the quality of the PPP-adjusted physical capital series depends to some extent on the quality of the investment price data used to construct the series. If the deflators are obtained primarily from price surveys conducted in rich countries and reflect mostly prices of non-agricultural capital goods, then the reported PPP-adjusted measure may potentially understate the sectoral difference in physical capital per worker by overstating agricultural capital particularly in poor countries.

2.4 Construction of Sector-Specific Human Capital Data

A large body of literature, both theoretical and empirical, exists on human capital. Lucas (1988) e.g. develops a theory of human capital in which he focuses on individuals' decisions to acquire knowledge and suggests that these decisions have significant consequences for productivity. According to Lucas (1988), neoclassical growth model without human capital is unable to account for observed diversity across countries and makes strong counterfactual prediction that international trade should induce rapid movement towards equality in capital-labor ratios and factor prices. On the empirical front e.g. Mankiw et al. (1992) argue that an augmented Solow model that includes accumulation of human and physical capital provides an excellent description of the cross-country data. Based on these seminal studies, we can safely argue that human capital is vital within the neoclassical growth framework in terms of explaining cross-country income data. In this part of the paper, I explain how I construct sector-specific human capital data.

2.4.1 Computing Sector-Specific Schooling Years

I combine available information on sectoral schooling from the work of Timmer (2000) and aggregate schooling[14] from the works of Barro and Lee (1996, 2010) and Hall and Jones (1999) to construct average "urban" and "rural" schooling and employ these constructed years for calculating human capital per worker in "non-agricultural" and "agricultural" sectors, respectively. Throughout this paper, when discussing sectoral human capital, I use the terms "urban" and "non-agricultural," as well as "rural" and "agricultural," synonymously.

Timmer (2000) reports data on rural and urban schooling that are derived from the data sources used by Barro and Lee (1996). Barro and Lee (1996) report aggregate schooling for all the countries in my sample except Morocco and Tanzania, which are reported by Hall and Jones (1999). In a recent work, Barro and Lee (2010) update their earlier data and the updated dataset includes aggregate schooling for all the countries in my sample. The aggregate schooling years reported by Barro and Lee (2010) are different from the earlier version of their data for the vast majority of the countries. Based on data availability from all these sources, the countries in my sample can be broadly divided into three categories. The three categories of countries together with how sectoral schooling years have been constructed for each category are explained below.

[14] The term "aggregate schooling" or "total schooling" refers to overall average schooling for a country.

Category 1: Countries for which sectoral schooling years are directly available from the work of Timmer (2000)

For 23 out of 43 countries in my sample, rural and urban schooling years for 1985 are directly reported by Timmer (2000). Since these observations are based on data sources which are used in an older version of the work by Barro and lee (1996), I update these observations using recent data reported by Barro and Lee (2010) in the following way. I calculate the ratio of urban schooling years to total schooling years for each of the 23 countries for 1985 where urban schooling is taken from the work of Timmer (2000) and total schooling is taken from the work of Barro and Lee (1996).[15] I multiply this ratio by total schooling years for 1985 reported by Barro and Lee (2010) to obtain the updated urban schooling years for each of the 23 countries for 1985. I obtain a measure of rural schooling years for each of the countries in this category for 1985 in the same way i.e. by multiplying the ratio of rural schooling years to total schooling years, calculated using data reported by Timmer (2000) and Barro and Lee (1996), by the total schooling years for 1985 taken from the work of Barro and Lee (2010).

Category 2: Countries for which sectoral schooling years are not directly available from the work of Timmer (2000) and total schooling according to Barro and Lee (1996) is less than 6.6 years

Datasets reported by Timmer (2000) as well as Barro and Lee (1996) include observations for the years 1960, 1965, 1970, 1975, 1980 and 1985. The data reveal a very strong relationship between rural and urban schooling years. At the same time, for most of the countries and years with total schooling greater than 6.6 years, the difference between rural and urban schooling years tends to be small or zero.[16] When analyzing these data, Vollrath (2009) also makes very similar observations in his paper.

Given these observations, for countries and years for which total schooling according to Barro and Lee (1996) is less than 6.6 years, I run the following simple OLS regression using sectoral schooling data from the work of Timmer (2000).[17]

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[15] Total schooling for Tanzania (which belongs to category 1) is taken from the work of Hall and Jones (1999) for calculating the ratio.

[16] The ratio of urban to rural schooling $\left(s_n / s_a\right)$ for countries and years with total schooling $s > 6.6$ years is very close to 1, whereas for countries and years with total schooling $s < 6.6$ years, s_n / s_a is almost double i.e. close to 2.

[17] The entire sample for which Timmer (2000) reports sectoral schooling data is considered when running this regression. Number of observations (countries and years) in Timmer's (2000) sample for which total schooling according to Barro and Lee (1996) is smaller than 6.6 years is 364. It should be noted that total schooling for Morocco, which belongs to category 2, is taken from the

$$s_a = -0.71 + 0.86 s_n, R^2 = 0.84, \text{number of observations} = 364$$
$$(8.81) \quad (43.05)$$

Here, s_a and s_n denote rural and urban schooling years, respectively. The terms in brackets are the corresponding t-statistics. The t-statistics corresponding to the intercept as well as the coefficient and the R^2 of the regression analysis clearly reveal the strong relationship between rural and urban schooling.

In addition to the above relationship, like Vollrath (2009), I also utilize the notion that total schooling years for each country in 1985 (taken from the work of Barro and Lee, 2010) is simply the weighted average of rural and urban schooling years where the weights are employment share in agriculture and non-agriculture in 1985, respectively. A total of 8 countries out of 43 in my sample belong to this category. For these countries, I utilize these two equations and solve for the two unknowns s_a and s_n.

Category 3: Countries for which sectoral schooling years are not directly available from the work of Timmer (2000) and total schooling according to Barro and Lee (1996) is greater than 6.6 years

A total of 12 countries out of my sample of 43 belong to this category. In a similar approach to Vollrath (2009), I assign total years of schooling from the work of Barro and Lee (2010) to both urban and rural sectors for these countries.[18]

The data on sectoral schooling years constructed in this paper improve upon the existing data constructed by several other authors (e.g., Cordoba and Ripoll, 2006; Chanda and Dalgaard, 2008; Vollrath, 2009). Although my method is similar to that of Chanda and Dalgaard (2008)[19] and Vollrath (2009), I improve the sectoral data by using the latest version of schooling data reported by Barro and Lee (2010) whereas their figures are derived from earlier versions of the data (Barro and Lee, 1996). My method differs from and requires less stringent assumptions, in comparison to the method employed by Cordoba and Ripoll (2006), who base their calculations of sectoral schooling on available urban/rural schooling data from UNESCO. For most of the countries, sectoral schooling data reported by UNESCO are from the 1970's or early 1990's. Applying these figures to 1985 requires the strong assumption that sectoral schooling remained unaffected by any structural change that the countries may have gone through during this period, which does not seem plausible.

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work of Hall and Jones (1999) and according to their work, total schooling in Morocco is less than 6.6 years.

[18] It should be noted that Vollrath (2009) assigns total years of schooling from the work of Barro and Lee (1996) to both urban and rural sectors for the countries for which total schooling is greater than 6.6 years.

[19] Chanda and Dalgaard (2008) primarily use Vollrath's data on sectoral schooling for 1985.

Table 3 reports the urban and rural schooling for all the countries in my sample. From the table it is evident that the difference between urban schooling and rural schooling is greater in the poor countries, compared to the rich ones. For example, the ratio of urban to rural schooling in the richest 10% of the countries in my sample is 60% of the ratio in the poorest 10%. I use these sectoral schooling years to compute sector-specific human capital.

Table 3
Average Years of Urban Schooling and Rural Schooling

Name of Country	Average Years of Urban Schooling	Average Years of Rural Schooling
United States	12.16	12.16
Canada	9.89	9.89
Australia	11.60	11.60
Norway	9.98	9.98
Netherlands	9.75	9.75
Italy	6.87	5.22
France	6.56	4.96
Sweden	9.52	9.52
New Zealand	11.67	11.67
Denmark	9.78	9.78
Finland	8.21	8.21
United Kingdom	7.67	7.67
Israel	9.94	9.94
Ireland	10.07	10.07
Japan	9.44	9.44
Venezuela	5.43	2.84
Syria	3.90	3.24
Greece	6.83	6.59
Iraq	2.33	1.31
Argentina	7.17	6.85
Iran	3.11	1.98
Portugal	6.52	5.67
Korea Republic	7.63	7.63
Uruguay	6.54	6.18
South Africa	5.02	3.63
Colombia	5.32	4.71
Costa Rica	6.68	5.06
Peru	6.76	4.38
Guatemala	4.32	2.11
Egypt	3.47	2.29
Turkey	4.65	3.88
Dominican Republic	5.69	4.39
Morocco	2.11	1.11
Sri Lanka	7.77	7.57
El Salvador	4.36	3.21
Honduras	4.55	2.93
Indonesia	4.18	3.36
Pakistan	3.76	1.43
Philippines	6.69	5.93
Zimbabwe	6.48	3.89
India	3.41	1.84
Kenya	7.39	3.84
Tanzania	4.22	2.73

2.4.2 Computing Sector-Specific Human Capital

I use the Mincer equations (Mincer, 1974) employed by Hall and Jones (1999) to compute human capital.[20] Based on the model presented by Hall and Jones (1999), human capital embedded in a worker can be represented by $h = e^{\varphi(s)}$, where $\varphi(s)$ represents the efficiency of a unit of labor with s years of schooling relative to one with no schooling i.e. $\varphi(0) = 0$. The derivative $\varphi'(s)$ is the rate of return to schooling based on Mincerian wage regression i.e. an additional year of schooling proportionally increases the efficiency of the worker by $\varphi'(s)$.

I use the quality-adjusted Mincerian returns reported by Schoellman (2011) to calculate quality-adjusted sector-specific human capital. These returns are not commonly used in the literature. Most authors employ the Mincerian returns reported by Psacharopoulos (1994) to construct human capital data (e.g., Hall and Jones, 1999; Cordoba and Ripoll, 2006; Chanda and Dalgaard, 2008; Vollrath, 2009). The computation of human capital, using Mincerian returns reported by Schoellman (2011), offers two benefits in comparison to the use of the returns reported by Psacharopoulos (1994). First, Schoellman (2011) reports returns to schooling for each country separately. Therefore, there is no need to make the strong assumption that returns to schooling are the same in each country. Human capital constructed using Mincerian returns reported by Psacharopoulos (1994) requires such assumption because Psacharopoulos (1994) does not report country-specific returns. Secondly, Schoellman (2011) uses the returns to schooling of foreign-educated immigrants in the United States to compute the education quality of their source countries and thus incorporates quality of schooling in his estimation of schooling returns, an attribute that is absent in returns reported by Psacharopoulos (1994). Figure 4 presents the relationship between GDP per worker and the ratio of urban to rural human capital. The figure depicts that overall, sectoral difference in human capital is higher in the poor countries compared to the rich ones.

The sectoral human capital data constructed in this paper is considerably different from the data constructed in other studies, such as Cordoba and Ripoll (2006) and Vollrath (2009). In comparison to my data, the human capital data constructed in their studies lead to a greater ratio of non-agricultural to agricultural human capital (h_n/h_a) on average. For the 43 countries in my sample, based on my construction of human capital data, the average h_n/h_a is 1.1. This average based on human capital data developed by Cordoba and Ripoll (2006)

[20] This method of computing human capital is widely used in the literature (see e.g. Caselli, 2005; Cordoba and Ripoll, 2006; Chanda and Dalgaard, 2008; Vollrath, 2009).

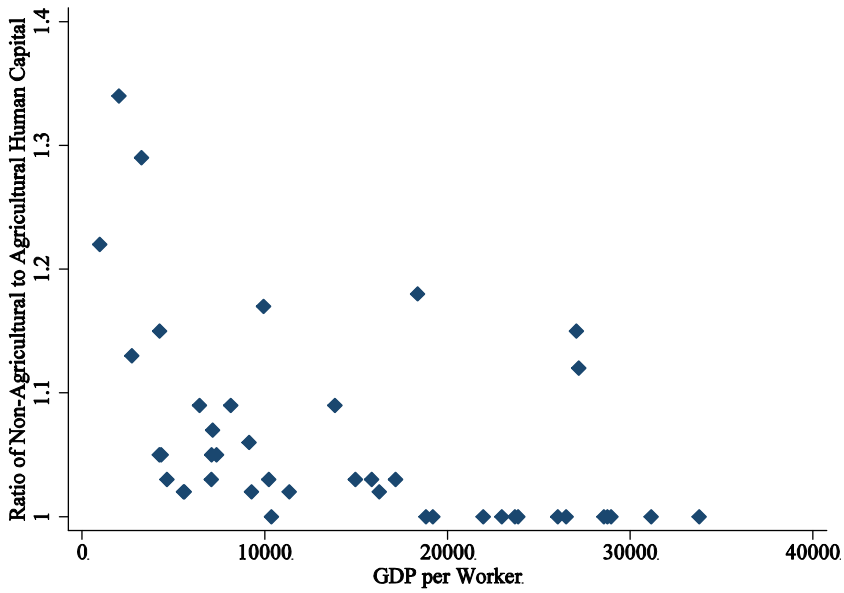

Figure 4: GDP per Worker and the Ratio of Non-Agricultural to Agricultural Human Capital

and Vollrath (2009) for comparable sample of countries are 2.0 and 1.5, respectively.[21] The differences in the sectoral human capital ratio between the rich and the poor countries, as implied by data constructed in this paper, are also different from their studies. Based on my calculations, h_n/h_a is 24% higher in the poorest 10% of the countries in my sample than the richest 10%. For the same sample of countries, human capital data constructed by Cordoba and Ripoll (2006) implies much larger difference (354%), primarily due to the manner in which they capture quality difference between urban and rural human capital (discussed in Appendix D), whereas the data constructed by Vollrath (2009) suggest that h_n/h_a in the poorest 10% of the countries is 18% lower than the richest 10%.[22]

Throughout this paper, I focus on the measure of human capital constructed using the quality-adjusted country-specific Mincerian returns reported

[21] The sample of countries in the paper by Cordoba and Ripoll (2006) does not include three of the countries (Iraq, Israel and Sweden) whereas the study by Vollrath (2009) does not include five of the countries (Iraq, Ireland, Israel, Morocco and Tanzania) that are included in my sample. Excluding the mentioned three or five countries from my sample, the average h_n/h_a, based on my construction of human capital data, stays 1.1.

[22] Note that Vollrath's sample does not include Tanzania. The poorest 10% of the countries in my sample, excluding Tanzania, are the Philippines, India, Zimbabwe and Kenya. Excluding Tanzania, based on my calculations, h_n/h_a in the poorest 10% of the countries is 20% higher than the richest 10%.

by Schoellman (2011). The importance of adding sector-specific quality-adjusted human capital to the model is reported in Table 5 in Section 4.[23]

3. Theoretical Framework of the Study

I utilize the basic framework of the two-sector general equilibrium model employed by Restuccia et al. (2008) and extend it by incorporating sector-specific human and physical capital.

3.1 Preferences and Production Technologies

There are two types of goods in the economy - agricultural and non-agricultural. Consumers have non-homothetic preferences with a subsistence requirement for the consumption of the agricultural good.

These preferences of the representative household are given by the following Stone-Geary utility function:

$$U = a\log\left(c_a - \bar{a}\right) + \left(1 - a\right)\log\left(c_n\right), 0 \le a < 1$$

The Stone-Geary utility function encapsulates the idea that the share of agriculture in GDP declines as income grows. Here, c_a and c_n denote consumption of the agricultural and non-agricultural goods, respectively; $\bar{a}$ denotes subsistence level of consumption[24] and a denotes utility weight over the two goods.

[23] I construct two other measures of human capital in addition to the one discussed above. I construct a measure of human capital using the returns reported by Psacharopoulos (1994) and a weighted quality-adjusted measure of human capital, where the returns to rural schooling are assumed to be lower than urban schooling. I develop the latter to capture the possible lower quality of human capital in rural areas compared to urban areas. The way I construct this measure differs from the methods other studies use to capture the same possibility. The differences, along with the details of the two additional measures and the results using all the different versions of human capital, are reported in Appendix D.

[24] The subsistence requirement captures the "food problem" argument developed by Schultz (1953), which states that in order to meet the basic food requirements, the lower the agricultural labor productivity, the greater the need to allocate a larger share of employment in the agricultural sector. This argument provides an explanation as to why poor countries with very low agricultural labor productivities allocate such large shares of employment in agriculture. Several authors have incorporated the "food problem" argument in studying cross-country income differences (e.g., Gollin et al., 2007; Restuccia et al., 2008).

Non-agricultural and agricultural production technologies are summarized by the following equations, respectively:

$$Y_n = K_n^{\beta}\left(AH_n\right)^{1-\beta}, 0<\beta<1, H_n = h_n L_n$$

where A denotes economy-wide productivity; and Y_n, K_n, H_n, h_n and L_n denote output (or GDP), stock of capital, aggregate human capital or effective labor, average level of human capital per worker and labor in the non-agricultural sector, respectively.

$$Y_a = X^{\alpha}(Z^{(1-\sigma-\gamma}K_a^{\gamma}(\kappa AH_a)^{\sigma})^{1-\alpha}, 0<\sigma<1, 0<\alpha<1, 0<\gamma<1, 0<(\sigma+\gamma)<1,$$
$$H_a = h_a L_a$$

Where X, Z and κ denote intermediate input provided by the non-agricultural sector[25], land and a parameter measuring the level of integration of the agricultural sector to the aggregate economy[26], respectively; and Y_a, K_a, H_a, h_a and L_a denote gross output[27], stock of capital, aggregate human capital or effective labor, average level of human capital per worker and labor in the agricultural sector, respectively. I assume $1-\beta=\sigma$ i.e. the income share of labor in both sectors is the same.

Through algebraic manipulations, the non-agricultural and agricultural production functions can be expressed as the following, respectively:

$$\frac{Y_n}{L_n} = (Ah_n)^{\sigma}\left(\frac{K_n}{L}\right)^{(1-\sigma)}\left(1-\frac{L_a}{L}\right)^{(\sigma-1)} \tag{1}$$

$$\frac{Y_a}{L_a} = \left(\frac{X}{Y_a}\right)^{\frac{\alpha}{1-\alpha}}\left(\frac{Z}{L}\right)^{1-\sigma-\gamma}\left(\frac{K_a}{L}\right)^{\gamma}\left(\kappa Ah_a\right)^{\sigma}\left(\frac{L_a}{L}\right)^{\sigma-1} \tag{2}$$

[25] Modern intermediate inputs capture, to a large extent, the level of agricultural modernization. The role of modernization in agriculture has been well established in a number of earlier studies (e.g., Schultz, 1964; Hayami and Ruttan, 1985; Huffman and Evenson, 1993), as well as recent ones (e.g., Restuccia et al., 2008; Yang and Zhu, 2009).

[26] See Restuccia et al. (2008) for the implications of including κ in the agricultural production function.

[27] It should be noted that Y_a denotes gross agricultural output rather than GDP and incorporates modern intermediate inputs in measuring agricultural production.

Here, L denotes total employment. The model does not make any distinction between population and employment and abstracts from any labor-leisure decision for the households. According to equation (2), gross output per worker in agriculture (Y_a/L_a) increases with intermediate input to agricultural gross output ratio (X/Y_a), land-to-employment ratio (Z/L), agricultural capital to total employment ratio (K_a/L), agricultural productivity parameter (κ), economy-wide productivity (A) and human capital per worker in agriculture (h_a), but decreases with employment share in agriculture (L_a/L).

3.2 Household's Problem

The representative household chooses c_a and c_n to maximize utility subject to budget constraint:

$$\max_{c_a,\, c_n}\left\{a\log\left(c_a - \bar{a}\right) + (1-a)\log\left(c_n\right)\right\} \text{ subject to } p_a c_a + c_n = y$$

where y denotes the income of the household and p_a is the price of agricultural good relative to non-agricultural good. The price of non-agricultural good is normalized to 1.

3.3 Firms' Problem

In the agricultural sector, the representative farmer chooses effective labor (H_a) and the use of intermediate input (X) to maximize profits:

$$\max_{X,H_a}\left\{p_a X^{\alpha}(Z^{1-\sigma-\gamma}K_a^{\gamma}\left(\kappa A H_a\right)^{\sigma})^{1-\alpha} - \pi X - w_a H_a\right\}$$

where π denotes the price of intermediate input relative to non-agricultural goods. It is assumed that π units of non-agricultural output is used to produce 1 unit of intermediate input. Therefore, the farmers require πX units of non-agricultural goods to get X units of intermediate inputs.[28] w_a denotes wage per unit of

[28] As explained by Restuccia et al. (2008), this cost (π) can be thought of as a barrier to the use of modern intermediate inputs. Appendix B explains how the costs of modern intermediate inputs are measured.

human capital in the agricultural sector. w_a is computed as W_a/h_a where W_a denotes wage per worker in the agricultural sector.

The non-agricultural firm, on the other hand, chooses H_n to maximize profits:

$$\max_{H_n}\{AH_n - w_n H_n\}$$

where w_n denotes wage per unit of human capital in the non-agricultural sector. w_n is computed as W_n/h_n where W_n denotes wage per worker in non-agriculture.

3.4 Cost of Skill Acquisition, Wage Gap and Labor Market Distortion

Several authors have used the notion of sectoral wage gap - the ratio of non-agricultural to agricultural wage in terms of wage per worker - as labor market frictions or distortions (e.g., Gollin et al., 2004; Cordoba and Ripoll, 2006; Restuccia et al., 2008). [29] In order to justify the existence of the wage gap in an environment with human capital, I utilize a simplified version of the idea developed by Caselli and Coleman (2001) and assume that individuals require additional skills in order to work in the non-agricultural sector.

Each individual can either work in the agricultural sector, requiring comparatively less schooling (s_a) and subsequently less human capital (h_a), or incur a cost in order to acquire the additional skills (corresponding to schooling s_n and subsequent human capital h_n) necessary to work in the non-agricultural sector. I assume that acquiring the schooling necessary for working in the agricultural sector is cost free; everyone in the economy has at least s_a years of schooling, and thus they possess h_a amount of human capital. The cost of acquiring the additional skills necessary to work in non-agriculture is modelled as a fraction θ of the non-agricultural wage per worker.

No-arbitrage condition in equilibrium implies that the wage in the non-agricultural sector net of this cost must be equal to the wage in agricultural sector, i.e.

$$(1-\theta)W_n = W_a, 0 \le \theta < 1$$

[29] The wage gap is approximated by the ratio of sectoral average or marginal product of labor in all these studies.

In terms of wage per unit of human capital, the above wage gap equation can be written as

$$(1-\theta)w_n h_n = w_a h_a \tag{3}$$

This cost of skill acquisition (θ) is termed as labor market distortion throughout this paper.

3.5 Competitive Equilibrium

Competitive equilibrium in this economy can be defined as a set of allocations $\{H_a, H_n, c_a, c_n, X\}$, prices $\{p_a, w_a, w_n\}$ and profits for agricultural firms, such that: (a) given prices, $\{H_a, X, H_n\}$ solve the firms' problem in each of the sectors; (b) given prices and profits, $\{c_a, c_n\}$ solve the representative household's problem; (c) The no-arbitrage condition in equation (3) holds and (d) all markets (labor market, agricultural goods' market and non-agricultural goods' market, respectively) clear, i.e.

$$L = L_a + L_n \tag{4}$$

$$Y_a = Lc_a \tag{5}$$

$$Y_n = Lc_n + \pi X \tag{6}$$

3.6 Solution of the Equilibrium

Utilizing equations (1), (2) and the equilibrium conditions, the following three expressions can be derived respectively for equilibrium share of employment in agriculture (L_a/L), equilibrium intermediate input to gross agricultural output ratio (X/Y_a) and equilibrium gross output per worker in agriculture (Y_a/L_a):[30]

[30] The detailed solution to the equilibrium, including the derivations of equations (7), (8) and (9) are provided in Appendix E.

$$\frac{L_a}{L} = \frac{(1-a)(1-\theta)}{a(1-\alpha)+(1-a(1-\alpha))(1-\theta)} \frac{\bar{a}}{Y_a/L_a} + \frac{a(1-\alpha)}{a(1-\alpha)+(1-a(1-\alpha))(1-\theta)} \tag{7}$$

$$\frac{X}{Y_a} = \left[\frac{\alpha}{1-\alpha} \frac{(1-\theta)(h_n/h_a)^{\sigma}}{\pi} \left(\frac{K_n/L}{(L_a/L)^{-1}-1} \right)^{1-\sigma} \frac{1}{\kappa^{\sigma}(Z/L)^{1-\sigma-\gamma}(K_a/L)^{\gamma}} \right]^{1-\alpha} \tag{8}$$

$$\frac{Y_a}{L_a} = \left[\frac{\alpha}{1-\alpha} \frac{(1-\theta)h_n^{\sigma}}{\pi} \left(\frac{K_n/L}{(L_a/L)^{-1}-1} \right)^{1-\sigma} \right]^{\alpha} \left[\kappa^{\sigma} \left(\frac{K_a}{L} \right)^{\gamma} \left(\frac{Z}{L} \right)^{1-\sigma-\gamma} h_a^{\sigma} \right]^{1-\alpha} A^{\sigma} \left(\frac{L_a}{L} \right)^{\sigma-1} \tag{9}$$

From equations (8) and (9), note that X/Y_a and Y_a/L_a are functions of L_a/L and other exogenous variables and parameters. Equation (7), on the other hand, expresses L_a/L as a function of Y_a/L_a and parameters. Substituting equation (9) into equation (7), I obtain an implicit function for L_a/L that can be solved numerically. Substituting the solution for L_a/L into equations (8) and (9), I can solve for X/Y_a and Y_a/L_a.

Aggregate GDP per worker can be derived as:

$$\frac{Y}{L} = \frac{GDP_a + GDP_n}{L} = \frac{p_a^* Y_a - \pi^* X + Y_n}{L} = \frac{Y_a}{L}\left(p_a^* - \pi^* \frac{X}{Y_a} \right) + \frac{Y_n}{L}$$

Substituting $\frac{Y_n}{L} = \left(\frac{K_n}{L} \right)^{(1-\sigma)} \left[Ah_n \left(1 - \frac{L_a}{L} \right) \right]^{\sigma}$ into the above expression, I obtain

$$\frac{Y}{L} = \frac{Y_a}{L_a}\frac{L_a}{L}\left(p_a^* - \pi^* \frac{X}{Y_a} \right) + \left(\frac{K_n}{L} \right)^{1-\sigma} \left[Ah_n \left(1 - \frac{L_a}{L} \right) \right]^{\sigma} \tag{10}$$

Here, $\{p_a^*, \pi^*\}$ denote international prices for agricultural output and intermediate input. I use equations (7), (8), (9) and (10) to perform the quantitative analysis in Section 4 of this paper.

4. Quantitative Analysis

In this part of the paper, I describe how the labor market distortions and economy-wide productivity are measured, explain the calibration process and present the results of the quantitative analysis focusing on the impacts of sector-specific human capital, physical capital and labor market distortions.

4.1 Measuring Labor Market Distortions

I use the equilibrium no-arbitrage condition to measure the labor market distortions. Using the equilibrium no-arbitrage condition, I obtain

$$\frac{1}{(1-\theta)} = \frac{w_n}{w_a}\frac{h_n}{h_a}$$

Here, $1/(1-\theta)$ is an increasing function of θ; thus, it is proportional to the equilibrium skill acquisition costs. Using the above condition, $1/(1-\theta)$ can be measured as the product of wage gap in terms of wage per unit of human capital (w_n/w_a) and sectoral human capital ratio (h_n/h_a). w_n/w_a is calculated as the ratio of sectoral marginal products of human capital (to measure the wage gap, marginal product in agriculture is calculated in terms of GDP in agriculture, rather than gross output).[31] Such model-based measure of labor market distortions has previously been used by several authors (e.g., Mulligan, 2002; Gollin et al., 2004; Cordoba and Ripoll, 2006; Chari et al., 2007; Restuccia et al., 2008; Vollrath, 2009). Utilizing the optimal conditions from the firms' problems (see Appendix E) to compute the sectoral marginal product ratio and considering GDP per worker in both the sectors, labor market distortions can be measured as (the human capital ratio gets cancelled out):[32]

$$\frac{1}{(1-\theta)} = \frac{GDP_n/L_n}{p_a GDP_a/L_a}$$

[31] I use this model-based measure of sectoral wage gap because actual data on sectoral wages, especially agricultural wages, are unavailable for most of the countries in my sample.

[32] Restuccia et al. (2008) report their measures of labor market distortions relative to USA and the calibrated value of distortions in the USA, from which it is possible to back out the data on relative prices of agricultural goods (p_a) for all the countries in my sample.

Figure 5 presents the relationship between GDP per worker and labor market distortions. The figure demonstrates that, overall, the distortions are inversely related to GDP per worker. Labor market distortions, on average, are much higher in poor countries as opposed to the rich ones.

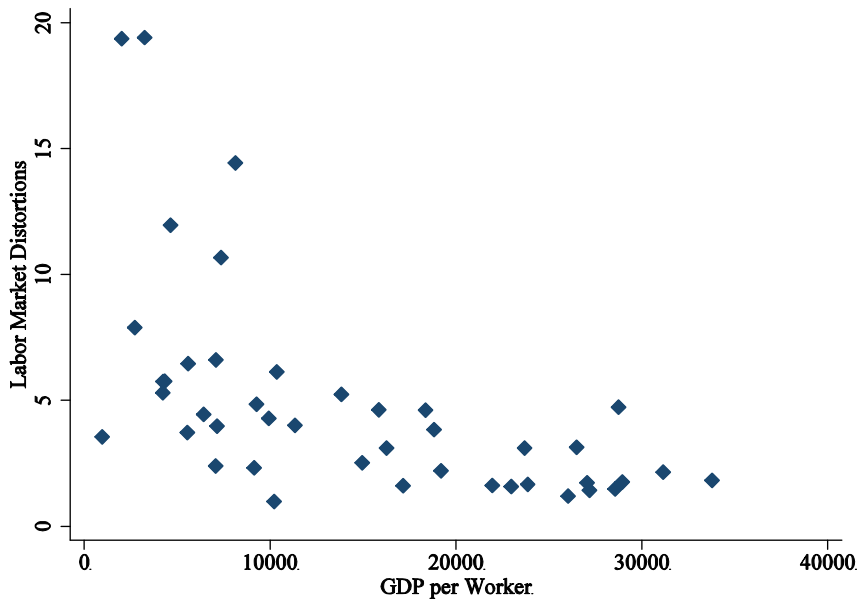

Figure 5: GDP per Worker and Labor Market Distortions

4.2 Measuring Economy-wide Productivity

Economy-wide productivity (A) for each of the countries in my sample is computed by targeting labor productivity in non-agriculture using the non-agricultural production function given the calibrated parameter value for σ (see section 4.3) and data on exogenous variables (non-agricultural physical and human capital per worker). A for each country varies with different versions of the model depending on whether the version includes sectoral human and/or physical capital (see Appendix A) and which measure of human capital is employed.

4.3 Calibration

I need six parameter values to quantitatively analyze the model: $\alpha, \sigma, \gamma, a, \bar{a}$ and κ. The USA is treated as the benchmark economy, where the cost of modern intermediate inputs (π) and the relative price of agricultural goods (p_a) are normalized to 1. The parameters are calibrated to the U.S. data for 1985.

The calibrations of α and σ are not affected by the inclusion of sectoral human or physical capital; therefore, these parameter values are identical to those reported by Restuccia et al. (2008). The income share of intermediate inputs in agriculture (α) is calibrated using the first order condition with respect to intermediate input (X) of the representative farmer's problem (see equation E.2 in Appendix E). Given the normalizations of π and p_a to 1, in equilibrium, α is equal to the intermediate input to gross agricultural output ratio (X/Y_a), which is equal to 0.4. The income share of labor (σ) is assumed to be the same across sectors and set to 0.7 following the income share of labor in agriculture reported by Hayami and Ruttan (1985) and Mundlak (2001). This implies that the income share of capital in non-agriculture $(\beta = 1 - \sigma)$ is 0.3.

The income share of capital in agriculture (γ) is set to 0.21, which is taken from the work of Jorgenson and Gollop (1992) following Caselli (2005) and Vollrath (2009). This implies that the income share of land in agriculture $(1 - \sigma - \gamma)$ is 0.09.

For the calibration of a and $\bar{a}$, the equilibrium condition for labor share in agriculture (L_a/L) (equation (7)) is utilized. a is calibrated by targeting L_a/L when the subsistence consumption requirement is not binding i.e. $\bar{a}$=0. When $\bar{a}$=0, L_a/L can be more or less interpreted as the long-run share of employment in agriculture, which is assumed to be 0.5% following Restuccia et al. (2008). The calibrated value of a equals 0.0046.[33] $\bar{a}$ is then calibrated by targeting the employment share in agriculture for the USA in 1985 (2.8%) given the values of other parameters. The calibrated value of $\bar{a}$ equals 752.6.

κ is calibrated targeting labor productivity in agriculture given calibrated values of the other parameters and the 1985 US data on the other variables using the agricultural production function (utilizing equation (2) for the baseline model). It should be noted that the calibration of κ is affected by inclusion of sectoral physical capital in the production technologies. Therefore, the value for κ varies across the different versions of the model depending on whether the version includes sectoral physical capital or not (see Appendix A). The value does not vary with the inclusion or which measure of human capital is used because non-

[33] Several authors (see Caselli and Coleman, 2001; Gollin et al., 2007) have assumed lower values for employment shares, which would imply a lower value of a. As suggested by Restuccia et al. (2008), a lower value of a would lead to the model explaining a greater proportion of the observed cross-country productivity differences.

agricultural and agricultural human capital for the benchmark economy are the same regardless of which measure of human capital is employed.

The calibrated values of the parameters, along with the targets used to calibrate them, are summarized in Table 4:

Table 4

Calibration of Parameter Values to U.S. Data

Parameter	Value	Target
α	0.4	Ratio of intermediate input to gross agricultural output
σ	0.7	Reported by Hayami and Ruttan (1985) and Mundlak (2001)
γ	0.21	Reported by Jorgenson and Gollop (1992)
a	0.0046	Long-run share of employment in agriculture
$\bar{a}$	752.6	Share of employment in agriculture
κ	5.02	Labor productivity in agriculture[a]

[a] This value is for the baseline model i.e. when the model includes sectoral physical and quality-adjusted human capital. The value for κ varies across different versions of the model depending on whether or not the production functions include physical capital (see Appendix A).

4.4 Results

I perform the quantitative analysis by assuming that the countries are closed economies. All the countries are the same as the benchmark economy except in terms of economy-wide productivity (A), land-to-employment ratio (Z/L), sector-specific human capital per worker (h_n, h_a), sector-specific physical capital (K_n, K_a), total employment (L) cost of intermediate input (π) and cost of skill acquisition or labor market distortion (θ).

Using equations (7), (8) and (9) respectively, the model predicts the equilibrium share of employment in agriculture (L_a/L), the intermediate input to agricultural output ratio (X/Y_a), and gross output per worker in agriculture (Y_a/L_a); using these results, the model predicts the aggregate labor productivity (Y/L) based on equation (10). In addition to the four variables mentioned above, I also calculate the model's predictions for GDP per worker in non-agriculture (Y_n/L_n) and agriculture (GDP_a/L_a) for each of the countries in my sample.[34]

[34] It should be noted that Y_n/L_n is the same as GDP_n/L_n and is computed based on equation (1), given exogenous variables $A, h_n, K_n/L$ and the model-based solution to L_a/L, GDP_a/L_a on the other hand, is computed as:

The results of the quantitative analysis are summarized and reported in Figure 6, Figure 7 and Table 5.

4.4.1 Implications of the Baseline Model

The baseline model includes sectoral physical and human capital, as well as variations in labor market distortions. As can be observed in Figure 6 and Figure 7, the model does an excellent job of capturing the sectoral pattern as well as the aggregate productivity differences across the different countries in my sample. Figure 6 presents the model's prediction of the relationship between GDP per worker and employment share in agriculture together with the observed relationship between the two variables from the data. The maroon markers represent the model's predictions whereas the blue ones represent the data. From the figure, it is evident that the model captures the negative relationship between aggregate labor productivity and employment share in agriculture reasonably well.

Figure 7 presents a country-wise comparison between the data and the model's prediction of GDP per worker. Again, as indicated by the figure, the model performs well in terms of capturing the data. The model's predictions of GDP per worker, for both the rich and the poor countries, are very similar to the true values. The predictions for the poor countries overall are slightly more overstated compared to the rich ones.

The baseline model performs well in terms of explaining the difference between the richest and the poorest countries also. According to the data derived from my sample, L_a/L in the poorest country is 29.4 times more than that of the richest country. The model predicts the employment share to be 27.7 times (94% of the difference implied by the data) higher in the poorest country than in the richest one. The data suggest that Y_a/L_a in the richest country is 118.6 times that of the poorest country, whereas the model predicts Y_a/L_a to be 35.2 times (30% of the difference implied by the data) higher in the richest country compared the poorest one. According to the data, GDP_a/L_a is 82.2 times higher in the richest country compared to the poorest one, whereas the model predicts this difference to be 28.0 times (34% of the observed difference). Finally, the data suggest that the richest country is 34.6 times more productive than the poorest country (in

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$$GDP_a/L_a = \frac{p_a^* Y_a - \pi^* X}{L_a} = \frac{Y_a}{L_a}\left(p_a^* - \pi^* \frac{X}{Y_a}\right)$$

Where $\{p_a^*, \pi^*\}$ denote international prices for agricultural output and intermediate input and X/Y_a and Y_a/L_a are calculated based on equations (8) and (9).

terms of GDP per worker: Y/L) whereas the model predicts the richest country to be 22.8 times (66% of the difference implied by the data) more productive compared to its poorest counterpart.

The model keeps performing well as I progress towards explaining differences between a greater number of rich and poor countries. For example, if I consider the differences between the two richest and the two poorest countries in my sample, the model explains 104% of the difference implied by the data in L_a/L, 34% of the difference in Y_a/L_a, 39% of the difference GDP_a/L_a and 58% of the difference in Y/L.

If I consider the differences between the richest 10% and the poorest 10% of the countries (the four richest and the four poorest countries) in my sample, the model explains 101% of the difference implied by the data in L_a/L, 32% of the difference in Y_a/L_a, 34% of the difference in GDP_a/L_a and 60% of the difference in Y/L.

4.4.2 How Much Do Sector-Specific Human and Physical Capital Add to the Prediction Power of the Model?

It is important to compare versions of the model that do and do not include sectoral human and/or physical capital in order to ascertain whether and how much the sectoral human and physical capital add to the explanatory power of the model.

In order to assess the explanatory power of the different versions of the model, I measure the extent to which each version explains the observed differences between the richest 10% and the poorest 10% of the countries in my sample.[35] In doing so, I focus on the following four variables: employment share in agriculture (L_a/L), gross output per worker in agriculture (Y_a/L_a), GDP per worker in agriculture (GDP_a/L_a) and aggregate output per worker (Y/L).

When the model does not include either human or physical capital, it explains 78% of the observed difference in L_a/L between the richest 10% and the poorest 10% of the countries in my sample. When only human capital is added, the model explains 86%; when only physical capital is added, the model explains 93%; and when both human and physical capital are added, the model

[35] In this section of the paper, I focus on the differences between the richest 10% and the poorest 10% of the countries (the four richest and the four poorest countries) in my sample. If, instead, I consider differences between, for example, the three richest and the three poorest or the five richest and the five poorest countries, I obtain similar results.

almost perfectly (101%) explains the observed difference in L_a/L between the richest 10% and the poorest 10% of the countries in my sample .

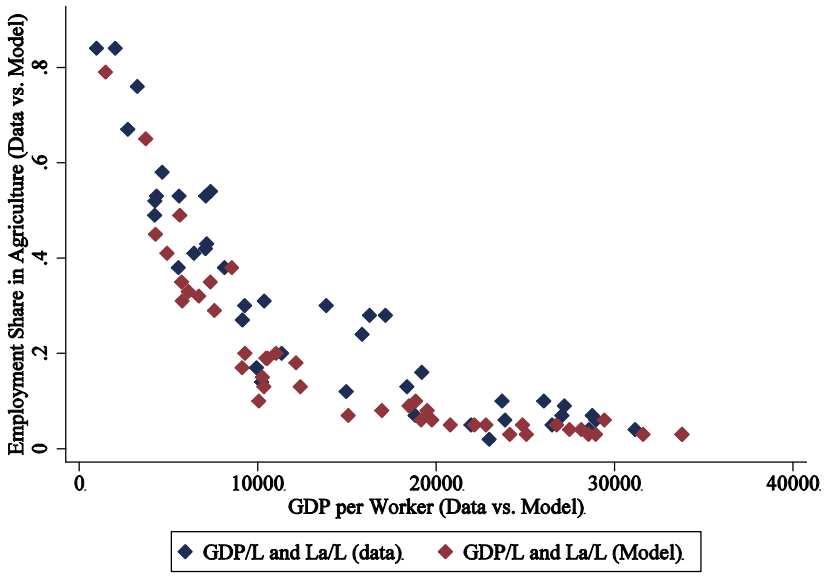

Figure 6: GDP per Worker and Employment Share in Agriculture (Data vs. Model)

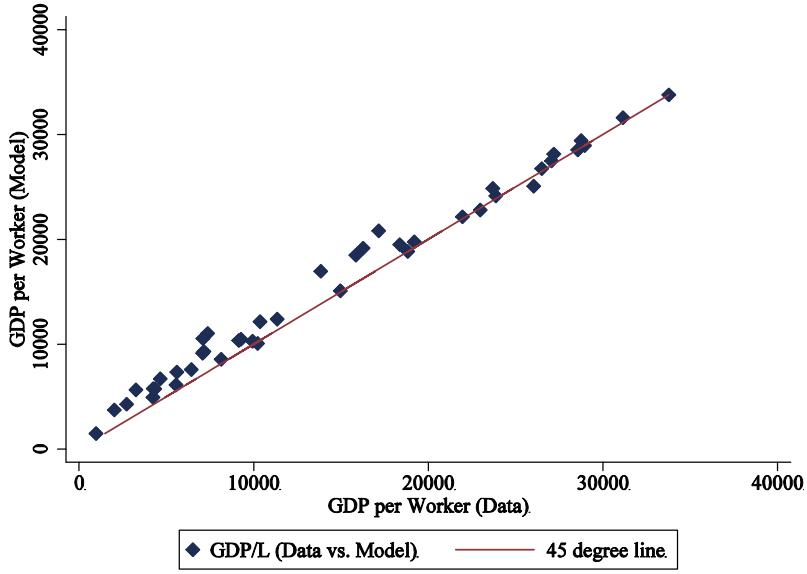

Figure 7: GDP per Worker – Data vs. Model

The version of the model without human and physical capital explains 25% of the observed difference in Y_a/L_a between the richest 10% and the poorest 10% of the countries in my sample. When only human capital is added, the model explains 28%; when only physical capital is added, the model explains 27%; and the version that includes both human and physical capital explains 32% of the observed difference in Y_a/L_a .

Without human or physical capital, the model explains 26% of the observed difference in GDP_a/L_a . When only human capital is added, the model explains 30%; when only physical capital is added, the model explains 29%; and when both are added, the model explains 34% of the observed difference in GDP_a/L_a between the richest 10% and the poorest 10% of the countries in my sample.

When the model does not include either human or physical capital, it explains 41% of the observed difference in Y/L between the richest 10% and the poorest 10% of the countries in my sample. When only human capital is added, the model explains 46% of the observed difference and when only physical capital is added, the model explains 55%. Finally, when both sector-specific human and physical capital are added, the model explains 60% of the difference in Y/L implied by the data. Therefore, compared to the version employed by Restuccia et al. (2008), the baseline model presented in this paper explains 19% more of the difference in output per worker between the richest 10% and the poorest 10% of the countries in my sample.

From these results, it is evident that the addition of both sector-specific human capital and sector-specific physical capital significantly enhances the model's explanatory power. The results also suggest that the inclusion of physical capital in the model is considerably more important compared to adding human capital.[36]

[36] In this section, I have focused on the quality-adjusted measure of human capital constructed utilizing the returns reported by Schoellman (2011). Table D.1 in Appendix D reports the results when different measures of human capital are added to a version of the model that includes physical capital and variations in labor market distortions, but does not include human capital. Only the inclusion of weighted quality-adjusted human capital seems to add significantly more explanatory power compared to the other measures of human capital in terms of explaining international productivity differences. When weighted quality-adjusted human capital is included in the model, it explains 66% of the observed difference in Y/L between the richest 10% and the poorest 10% of the countries in my sample, compared to 55% when the model does not include human capital. The version of the model that includes human capital constructed based on returns reported by Psacharopoulos (1994) explains 60% of the observed difference just like the version that incorporates human capital constructed using returns reported by Schoellman (2011).

Table 5
Importance of Sector-Specific Physical Capital, Human Capital and Labor Market Distortions in Explaining Cross-Country Income Differences

Different Versions of the Model	L_a/L		Y_a/L_a		GDP_a/L_a		Y_n/L_n		Y/L	
	$\frac{P10\%}{R10\%}$	% of Difference Explained	$\frac{R10\%}{P10\%}$	% of Difference Explained	$\frac{R10\%}{P10\%}$	% of Difference Explained	$\frac{R10\%}{P10\%}$	% of Difference Explained	$\frac{R10\%}{P10\%}$	% of Difference Explained
(1) Data	15.9	-	64.7	-	48.3	-	3.5	-	13.7	-
(2) Without human capital, physical capital and variation in labor market distortions	7.3	46%	6.9	11%	6.4	13%	3.5	100% [a]	4.0	29%
(3) With variation in labor market distortions (Restuccia et al., 2008)	12.3	78%	16.1	25%	12.7	26%	3.5	100%	5.7	41%
(4) With variation in labor market distortions and human capital	13.7	86%	17.9	28%	14.3	30%	3.5	100%	6.2	46%
(5) With variation in labor market distortions and physical capital	14.7	93%	17.8	27%	13.8	29%	4.4	125% [b]	7.6	55%
(6) With human capital and physical capital	10.2	64%	10.0	15%	9.2	19%	5.0	142%	6.0	44%
(7) With variation in labor market distortions, human capital and physical capital (Baseline Model)	16.0	101%	20.7	32%	16.4	34%	4.2	120%	8.2	60%

Notations: $R10\%$ denotes the richest 10% and $P10\%$ denotes the poorest 10% of the countries in my sample.

[a] These versions of the model explain 100% of the observed difference in GDP per worker in non-agriculture by construction given the non-agricultural production function (see Appendix A).

[b] For these versions, Y_n/L_n is computed using equation (1) and varies from the data only because the model's prediction of L_a/L differs from the actual L_a/L. The way the equation is set up, if the model predicts a smaller difference in L_a/L between the poor and the rich countries than the data, then it would predict a greater difference in Y_n/L_n between the rich and the poor countries, compared to the data. The closer the model's prediction gets to the data in explaining the difference in L_a/L, the lesser is the over-prediction of the difference in Y_n/L_n.

4.4.3 How Important Are Labor Market Distortions?

In this part of the paper, I report the results of the quantitative analysis focusing on the importance of labor market distortions. For this purpose, I perform the following experiment. First, I assume that all the countries in my sample have the same level of labor market distortions as the benchmark economy and compute the model's predictions. Next, I allow the distortions to vary across countries, compute the results and compare the predictions with the predictions of the model where distortions are fixed. I assess whether and by how much the explanatory power of the model improves as I add the variations in labor market distortions.

In an environment with no human and physical capital, Restuccia et al. (2008) illustrate the importance of labor market distortions in explaining cross-country income differences.[37] Using my sample of 43 countries, when I do not include human or physical capital in the model (which is the same as the one used by Restuccia et al., 2008), I find similar results. One can understand the importance of adding labor market distortions in an environment without human or physical capital by comparing the predictions of the versions of the model reported in rows (2) and (3) of Table 5.

In terms of explaining the difference between the richest 10% and the poorest 10% of the countries in my sample, the version of the model without variation in distortions explains 46% of the observed difference in L_a/L, which substantially improves to 78% when variation in distortions is added. The version of the model without variation in distortions explains 11% of the observed difference in Y_a/L_a, which improves to 25% when variation in distortions is added. The version of the model without variation in distortions explains 13% of the observed difference in GDP_a/L_a, which improves to 26% when variation in distortions is added. Finally, without variation in distortions, the model explains 29% of the observed difference in Y/L between the richest 10% and the poorest 10% of the countries in my sample, which significantly improves to 41% when variation in distortions is added.

It is interesting to see whether labor market distortions remain as important once I control for variations in sector-specific human and physical capital. In order to check that, I perform the same experiment with the version of the model that incorporates both human and physical capital. The significance of adding labor market distortions, even after controlling for sectoral human and

[37] For their sample of 86 counties, without labor market distortions, their model explains a factor of 6.2 or 18% of the observed difference of 34.3 in labor productivity between the richest 5% and the poorest 5% of the countries in their sample. As they add the distortions, their model's prediction improves substantially as it explains a factor of 10.8 or 31% of the observed difference.

physical capital, becomes clear by comparing the predictions of the versions of the model reported in rows (6) and (7) of Table 5.

Without variation in distortions, the model explains 64% of the observed difference in L_a/L between the richest 10% and the poorest 10% of the countries in my sample, which improves to 101% when variation in distortions is added. The version of the model without variation in distortions explains 15% of the observed difference in Y_a/L_a, which improves to 32% when variation in distortions is added. The version of the model without variation in distortions explains 19% of the observed difference in GDP_a/L_a, which improves to 34% when variation in distortions is added. Finally, when there is no variation in distortions, the model explains 44% of the observed difference in Y/L between the richest 10% and the poorest 10% of the countries in my sample, which considerably improves to 60% when variation in distortions is added.

It is therefore evident that regardless of whether cross-country differences in sector-specific human and physical capital are incorporated in the analysis or not, adding variation in labor market distortions significantly improves the model's performance in capturing the data. In fact, if one analyzes the results reported in Table 5, it becomes apparent that in terms of explaining productivity differences, both at the sectoral and the aggregate level, between the rich and the poor countries, adding variation in labor market distortions improves the explanatory power of the model by more, in comparison to the addition of either human or physical capital.[38] For example, in terms of explaining the difference in GDP_a/L_a between the richest 10% and the poorest 10% of the countries in my sample, human capital adds 4% (improves from 26% to 30%), physical capital adds 3% (improves from 26% to 29%) while variation in labor market distortions adds 15% to the explanatory power of the model (improves from 19% to 34%). In terms of explaining the difference in aggregate labor productivity (Y/L) between the richest 10% and the poorest 10% of the countries in my sample, human capital adds 5% (improves from 41% to 46%), physical capital adds 14% (improves from 41% to 55%) and variation in labor market distortions add 16% (improves from 44% to 60%) to the explanatory power of the model. Overall, the exercise suggests that labor market distortions are indeed important and essentially play a

[38] To gauge the improvement in the model's prediction power due to the addition of human capital, I compare the results reported in row (3) and row (4); to determine the improvement due to the addition of physical capital, I contrast the results reported in row (3) and row (5); and finally to measure the importance of labor market distortions, I compare the results reported in row (6) and row (7).

more important role compared to either sector-specific human or physical capital in explaining cross-country income differences.[39]

5. Conclusion

In this paper, using a sample of 43 countries, I explain the cross-country differences in aggregate labor productivity observed in data by focusing on the even larger productivity differences in the countries' agricultural sectors. The channels that I focus on in this paper are sector-specific human capital, sector-specific physical capital and labor market distortions.

I extend the two-sector general equilibrium model employed by Restuccia et al. (2008) by incorporating sectoral human and physical capital in their framework. I utilize available information from the work of Crego et al. (2000) who report sector-wise investments in domestic prices and apply a PPP price index on their data and employ the perpetual inventory method explained by Caselli (2005) to construct a PPP-adjusted measure of sectoral physical capital. I develop sector-specific schooling years using available information from the works of Barro and Lee (1996, 2010), Hall and Jones (1999) and Timmer (2000) and construct quality-adjusted measure of sectoral human capital utilizing Mincerian returns reported by Schoellman (2011). I observe that human and physical capital per worker in both non-agriculture and agriculture in the poor countries are lower than those in the rich ones and the differences are larger in the

[39] One may argue that instead of comparing results reported in rows (6) and (7), if we compare rows (2) and (3) to measure the importance of labor market distortions, then we find that variation in distortions adds 12% (improves from 29% to 41%) to the prediction power in terms of explaining the difference in Y/L between the rich and the poor countries, which is lower than the 14% added by physical capital. First of all, it should be noted that adding variation in distortions even in this context improves the prediction power of the model by significantly more compared to adding physical capital in explaining L_a/L, gross output per worker in agriculture Y_a/L_a as well as GDP_a/L_a. The reason why physical capital adds more to the prediction power of the model compared to labor market distortions in terms of explaining difference in Y/L in this context is the following. As physical capital is added (see row 3 and row 5 in table 5), it leads to an over prediction (from 100% to 125%) of the difference in GDP per worker in non-agriculture $\left(GDP_n/L_n\right)$ between the rich and the poor countries whereas addition of variation in labor market distortions (see row 2 and row 3) does not change the prediction of the difference in GDP_n/L_n given how those versions of the model are set up. Secondly, results reported in rows (2) and (3) highlight the importance of labor market distortions within the framework of Restuccia et al. (2008) whereas, results reported in rows (6) and (7) emphasize the significance of labor market distortions within the framework introduced in this paper. Therefore, to appreciate the importance of labor market distortions relative to sectoral human and physical capital, it is more appropriate to compare the results reported in rows (6) and (7) as opposed to rows (2) and (3).

agricultural sectors. I show that the inclusion of sectoral human and physical capital in the two-sector general equilibrium model significantly improves the model's explanatory power. The improvement is greater with the addition of only physical capital, as opposed to the addition of only human capital.

I model labor market distortions as the costs of acquiring the additional skills required to work in the non-agricultural sector and measure them as the product of sectoral wage gap (in terms of wage per unit of human capital) and sectoral human capital ratio. I demonstrate that labor market distortions continue to play an important role in explaining cross-country income differences even after controlling for sectoral human and physical capital. Adding variation in labor market distortions improves the explanatory power of the model by more compared to the inclusion of either physical or human capital, which indicates that the role of labor market distortions outweighs the role of either sectoral human or physical capital.

One of the limitations of this paper is that I treat human and physical capital as exogenous variables. Therefore, this paper does not mention how human and physical capital are accumulated and what leads to the large sectoral differences in human and physical capital per worker that we observe in the poor countries. The paper also does not explain why the labor market distortions i.e. the costs of acquiring the additional skills required to work in the non-agricultural sector are larger in the poor countries compared to the rich ones. These questions leave scope for future research.

The policy implications of the analysis are that, in addition to reducing the costs of modern intermediate inputs used in agriculture, poor countries should endeavour to build up human and physical capital primarily in the rural or agricultural sector, and more importantly, reduce labor market distortions by reducing costs of accumulating human capital necessary to work in the non-agricultural sector.

Appendix A: How the Various Versions of the Model Differ from the Baseline Model

The different versions of the model are identical, with the exception of the following attributes.

Version without Human and Physical Capital (Restuccia et al., 2008):

Non-agricultural production function: $Y_n = AL_n$ (A for each of the countries in my sample is computed using this equation for this version of the model.)

Agricultural production function: $Y_a = X^{\alpha}(Z^{1-\sigma}\left(\kappa A L_a\right)^{\sigma})^{1-\alpha}$

Expression for equilibrium share of employment in agriculture $\left(L_a/L\right)$:

$$\frac{L_a}{L} = \frac{\left(1-a\right)\left(1-\theta\right)}{a\left(1-\alpha\right)\sigma+\left(1-a\left(1-\alpha\right)\right)\left(1-\theta\right)}\frac{\bar{a}}{Y_a/L_a}+\frac{a\left(1-\alpha\right)\sigma}{a\left(1-\alpha\right)\sigma+\left(1-a\left(1-\alpha\right)\right)\left(1-\theta\right)}$$

Expression for equilibrium intermediate input to gross agricultural output ratio $\left(X/Y_a\right)$:

$$\frac{X}{Y_a} = \left[\frac{\alpha}{\sigma\left(1-\alpha\right)}\frac{\left(1-\theta\right)}{\pi}\frac{A^{1-\sigma}}{\kappa^{\sigma}\left(Z/L\right)^{1-\sigma}}\right]^{1-\alpha}\left(L_a/L\right)^{(1-\alpha)(1-\sigma)}$$

Expression for equilibrium gross output per worker in agriculture $\left(Y_a/L_a\right)$:

$$\frac{Y_a}{L_a} = A^{\sigma+\alpha(1-\sigma)}\kappa^{\sigma(1-\alpha)}\left[\frac{\alpha}{\sigma\left(1-\alpha\right)}\frac{\left(1-\theta\right)}{\pi}\right]^{\alpha}\left[\frac{\left(Z/L\right)}{L_a/L}\right]^{(1-\alpha)(1-\sigma)}$$

Expression for equilibrium aggregate GDP per worker $\left(Y/L\right)$:

$$\frac{Y}{L} = \frac{Y_a}{L_a}\frac{L_a}{L}\left(p_a^* - \pi^*\frac{X}{Y_a}\right)+A\left(1-\frac{L_a}{L}\right)$$

Labor market distortions are measured as:

$$\frac{1}{\left(1-\theta\right)} = \frac{GDP_n/L_n}{p_a\sigma GDP_a/L_a}$$

Note the σ in the denominator. It is there because the income shares of labor across sectors are different in this version of the model. Value for κ for the benchmark economy: $\kappa = 34.1$

Version with Only Human Capital:

Non-agricultural production function: $Y_n = AH_n$ (A for each of the countries in my sample is computed using this equation for this version of the model and varies based on the version of human capital used.)

Agricultural production function: $Y_a = X^{\alpha}(Z^{1-\sigma}\left(\kappa AH_a\right)^{\sigma})^{1-\alpha}$

Expression for equilibrium share of employment in agriculture $\left(L_a/L\right)$: Identical to the version of Restuccia et al. (2008).
Expression for equilibrium intermediate input to agricultural output ratio $\left(X/Y_a\right)$:

$$\frac{X}{Y_a} = \left[\frac{\alpha}{\sigma\left(1-\alpha\right)}\frac{\left(1-\theta\right)h_n/h_a}{\pi}\frac{A^{1-\sigma}}{\kappa^{\sigma}\left(Z/L\right)^{1-\sigma}}\right]^{1-\alpha}\left(h_aL_a/L\right)^{(1-\alpha)(1-\sigma)}$$

Expression for equilibrium labor productivity in agriculture $\left(Y_a/L_a\right)$:

$$\frac{Y_a}{L_a} = A^{\sigma+\alpha(1-\sigma)}\kappa^{\sigma(1-\alpha)}\left[\frac{\alpha}{\sigma\left(1-\alpha\right)}\frac{\left(1-\theta\right)h_n/h_a}{\pi}\right]^{\alpha}\left[\frac{\left(Z/L\right)}{h_aL_a/L}\right]^{(1-\alpha)(1-\sigma)}h_a$$

Expression for equilibrium aggregate GDP per worker $\left(Y/L\right)$:

$$\frac{Y}{L} = \frac{Y_a}{L_a}\frac{L_a}{L}\left(p_a^* - \pi^*\frac{X}{Y_a}\right) + Ah_n\left(1-\frac{L_a}{L}\right)$$

Measure for labor market distortions and κ is identical to the version of Restuccia et al. (2008).

Version with Only Physical Capital:

All the attributes of this version are identical to the baseline model, which is explained in Section 3, except the following: $h_a = h_n = 1$ everywhere. Values for A are different in this version compared to the baseline model since human capital affects non-agricultural production function.

Appendix B: Measuring Costs of Intermediate Inputs

I use the measure used by Restuccia et al. (2008). They use data provided by FAO to measure the costs of intermediate inputs. The FAO reports country-specific prices, paid by farmers at their farm gates, of intermediate inputs that are used in agricultural production. [40] These PPP prices are roughly equal to the ratio of expenditures on intermediate inputs in local currency for every country (πX) to expenditures on intermediate inputs in international prices $(\pi^* X)$. In accordance with the model, the price of the non-agricultural good is treated as the numeraire and the price of the intermediate input is expressed relative to the price of the non-agricultural output for every country. Then, these prices are calculated relative to the U.S. The costs of intermediate inputs can thus be expressed as:

$$\frac{\left(\pi X/\pi^* X\right)/\left(p_n Y_n/p_n^* Y_n\right)}{\left[\left(\pi X/\pi^* X\right)/\left(p_n Y_n/p_n^* Y_n\right)\right]^{US}}$$

From the above expression, using simple algebraic steps, $(\pi/p_n)/(\pi/p_n)^{US}$ can be obtained, which is simply the price of intermediate inputs as a ratio of the price of non-agricultural output relative to USA. This is what Restuccia et al. (2008) report as costs of intermediate inputs; I also use this measure in the quantitative analysis.

Figure B.1 demonstrates that the costs of these intermediate inputs are inversely related to GDP per worker i.e. these costs that reflect barriers to intermediate input use are generally higher in the poor countries, in comparison to the rich ones.

[40] In the FAO data, intermediate inputs include pesticides, fertilizers, fuel and energy, electricity and other miscellaneous items.

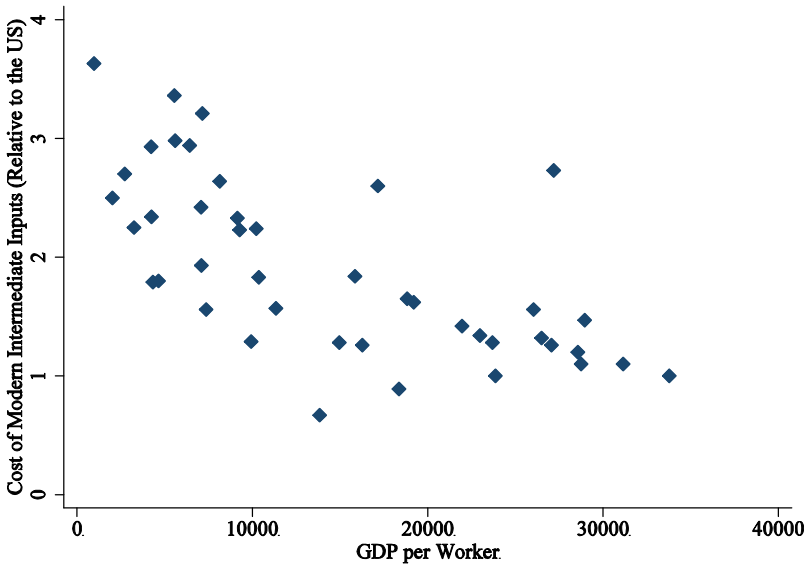

Figure B.1: GDP per Worker and Cost of Modern Intermediate Inputs

Appendix C: Capital per Worker When Using PPP-Unadjusted Measure

Table C.1 reports country-wise physical capital per worker in non-agriculture and agriculture when the PPP-unadjusted measure of sectoral physical capital is used. As discussed in Section 2.3, this measure of sectoral physical capital per worker is different from the PPP-adjusted measure and overstates the difference in physical capital per worker in both sectors, particularly in agriculture, between the rich and the poor countries.

Table C.1
Sector-Specific Physical Capital per Worker (PPP-unadjusted)[a]

Country	Capital per Worker in Non-agriculture	Capital per Worker in Agriculture
United States	76,203	91,767
Canada	67,142	110,913
Australia	74,405	49,114
Norway	98,920	94,180
Netherlands	68,368	77,095
Italy	62,605	47,458
France	66,332	41,486
Sweden	69,032	66,184
New Zealand	53,998	51,546
Denmark	58,792	75,402
Finland	77,407	64,777
United Kingdom	42,139	51,812
Israel	46,209	40,936
Ireland	35,341	24,820

Country	Capital per Worker in Non-agriculture	Capital per Worker in Agriculture
Japan	68,940	50,156
Venezuela	42,549	13,209
Syria	29,957	8,221
Greece	35,706	6,005
Iraq	59,941	23,586
Argentina	32,414	16,250
Iran	55,941	8,140
Portugal	13,042	2,435
Korea Republic	20,044	3,877
Uruguay	12,075	2,832
South Africa	21,238	5,995
Colombia	11,880	1,214
Costa Rica	15,630	4,309
Peru	13,982	1,227
Guatemala	16,983	1,217
Egypt	12,386	1,876
Turkey	12,653	1,163
Dominican Republic	10,977	712
Morocco	8,838	337
Sri Lanka	6,343	120
El Salvador	14,633	933
Honduras	15,282	1,232
Indonesia	7,957	127
Pakistan	3,868	530
Philippines	4,400	283
Zimbabwe	12,422	457
India	3,554	339
Kenya	10,784	201
Tanzania	10,170	182

[a] The numbers are rounded up/down.

Appendix D: Results with Different Measures of Human Capital

In addition to the measure of human capital constructed using the country-specific quality-adjusted Mincerian returns reported by Schoellman (2011), I also construct a measure of human capital using the Mincerian returns reported by Psacharopoulos (1994), which have been used by several authors (e.g., Hall and Jones, 1999; Cordoba and Ripoll, 2006; Chanda and Dalgaard, 2008; Vollrath, 2009). Psacharopoulos (1994) studies return to schooling estimates for a wide range of countries. As per his estimation of Mincerian wage regression, it is assumed that $\varphi(s)$ is piecewise linear. Based on his work, I assign a rate of return of 13.4% for the first 4 years of schooling, corresponding to Psacharopoulos's results for sub-Saharan Africa; 10.1% for the next 4 years, the world average as a whole; and 6.8% for each year after the eighth year of schooling, based on Psacharopoulos's reports for the OECD countries. These returns are useful because they can be applied to a wide range of countries and demonstrate the neat characteristic of diminishing returns to schooling. In spite of some useful and neat properties, returns to schooling reported by Psacharopoulos (1994) have certain

problems that need to be addressed. First, computing human capital using these returns involves the strong assumption that returns to schooling are the same in every country. Second, while estimating these returns, Psacharopoulos (1994) makes no distinction in quality of education between the rich and the poor countries.

Neither Psacharopoulos (1994) nor Schoellman (2011) makes any distinction between the quality of urban and rural human capital. The quality of rural human capital may very likely be lower than the quality of urban human capital, especially in the poor countries, as a result of factors such as low parental human capital (Cordoba and Ripoll, 2006), poor quality of teachers, lack of infrastructure in the rural areas e.g. lack of electricity, furniture, etc. Several authors have applied various techniques in order to capture this lower quality of rural human capital.

Cordoba and Ripoll (2006) e.g. construct a dynamic version of the Harris-Todaro (1970) migration model and derive an expression for the sectoral productivity gap as a function of migration costs.[41] They calibrate the migration costs for the US economy and assume that these costs do not differ across countries. They assume that the quality of urban human capital does not differ across countries either and define the rural quality of human capital as the part of the sectoral productivity gap that cannot be explained by migration costs as implied by their model and sectoral human capital ratio (constructed based on returns reported by Psacharopoulos, 1994). Their specification results in small migration costs and implies that the low quality of rural human capital captures the largest portion of the labor productivity gap, some of which, in reality, may be due to labor market distortions.

Based on the work of Orazem (2006), Chanda and Dalgaard (2008) assume that returns to schooling in agriculture are approximately 90% of the returns to schooling in non-agriculture. Vollrath (2009), on the other hand, calculates rural returns to schooling by using values that are equal to one-half of the returns (Mincerian returns reported by Psacharopoulos, 1994) in the urban sector. Their methods have the strong underlying assumption that returns to rural schooling are equally lower than the urban returns for all the countries, regardless of how productive the agricultural sectors of these countries are.

In order to capture the possible lower quality of human capital in the rural areas compared to urban areas, particularly in the poor countries, I carry out an experiment and construct a third measure of human capital. In a similar approach to Chanda and Dalgaard (2008) and Vollrath (2009), instead of applying an arbitrary constant value, I weigh the returns in the urban sector (quality-adjusted Mincerian returns reported by Schoellman, 2011) by the country's GDP per

[41] Here, migration implies migration from agricultural sector to non-agricultural sector.

worker in the agriculture relative to USA. I use these weighted Mincerian returns to schooling to calculate the rural human capital for all the countries in my sample. This method implies that the returns to rural schooling are identical to the returns to urban schooling for the benchmark economy (United States); while for the other countries, the returns to rural schooling are less than the returns to urban schooling. In fact, unlike Chanda and Dalgaard (2008) and Vollrath (2009), returns to rural schooling are lower for countries with lower agricultural labor productivity.

Table D.1 reports the results when different measures of human capital are added to a version of the model that includes physical capital and variations in labor market distortions, but does not include human capital. In terms of explaining the difference in GDP per worker (Y/L) between the richest 10% and the poorest 10% of the countries in my sample, human capital, constructed using returns reported by Psacharopoulos (1994) and Schoellman (2008), improves the model's explanatory power by the same amount (60% from 55%). Human capital, constructed using the weighted quality-adjusted rural returns, adds more to the prediction power of the model by explaining 66% of the observed difference in Y/L between the richest 10% and the poorest 10% of the countries in my sample.

Table D.1
Importance of Sector-Specific Human Capital (Different Measures) in Explaining Cross-Country Income Differences[a]

	L_a/L		Y_a/L_a		Y/L	
Different Versions of the Model	$\frac{P10\%}{R10\%}$	**% of Difference Explained**	$\frac{R10\%}{P10\%}$	**% of Difference Explained**	$\frac{R10\%}{P10\%}$	**% of Difference Explained**
(1) Data	15.9	-	64.7	-	13.7	-
(2) Without human capital	14.7	93%	17.8	27%	7.6	55%
(3) With human capital (Psacharopoulos's returns)	16.3	102%	19.9	31%	8.2	60%
(4) With quality-adjusted human capital (Schoellman's returns)	16.0	101%	20.7	32%	8.2	60%
(5) With weighted quality-adjusted human capital	14.9	94%	20.7	32%	9.1	66%

Notations: $R10\%$ denotes the richest 10% and $P10\%$ denotes the poorest 10% of the countries in my sample.
[a]All the versions here include physical capital and labor market distortions.

Appendix E: Detailed Solution of the Equilibrium

The profit maximization problem of the non-agricultural firm implies

$$w_n = \sigma \frac{Y_n}{h_n L_n}$$

Using equation (1), this can be expressed as

$$w_n = \sigma A^{\sigma} \left(\frac{K_n}{L} \right)^{1-\sigma} \left(1 - \frac{L_a}{L} \right)^{\sigma-1} h_n^{\sigma-1} \tag{E.1}$$

From the profit maximization problem in the agricultural sector, the first-order condition with respect to X implies

$$\alpha p_a \frac{Y_a}{X} = \pi$$

Thus, taking the prices as given, the following expression for the optimal choice of intermediate input to agricultural output ratio for the representative farmer is obtained:

$$\frac{X}{Y_a} = \alpha \frac{p_a}{\pi} \tag{E.2}$$

The first-order condition with respect to H_a implies

$$p_a \sigma (1 - \alpha) \frac{Y_a}{h_a L_a} = w_a \tag{E.3}$$

Substituting the no-arbitrage condition from equation (3) and utilizing equation (E.1), equation (E.3) becomes

$$p_a \sigma (1 - \alpha) \frac{Y_a}{h_a L_a} = (1 - \theta) \sigma A^{\sigma} \left(\frac{K_n}{L} \right)^{1-\sigma} \left(1 - \frac{L_a}{L} \right)^{\sigma-1} \frac{h_n^{\sigma}}{h_a}$$

From this, p_a can be expressed as

$$p_a = (1-\theta) A^{\sigma} \left(\frac{K_n/L}{1-(L_a/L)} \right)^{1-\sigma} h_n^{\sigma} \frac{L_a}{Y_a} \frac{1}{(1-\alpha)} \tag{E.4}$$

Substituting this expression for p_a into equation (E.2), I obtain

$$\frac{X}{Y_a} = \alpha(1-\theta) A^{\sigma} \left(\frac{K_n}{L} \right)^{1-\sigma} \left(1 - \frac{L_a}{L} \right)^{\sigma-1} h_n^{\sigma} \frac{L_a}{Y_a} \frac{1}{(1-\alpha)} \frac{1}{\pi}$$

Substituting Y_a/L_a from equation (2) into the above equation and performing algebraic manipulations, I attain the expression for the equilibrium intermediate input to gross agricultural output ratio (X/Y_a) in equation (8). Substituting X/Y_a from equation (8) into equation (2) and carrying out algebraic manipulations, I obtain the expression for equilibrium gross output per worker in agriculture (Y_a/L_a) in equation (9).

The utility maximization problem of the household implies:

$$c_a = \bar{a} + a p_a^{-1} \left(y - p_a \bar{a} \right) \tag{E.5}$$

$$c_n = (1-a)(y - p_a \bar{a}) \tag{E.6}$$

Combining equations (E.5) and (E.6), I attain

$$c_a = \bar{a} + \frac{a}{(1-a)} p_a^{-1} c_n$$

Substituting the market-clearing conditions for c_a (equation 5) and c_n (equation 6) into the above equation, I obtain

$$\frac{Y_a}{L} = \bar{a} + \frac{a}{(1-a)} \frac{1}{p_a} \left[\frac{Y_n}{L} - \frac{\pi X}{L} \right] \tag{E.7}$$

Note that

$$\frac{Y_n}{L} = \frac{K_n^{\beta}\left(AH_n\right)^{1-\beta}}{L} = K_n^{1-\sigma}\left(Ah_n\right)^{\sigma}\frac{L_n^{\ \sigma}}{L} = K_n^{1-\sigma}\left(Ah_n\right)^{\sigma}\frac{1}{L^{1-\sigma}}\left(\frac{L-L_a}{L}\right)^{\sigma}$$

which implies

$$\frac{Y_n}{L} = \left(\frac{K_n}{L}\right)^{1-\sigma}\left[Ah_n\left(1-\frac{L_a}{L}\right)\right]^{\sigma} \tag{E.8}$$

Again, note that

$$\frac{\pi X}{L} = \frac{\pi X}{Y_a}\frac{Y_a}{L_a}\frac{L_a}{L} \tag{E.9}$$

From equation (E.2), I attain

$$\frac{\pi X}{Y_a} = \alpha p_a$$

Substituting the above expression in equation (E.9), I obtain

$$\frac{\pi X}{L} = \alpha p_a \frac{Y_a}{L_a}\frac{L_a}{L}$$

Substituting equation (E.4) into the above equation, I attain

$$\frac{\pi X}{L} = \frac{\alpha\left(1-\theta\right)\left(Ah_n\right)^{\sigma}}{1-\alpha}\left(\frac{K_n/L}{1-\left(L_a/L\right)}\right)^{1-\sigma}\frac{L_a}{L} \tag{E.10}$$

Substituting equations (E.4), (E.8) and (E.10) into equation (E.7) and solving for L_a/L, I obtain the expression for the equilibrium share of employment in agriculture $\left(L_a/L\right)$ in equation (7).

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