The Vanishing Productivity Gap: The Indian Case

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Abstract

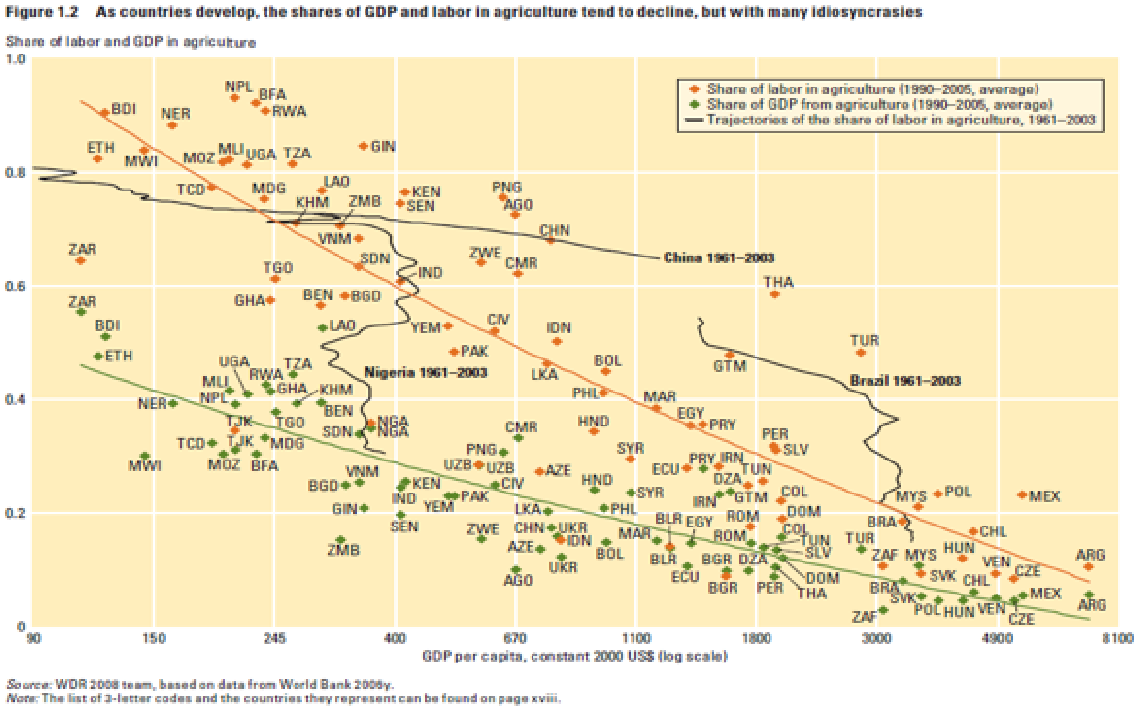
Recent research has pointed to large gaps in labor productivity between agriculture and non-agriculture sectors, especially so in developing countries. An influential paper by Gollin, Lagakos, and Waugh (2014) showed that these gaps persist even after allowing for the lower human capital of the agricultural labor force and the lower hours of work in agriculture. These findings suggest misallocation of labor across sectors and would call for policies that facilitate greater mobility across sectors. In examining this issue for India, this paper extends the Gollin, Lagakos, and Waugh (GLW) analysis in two directions. First, the paper relaxes the GLW assumption of uniform labor intensity across sectors. Second, the paper acknowledges the heterogeneity in the non-agricultural sector. A parallel literature has argued that large firms are much more productive than small firms. The Indian non-agricultural sector is well known for being dominated by the unorganized sector consisting of small firms (typically less than 10 workers or less than 20 workers if the firm uses electricity in production). The paper compares the labor productivity of agriculture with that of the unorganized as well as the organized sector. It turns out the major productivity gaps are with the organized sector and not with the unorganized sector. The sectoral misallocation of labor is not the serious problem. The lower productivity of the unorganized sector is the root of the productivity gap phenomenon.

1 Introduction

A robust stylized fact is that in the process of development, the share of agriculture in employment is greater than the share of the sector in income. Figure-1 illustrates it in a cross-sectional sample of countries. The figure demonstrates the well known pattern of structural transformation: that of the relative decline of agriculture in income and employment. But the figure also shows that the process of structural transformation is far from smooth - that the decline in the employment share lags the decline in income share. This seems to be as strong a stylized fact as the relative decline in the sector. Furthermore, the gap between the employment and income share is largest at low levels of per capita GDP.

The gap between agriculture's employment and income share means that a worker in the agriculture sector is less productive than her counterpart in the non-agricultural sector. Calculations based on national income and product accounts suggests that the productivity gap between the sector across countries is of order three on an average. However, for the poorest quartile of coun-

Figure 1: Share of Agriculture in Labor and Output (Source: World Development Report 2008)



tries, the productivity gap rises nearly to six compared to about two for the richest quartile of countries[1].

Previous work has argued that low agricultural productivity in the poor countries is one reason for aggregate productivity differences between rich and poor countries (Restuccia et.al; 2008, Vollrath, 2009). Explanations for this have also been proposed in terms of self-selection of human capital in the low productivity sectors (Young, 2013). The persistence of these gaps has serious consequences. McMillan and Rodrik (2011) emphasize that labor flows from low productivity to high productivity sectors is the major cause of overall increases in productivity.

But could the productivity gap be mostly due to measurement errors? In a major contribution, Gollin, Lagakos and Waught (2013) re-measured the productivity gap after taking into account two salient features: lower hours of work in agriculture and lower levels of human capital in agriculture relative to other sectors. They showed that these adjustments reduce the productivity gap but does not eliminate it - it is about two on average for the combined sample of rich and poor countries and is about three for the poorest quartile.

The discussion on the agricultural productivity gap and the resulting mis-allocation of resources has ignored substantial heterogeneity in the non-farm sector. This is the point of departure for this paper. Developing country non-farm sectors are typically characterized by a large number of small firms with a few or no employees. However, large firms do exist and worker productivity is higher in large firms and, therefore, share of large firms in income is higher than their share in employment[2]. Such heterogeneity prompts the question whether the observed agriculture productivity gap is driven by the larger firms in the nonfarm sector that are numerically small but economically substantial. If that is so, then the appropriate policy focus will shift from the frictions that hinder labor mobility from agriculture to other sectors to the factors that prevent small firms to scale up

[1] Gollin, Lagakos, and Waugh (2014)
[2] For a survey of evidence across countries, see Bloom et.al (2014)

and become as productive as the larger firms.

I examine this important issue in the context of India. Government statistics on employment define the organized sector as all establishments belonging to the government and all nonagricultural establishments in the private sector employing ten or more persons. The rest (including agriculture) constitute the unorganized sector. By this definition, the unorganized sector amounts to 93 percent of all employment and 85 percent of non-farm employment. On the other hand, the unorganized sector contributes 58 percent of national domestic product and 45 percent of nonfarm domestic product. The disparity between the contribution of the unorganized sector to employment and to income therefore merits a naunced investigation of the agricultural productivity gap - in particular, it calls for a disaggregation of the nonfarm sector into an organized and an unorganized sector.[3]

In this paper, the benchmark case is a three-sector model with perfect competition and perfect labor mobility, three sectors being- agriculture, unorganized non-agriculture, and organized non-agriculture. If we assume labor intensities in the production function to be equal across sectors, then that would result in an ideal agricultural productivity gap to be equal to one. This can then be compared to the productivity gap that is observed. The deviation from the ideal indicates the nature of frictions that prevent the ideal from being realized. While this is the idea pursued here, we follow Gollin, Lagakos and Waugh (2014) in making adjustments for sectoral differences in human capital and also in days of employment. However, unlike Gollin, Lagakos and Waugh (2014), the paper does not assume uniform labor intensities in the production function. Indeed, it is unlikely that production functions are identical between the unorganized small firm sector and the organized large firm sector.

The principal finding is that the agricultural productivity gap does not exist when the agriculture is compared to the unorganized nonfarm sector. The productivity gap between agriculture and the organized non-farm sector is substantial but is no more than the productivity gap between the unorganized and organized non-farm sectors. The findings suggest that the principal cause for low aggregate productivity is not low productivity in the agricultural sector alone but in all of the unorganized sector - both farm and nonfarm. Since small firms are characteristic of the typical developing country, the findings here suggest that similar results may obtain for other countries too.

The rest of the paper is organized in the following manner: Section-2 describes the standard literature view of the two-sector model of agriculture productivity gap. Section-3 presents a more general theory of the agricultural productivity gap (APG) considering a K-sector model and then for our purpose theory of APG in the context of the three-sector model. Section-4 calculates the benchmark/ideal level of APG. Section-5 calculates raw APG in three sector setting and section-6 improves this measure by adjusting for labor input differences across sectors. Section-7 presents the adjusted APG calculations and section-8 performs robustness checks. Section-9 concludes.

2 The Two Sector Agricultural Productivity Gap

The literature view productivity gap in two-sector setting and sectors being agriculture and non-agriculture. There is a consensus in the literature that there is a productivity gap between the aforementioned two sectors which implies that labor force as a resource is mis-allocated. We explore this standard view of the productivity gap with Indian data.

[3] Ghani, Kerr, and O'Connell (2013), Kotwal, Ramaswami and Wadhwa (2011)

2.1 Theory and Benchmark Results

We follow standard two-sector neoclassical model with Cobb-Douglas production functions in the agricultural and non-agricultural sectors. We assume free labor mobility across sectors and competitive labor markets. We follow Gollin, Lagakos, and Waugh (2014) model of agriculture productivity gap. One important assumption in the model is that the labor share in production is given by θ in each sector. So our production functions are:

$$Y_a = A_a L_a^{\theta} K_a^{1-\theta} \qquad \text{and} \qquad Y_n = A_n L_n^{\theta} K_n^{1-\theta} \tag{1}$$

where subscripts a and n denote agriculture and non-agriculture respectively; and variables Y, L, and K represent value added, labor input, and capital input respectively at aggregate level.

The assumption of free labor mobility implies that the equilibrium wage for labor across the two sectors is the same. The assumption of competitive labor markets implies that workers are paid the value of their marginal product and that firms hire labor up to the point where the marginal value product of labor equals the wage. Thus, marginal value products are equalized. Denoting value added as VA and letting p_a denote the relative price of Y_a, , the production function in equation (1) implies the ratio of marginal value products, and average value products, to be:

$$\frac{\frac{VA_n}{L_n}}{\frac{VA_a}{L_a}} = \frac{\frac{Y_n}{L_n}}{\frac{p_a Y_a}{L_a}} = 1 = \frac{\text{Value Added Per Worker in Non-Agriculture Sector}}{\text{Value Added Per Worker in Agriculture Sector}} \tag{2}$$

We call this ratio of value added per worker in non-agriculture to agriculture, the agricultural productivity gap, or APG. Therefore, APG=1 is our benchmark case. Important thing to note here is that the assumption $\theta_a = \theta_n$ is crucial for saying benchmark APG to be equal to one.

The mechanism is that if the APG > 1, there would seem to be an incentive for workers to move from agriculture to non-agriculture, simultaneously pushing up the marginal product of labor in agriculture and pushing down the marginal product of labor in non-agriculture. This process should tend to move the sectoral average products toward equality i.e. our benchmark case.

An important point to note in condition (2) is that it does not depend on any assumptions on other factor markets. Thus, the model implies that if equation (2) does not hold in the data, the explanation must lie in either measurement problems related to labor inputs or value added, or in frictions of some kind in the labor market, nothing else.

2.2 The Two Sector Agricultural Productivity Gap (APG) in India: Measurement

We use national income accounts data to calculate sector-wise value added per worker. The data and method of estimations are discussed in detail in later sections so, for now, let's take the estimates as given. We present the value added per worker numbers in a table below.

Table 1: Value Added per Worker For Two Sectors(Rs.)

Sector	1993-94	1999-2000	2004-05
Agriculture(a)	17129	19500	22422
Non-agriculture(n)	58090	77210	88109

Source: Planning Commision.

2.2.1 Raw Agriculture Productivity Gap

We calculate the agriculture productivity gap at face value by simply dividing the value added per worker in the non-agriculture sector by the value added per worker in the agriculture sector. We call this productivity gap 'raw' because it does not consider any differences in factor inputs.

Table 2: Raw Agricultural Productivity Gap (APG)

Year	Raw APG
1993-94	3.39
1999-2000	3.96
2004-05	3.93

2.2.2 Differences in Labor Inputs Across Sectors

The 'raw' APG presented in section-2.2.1 is a calculation at face value which says that a worker in the non-agriculture sector is around three-and-half to four times productive relative to her counterpart in the agriculture sector. The higher productivity in the non-agriculture sector maybe because the worker in non-agriculture work more hours in a year and hence producing more output. Similarly, a worker in the non-agriculture sector might be more productive simply because she is more educated. Therefore, one may be interested in knowing that "An average worker who is equal to average agriculture worker in terms of labor hours worked in a year and human capital level. Is she more productive than her agriculture counterpart?" Which in other words can be stated as: If we adjust for sectoral differences in labor inputs such as labor hours worked and human capital availability, does the gap still exist? To address this question, we calculate the adjustment factors which account for the differences in factor inputs across sectors. For the year 2004-05, the estimates of the labor hours per worker adjustment factor and the human capital adjustment factor are equal to 1.56 and 1.21 respectively. The methodology of computing these adjustment factors is discussed in later sections.

Table 3: Sectoral Differences in Human Capital and Labor Hours Worked

Labor Input	Adjustment Factor for 2004-05
Labor Hours Worked	1.56
Human Capital	1.21

2.2.3 Adjusted Agriculture Productivity Gap

The total adjustment factor for sectoral differences in labor inputs is a multiplication of the adjustment factors for human capital and labor hours worked. For the year 2004-05, the total adjustment factor is 1.89 is supposed to divide the 'raw' APG number to give us adjusted APG. We find that adjusted APG is 2.08. It means that "The labor in the non-agriculture sector is on an average twice as productive as labor in the agriculture sector after taking level of human capital and labor hours worked differences into account."

This adjusted or residual APG of order two implies that labor is misallocated across sectors. It is locked in the less productive agriculture sector when it should be moving to the more productive non-agriculture sector. The policy implication of this result is that frictions in labor mobility should be addressed to encourage the labor movement out of the agriculture sector. The magnitude of our adjusted APG is very close to the adjusted APG estimated by Gollin et al (2014).

2.3 Limitations

Followings are the some of the limitations of the standard two sector computations of the agriculture productivity gap that are addressed in this paper.

1. **Homogeneous Non-agriculture Sector**: As noted in the introduction, the two-sector analysis assumes that the non-agriculture sector is almost homogeneous. But Pratap and Quintin (2006) and Ghani, Kerr, and O'Connell (2013) note that there exists a large unorganized component in the non-agriculture sector in developing countries. This unorganized component is very different from the organized component of the non-agriculture sector in terms of labor productivity and social security cover(s) available to the workers. According to National Income Accounts data, the organized component on an average has five times more productive labor than the unorganized component of the non-agriculture sector. This discussion implies that it is not very meaningful to consider the non-agriculture sector to be homogeneous.

2. **Assumption of Same Labor Intensity in Production Across Sectors:** Gollin et al (2014) model assumes that labor share in output in agriculture and non-agriculture sectors is same i.e. $\theta_a = \theta_n$ in the theoretical model discussed in this section. Though Gollin et al (2014) says that this is a reasonable assumption but there is no obvious reason to believe it without confirmation. It would be better if we can check the plausibility of it in the context of India. This is important because if $\theta_a \neq \theta_n$ then the benchmark APG level would be different and not one. For example:- suppose if new benchmark level APG is 2.08, and our adjusted APG is 2.08 then we can say that adjusting for labor hours and human capital differences across sectors explains the APG.

3. **Functional Form for Human Capital:** Like in Gollin, Lagakos and Waugh (2014), the above calculations assumed a constant rate of return on education for all years and for all states. However, there is some evidence in the literature that return on an additional year of schooling is strictly convex as in Tushar Agarwal (2012).

3 Generalizing the Agricultural Productivity Gap

We consider a general setting where we allow the economy to have K number of sectors. Labor will move out of one sector if the other sectors are more productive. The magnitude by which the other sectors are more productive can be calculated as the ratio of labor productivity in the sector under consideration relative to the agriculture sector. This ratio of productivity, measured as the ratio of value added per worker in a sector i to value added per worker in the agriculture sector is our agriculture productivity gap for the sector i (APG_i).

3.1 Framework

Consider a K sector neoclassical model with Cobb-Douglas production functions in each sector with free labor mobility across sectors and competitive labor markets. We assume that the labor share in production is given by θ_i in a sector i. Our production function for a sector i is:

$$Y_i = A_i L_i^{\theta_i} K_i^{1-\theta_i} \tag{3}$$

where, $i = 1, 2, ..., K$, and variables Y, A,L, and K represent aggregate value added, technology used, labor input, and capital (and/or land) input respectively.

Now consider two sectors i and j, their production functions are:

$$Y_i = A_i L_i^{\theta_i} K_i^{1-\theta_i} \qquad \text{and} \qquad Y_j = A_j L_j^{\theta_j} K_j^{1-\theta_j} \tag{4}$$

The marginal product of labor for sector i is:

$$MPL_i = \theta_i A_i L_i^{\theta_i - 1} K_i^{1-\theta_i} = \theta_i \frac{Y_i}{L_i} \tag{5}$$

Similarly marginal product of labor for sector j is:

$$MPL_j = \theta_j A_j L_j^{\theta_j - 1} K_j^{1-\theta_j} = \theta_j \frac{Y_j}{L_j} \tag{6}$$

The assumption of free labor mobility implies that the equilibrium wage for a marginal worker across any two sectors is equal but average wages across two sectors may not be equal because we allow for differences in labor share in the production function of the sectors. The assumption of competitive labor markets implies that workers are paid the value of their marginal product and that firms hire labor up to the point where the marginal value product of labor equals the wage. Thus, marginal value products across sectors are equalized.

Suppose p_{ij} is the price of output of sector j relative to sector i. Equating value of marginal products across sectors gives:

$$\theta_i \frac{Y_i}{L_i} = p_{ij} \theta_j \frac{Y_j}{L_j} \tag{7}$$

This can be written as:

$$\theta_i \frac{Y_i}{L_i} = p_{ij} \theta_j \frac{Y_j}{L_j} \quad \Rightarrow \quad \frac{\theta_i \frac{Y_i}{L_i}}{p_{ij} \theta_j \frac{Y_j}{L_j}} = 1 \quad \Rightarrow \quad \frac{\frac{Y_i}{L_i}}{p_{ij} \frac{Y_j}{L_j}} = \frac{\theta_j}{\theta_i} \tag{8}$$

Notice that Y_i and $p_{ij} Y_j$ represents the value added in the sector i and j respectively. Hence equation (8) can further be written as:

$$\Rightarrow \quad \frac{\frac{VA_j}{L_j}}{\frac{VA_i}{L_i}} = \frac{\theta_i}{\theta_j} \quad \Rightarrow \quad \frac{\text{Value Added per Worker in Sector j}}{\text{Value Added per Worker in Sector i}} = \frac{\theta_i}{\theta_j} \tag{9}$$

If the ratio of value added per worker in sector j to the value added per worker in sector i is greater than $\frac{\theta_i}{\theta_j}$, then given competitive labor markets and perfect labor mobility, the worker has got an incentive to move to the sector j. There would seem to be an incentive for workers to move from sector i to sector j, simultaneously pushing up the marginal product of labor in i and pushing down the marginal product of labor in j. This process should tend to move the ratio of sectoral average products toward the inverse of the ratio of labor share in production function i.e.

towards $\frac{\theta_i}{\theta_j}$, which is our benchmark case. An important point to note in equation (9) is that it does not depend on any assumptions on other factor markets. In particular, the value of marginal labor productivity should be equalized across sectors even in the presence of market imperfections that lead to mis-allocation of other factors of production. For example, capital markets could be severely distorted, but firm decisions and labor flows should nevertheless drive marginal value products—and hence value added per worker—to be equated. Thus, the model implies that if equation (9) does not hold in the data, the explanation must lie in either measurement problems related to labor inputs or value added, or in frictions of some kind in the labor market, nothing else.

3.2 A Three Sector Model

As discussed earlier,suppose there are three sectors:- agriculture, unorganized non-agriculture, and organized non-agriculture. The production function in these sectors are:

$$Y_a = A_a L_a^{\theta_a} K_a^{1-\theta_a} \qquad Y_u = A_u L_u^{\theta_u} K_u^{1-\theta_u} \qquad \text{and} \qquad Y_o = A_o L_o^{\theta_o} K_o^{1-\theta_o} \tag{10}$$

where subscripts a, u, and o denote agriculture, unorganized non-agriculture, and organized non-agriculture sectors. And variables Y, A, L, and K represent aggregate value added, technology used, labor input, and capital (and land) input.

Equation (9) implies that:

$$\frac{\frac{VA_u}{L_u}}{\frac{VA_a}{L_a}} = \frac{\theta_a}{\theta_u} \qquad \text{and} \qquad \frac{\frac{VA_o}{L_o}}{\frac{VA_a}{L_a}} = \frac{\theta_a}{\theta_o} \tag{11}$$

Value added per worker is a measure of the productivity of workers in a sector. We are interested in the productivity gap relative to the agriculture sector, so the ratios on the left-hand side of two-part of the equation (11) can be called Agricultural Productivity Gap (APG). Then equation (11) says that under ideal conditions of free mobility of labor across sectors, the APG is the following:

$$APG = \frac{\frac{VA_j}{L_j}}{\frac{VA_a}{L_a}} = \begin{cases} \frac{\theta_a}{\theta_u} & \text{if j= Unorganized Non-Agri sector} \\ \frac{\theta_a}{\theta_o} & \text{if j= Organized Non-Agri sector} \end{cases}$$

The APG in the data will be compared to these ideal/benchmark levels given above.

4 Estimating Theoretical Benchmark Levels of Productivity Gap

To estimate the benchmark levels of APG, we need to get an estimate of the relative θs or labor shares. Under perfect competition and the Cobb-doubles production function assumption,

$$\theta_i = \frac{w_i L_i}{Q_i} = \frac{\text{Total Wages in Sector i}}{\text{Total Output in Sector i}} \tag{12}$$

For our three-sector model, we need to estimate θ_a, θ_u, and θ_o. We need to have sector-wise data on aggregate output and aggregate wage bill. Output data is available from national accounts and the wage bill data from employment surveys. However, while the latter can be disaggregated into organized and unorganized sector, such a disaggregation is not available for output data.

Table 4: Distribution of Employment Across Activities(in %)

Economic Activity	Organized	Unorganized
Mining	2.40	0.34
Manufacturing	30.43	20.07
Electricity, Gas, Water supply	2.82	0.35
Construction	3.54	1.21
Trade, Repair,Hotels-Restaurants	5.33	28.08
Transport, Storage, Communication	9.26	9.63
Financial services	3.83	1.04
Real estate, Dwelling, Professional services	3.41	2.71
Public Administration and Defence	8.88	0.95
Other services	20.23	20.96
Unknown Activity	9.86	14.66
Total	100	100

From the employment data, Table 4 computes the distribution of organized and unorganized employment by various economic activities classified at the one-digit level.

From this table, we see that it is the manufacturing sector that accounts for the most number of organized sector jobs. On the other hand, the unorganized sector is concentrated in "Trade,Repair,Hotels-Restaurants". For the purpose of computing the labor shares, we consider the former as representative of the organized sector and the latter as representative of the unorganized sector.

Under these assumptions, the estimated labor shares of three sector for the year 2011-12 are tabulated below:

Table 5: Sectorwise Labor Share (θ_i) for Year 2011-12

Sector	Total Wage	Total Output	θ
Agriculture	$7.73 \text{x} 10^{12}$	$1.95 \text{x} 10^{13}$	0.396
Unorganized Non-Agriculture	$3.30 \text{x} 10^{12}$	$1.3 \text{x} 10^{13}$	0.254
Organized Non-Agriculture	$8.72 \text{x} 10^{12}$	$6.54 \text{x} 10^{13}$	0.133

The major issue in using the estimates of labor share in Table 5 is whether the assumption of a representative economic activity is justified.

To see how good are these choices, we compare the wages in the representative sector with the wages in the sector they are supposed to represent. The average weekly earnings of Trade, Repair, Hotels-Restaurants activity is Rs. 1433 per week against the weekly earnings of Rs.1390/week for all of the unorganized sector. Furthermore, about 90 percent of employment in the Trade, Repair, Hotels-Restaurants belongs to the unorganized sector. So it seems that choosing Trade, Repair, Hotels-Restaurants as a representative of the unorganized non-agriculture sector is a fair choice.

The average wage in the manufacturing activity is Rs.1800/week against the Rs. 3090/week in all of organized sector. Furthermore, about half of the manufacturing sector labor is unorganized. This weakens our claim that Manufacturing activity represents the organized non-agriculture sector.

Radhicka Kapoor(2010), using ASI and NSS unit level data 2010, estimates that 65.02 % output in manufacturing is contributed by organized establishments, this gives us total output for 'organized manufacturing'. We can easily estimate total wages in organized manufacturing sector using employment data. This exercise allows us to estimate labor share for only organized manufacturing sector. We observe that resulting θ, doesn't differ much from 0.133 estimated in Table 5. We conclude that use of the manufacturing sector as representative of the organized sector is not misleading.

4.0.1 Estimation of Benchmark APGs:

Using equation (9), we define APG_i as ratio of value added per worker in sector i to value added per worker in agriculture sector. i.e.

$$APG_i = \frac{\text{Value Added per Worker in Sector j}}{\text{Value Added per Worker in Sector i}} = \frac{\theta_i}{\theta_j}$$

Using estimated θ_is from section-(**??**), this implies,

Table 6: Sectorwise Estimation of Benchmark APG Levels for Year 2011-12

Sector	Benchmark APG Level
Unorganized Non-Agriculture	1.56
Organized Non-Agriculture	2.97

These benchmark APG levels imply that ideally on average, a worker in the unorganized non-agriculture sector should be roughly one and half times productive than a worker in the agriculture sector. Similarly, a worker in the organized non-agriculture sector should be around three times productive than her counterpart in agriculture.

Therefore our estimated benchmark APG levels can be given as:

$$\mathbf{APG}_i = \begin{cases} \mathbf{1.56} & \text{For i= Unorganized Non-Agri sector} \\ \mathbf{2.97} & \text{For i= Organized Non-Agri sector} \end{cases}$$

Since the representative economic activity of unorganized sector contains 10% of its labor-force in the organized sector, this may bias the estimate of the θ_u. Because the presence of 10% organized sector in the representative activity implies that the estimated θ_u is a convex combination of the original θ_u and θ_o. We have estimated that $\theta_o < \theta_u$, this implies that estimated θ_u is lower than real θ_u which would be an estimate if 100% of the labor in representative activity was unorganized. This implies that 0.254 is the lower-bound for θ_u. And benchmark APG for the unorganized non-agriculture sector which contains θ_u in the denominator is overestimated. Therefore the benchmark level of productivity gap between the unorganized non-agriculture sector and agriculture sector is less than or equal to 1.56. Following a similar line of reasoning, we can say that manufacturing economic activity contains some of the unorganized sector in it. The current estimate of θ_o is a convex combination of unorganized manufacturing and organized manufacturing activities, therefore we expect the real θ_o to be lower than 0.133. This implies that the benchmark APG which contains θ_o in the denominator should be biased upwards i.e. APG between organized non-agriculture and agriculture sector should be greater than or equal to 2.97.

In sum, we can say that the APG benchmark for unorganized non-agriculture sector possibly be biased upwards and for organized non-agriculture sector, it possibly is biased downwards.

5 Raw Agricultural Productivity Gap Calculations

Raw agricultural productivity gap is defined as the ratio of value added per worker in a sector to value added per worker in the agriculture sector. We call it 'raw' because this is the gap at face value which doesn't take sectoral input differences into account. We tabulate the value added per worker for the sectors understudy and then derive the raw APG table from it. Value added per worker in three sectors is directly available in a publication by CSO, so we need not go for aggregate output and then aggregate labor force working in the sectors to estimate the value added per worker ratios.

Table 7: Value Added per Worker For Three Sectors(Rs.)

Sector	1993-94	1999-2000	2004-05
Agriculture(a)	17129	19500	22422
Unorganized Non-Agri(u)	36327	45247	49611
Organized Non-Agri(o)	143141	227211	324701

Source: National Income Accounts.

Table 8: Raw APG

Sector	1993-94	1999-2000	2004-05
Unorg. Non-Agri	2.12	2.32	2.21
Org. Non-Agri	8.35	11.65	14.48

We observe that raw APG for unorganized non-agriculture and organized non-agriculture sectors differ substantially, thus it confirms our claim of the non-agriculture sector is considerably heterogeneous.

The observation from raw APG says that an average worker in the organized non-agriculture sector is fourteen times more productive than an average worker in the agriculture sector. But one can ask, is it really the case? are average workers in the two sectors comparable? The answer is no because average workers in the sectors under discussion here differ in average availability of work in a year and human capital available with them. Therefore it appears, at face value, that labor productivity in the organized non-agriculture sector is fourteen times that of agriculture sector but in reality, it may be lower if we account for the labor inputs differences. The following subsection is dedicated to addressing this issue.

6 Improved Measurement of Labor Inputs Across Sectors

We discussed in section-**??** that raw APG i.e. the productivity gap relative to the agriculture sector calculated at face value should be adjusted for appropriate differences in labor inputs into the sectors. The important labor inputs which differ across sectors are labor hours worked by workers and the human capital of the workers. The following two subsections are dedicated to estimating these differences.

6.0.1 Calculation of differences in labor hours worked per worker

The following table contains the average number of hours worked by a worker in a sector for the years 2004-05 and 2011-12. We have used the yearly measure of labor hours to avoid the effect of seasonality. The method of estimating these labor hour numbers is already described in section-??.

Table 9: Yearly Labor Hours Worked per Worker

Sector	2004-05	2011-12
Agriculture(a)	1230.15	1142.27
Unorganized Non-Agri(u)	1877.98	1506.48
Organized Non-Agri(o)	2390.70	2572.90

Source: IHDS Survey.

We make a reasonable assumption that additional number of hours worked in each sector increases output linearly. This allows us to calculate the adjustment factor for labor hours differences by simply dividing the labor hours worked in the sectors under discussion. Using the table above we calculate the adjustment factors with which the APG should be adjusted for differences in labor hours as labor input across sectors.

Table 10: Adjustment Factors for Labor Hours Differences

Sector	2004-05	2011-12
Unorganized Non-Agri(u)	1.53	1.32
Organized Non-Agri(o)	1.94	2.25

6.0.2 Calculation of differences in human capital per worker

We calculate the human capital differences across sectors using years of schooling from NSS data and returns on education using World Development Report's background paper Montenegro and Patrinos (2013). We assume a constant marginal rate of return on an additional year of schooling and it's value is 7% as estimated by Montenegro and Patrinos (2013) for South Asia. Using Mincerian form our formula for human capital estimation for a worker who has attained *EducationYrs* years of school can be given as follows:

$$\text{Human Capital} = e^{0.07*EducationYrs} \tag{13}$$

The NSS data gives education information like the level of education attained by a worker. We convert it into a continuous variable *year of schooling* using the coding given in the conversion table.

Using the conversion table, we calculate the differences in years of education across sectors for different years.

Using the formula for human capital and estimates of sector-wise years of schooling, we estimate sector-wise human capital. We assume that rate of return in formula (7%) holds true for the years 1999-2000, 2004-05, and 2011-12, this seems like a strong assumption, we calculate human capital using heterogeneous returns to education later in the paper but for the simplicity, we use this as of now.

Table 11: Conversion of Level of Education into Years of Education

Edu Level	Years
Not literate	0
literate without any schooling	2
literate without formal schooling: through NFEC/AIEP	2
literate without formal schooling: through TLC/ AEC	unknown
literate without formal schooling: others	unknown
Below primary	2.5
Primary	5
Upper Primary/Middle	8
Secondary	10
Higher Secondary	12
Diploma/Certificate course	14
Graduate	15
Post Graduate and More	17

Table 12: Sectorwise Average Years of Education Attained by Workers

Sector	1999-2000	2004-05	2011-12
Agriculture(a)	2.14	3.62	4.30
Unorganized Non-Agri(u)	5.78	6.40	6.87
Organized Non-Agri(o)	8.68	9.67	9.63

Source: NSS.

Table 13: Sectorwise Average Human Capital per Worker

Sector	1999-2000	2004-05	2011-12
Agriculture(a)	1.16	1.29	1.35
Unorganized Non-Agri(u)	1.50	1.57	1.62
Organized Non-Agri(o)	1.87	1.97	1.96

Source: NSS.

We take human capital as labor input which is different across sectors as tabulated above. On the lines of adjustment factors calculated for labor hours input, we calculate the adjustment factors with which raw APG should be adjusted. The estimates for adjustment factors are tabulated below:

Table 14: Adjustment Factors for Human Capital Differences

Sector	1999-2000	2004-05	2011-12
Unorganized Non-Agri(u)	1.29	1.22	1.20
Organized Non-Agri(o)	1.61	1.53	1.45

7 Adjusted Agricultural Productivity Gap Calculations

As we discussed earlier, there is a need for adjusting for labor inputs. Adjusting for sectoral differences in both labor hours and human capital as labor inputs can be done by an adjustment factor which is a multiplication of their labor hours and human capital adjustment factors. We use tables containing information on adjustment factors for human capital and labor hours adjustment factors to estimate the total adjustment factor for labor inputs. Our discussion here is limited with the availability of the data. We have data on human capital adjustment for the years 1999-2000, 2004-05, and 2011-12, we have data on labor hours adjustment for the later two years, and data on productivity gap is available for 1993-94, 1999-2000, and 2004-05. So we do our analysis for the year 2004-05.

Table 15: Total Adjustment Factors for APG for the Year 2004-05

Sector	Labor-Hours	Human-Capital	Total
Unorganized Non-Agri(u)	1.53	1.22	1.87
Organized Non-Agri(o)	1.94	1.53	2.97

Total adjustment factor table tells us that the APG calculated at face value i.e. raw APG is needed to be adjusted by a factor of 1.87 and 2.97 for unorganized and organized non-agriculture sectors respectively. We present the adjusted APG with their benchmark as calculated in the section-**??**.

Table 16: Adjusted APG for the Year 2004-05

Sector	RawAPG	AdjFac	AdjAPG	Benchmark
Unorg. Non-Agri	2.21	1.87	**1.18**	1.56
Org. Non-Agri	14.48	2.97	**4.88**	2.97

The adjusted APG table tells a different story altogether. It says that the residual productivity gap or adjusted productivity gap for the unorganized non-agriculture sector is lower than the benchmark level! This implies that there is a limited incentive for a worker to move out in the non-agriculture sector if the later is unorganized. In other words, there is no misallocation of labor between agriculture and unorganized non-agriculture sectors. In other words, there is no misallocation of labor in the low productive sectors and these two sectors put together employee 85% of the labor force. It refutes the claim that there is a persistent productivity gap between the agriculture and non-agriculture sector in the context of the unorganized part of the later. While we observe a higher APG relative to the benchmark level for the organized component of the non-agriculture sector, which is a result in line with Gollin et al (2014). But the magnitude of this adjusted APG between the organized non-agriculture and the agriculture sector is less than two, hence not replicating Gollin et al (2014)'s story.

8 Robustness Check

8.1 Wage Gap Across Sectors

In the literature, the labor productivity is measured by both value added per worker and wage. For example, Herrendorf and Schoellman (2013) uses both value added per worker and wage as the measures of productivity. The motivation for wages to be used as a measure of productivity comes from lesser assumptions required on the market. Wages across sectors should be equalized given perfect labor mobility. It is straight forward to say that perfect labor mobility implies wages to be equal across all sectors otherwise labor can move to the sector which is offering more wages. Note that the decision-making process for labor will not take total income into account, it will take only labor income i.e. wage into account. For example, a farmer gets Rs. 50 as labor income and Rs. 70 as capital income from her farm, and at the same time she can get wage equal to Rs. 80 in the non-agriculture sector. The decision-making process implies that the farmer will supply her labor to the non-agriculture sector which is paying Rs. 80 as labor income. And the farmer will continue to get capital income from the land because she can hire another guy to do farming for wage equals to Rs. 50, therefore her total income now will increase by Rs. 30.

It may look like that using wage as a measure of productivity is a superior choice to value added per worker. But the same is not the case because in the context of India wages are not available for the self-employed workers which consist of a large portion of the workforce in agriculture and unorganized non-agriculture sectors. Therefore we miss information on a large portion of the workforce if we just use the wage as a measure of productivity. On the other hand, the value added per worker takes into account the production by the self-employed workers as well. So we can not explicitly call one measure of productivity superior to the other one. Therefore in our analysis, we use both of these measures to find productivity gaps in our three-sector model.

In the last section, we have discussed labor productivity gaps across sectors using value added per worker for 2004-05, we couldn't do it for other years because of the limited availability of data. Here, we have sector-wise data on wages for the years 1999-2000, 2004-05, and 2011-12. Analysis with the wage gap is important because it will make our findings more refined. We divide NSS observations into the three sectors as discussed earlier in section-**??**, the sample size for each year in each sector was greater than 5000. We present the sector-wise wages for three years.

Table 17: Sectorwise Average Weekly Wages in Rupees

Sector	1999-2000	2004-05	2011-12
Agriculture	245.08	346.10	767.56
Unorg. Non-Agri	544.34	682.84	1390.12
Org. Non-Agri	1014.23	1531.61	3059.65

Source : NSS.

We construct a wage gap table using the information on wages from the table above. The table contains wage gaps at their face value, analogous to our raw APG in discussion. With similar line of reasoning as of value added per worker, wage gaps should be adjusted for differences in labor inputs. Labor hours adjustment factors for the year 1999-2000 are not available so assume 2004-05 numbers are true for 1999-2000.

Table 18: Wage Gap Relative to Agriculture Sector

Sector	1999-2000	2004-05	2011-12
Unorg. Non-Agri	2.22	1.97	1.81
Org. Non-Agri	4.14	4.42	3.99

At the beginning of this sub-section, we discussed that perfect labor mobility implies wages

Table 19: Total Adjustment Factors for Wage Gap

Sector	1999-2000	2004-05	2011-12
Unorganized Non-Agri(u)	1.97	1.87	1.58
Organized Non-Agri(o)	3.08	2.97	3.26

Table 20: Adjusted Wage Gap

Sector	1999-2000	2004-05	2011-12
Unorg. Non-Agri	1.12	0.95	0.87
Org. Non-Agri	1.34	1.49	1.22

being equal across all sectors. Therefore the benchmark wage gap relative to the agriculture sector should be equal to unity for both organized non-agriculture and unorganized non-agriculture sectors. In the adjusted wage gap table, the adjusted wage gap between the unorganized non-agriculture and agriculture sector is less than one. This implies that for the given number of hours worked and human capital, workers are paid lesser wages in the unorganized non-agriculture sector than in the agriculture sector. Hence, it rules out the possibility that the unorganized non-agriculture sector to be more productive than the agriculture sector. Similarly, the wage gap for the organized non-agriculture sector is considerably greater than one, which says that there is a productivity gap between organized non-agriculture and agriculture sectors.

Hence the robustness check using wage as an alternate measure of productivity reiterates our findings in section-4 where we use value added per worker as a measure of productivity.

8.2 Further Improved Measurements of Labor Inputs : Heterogeneous Returns to Education

For the calculation of human capital, we have used a constant homogeneous rate of return on each additional year of schooling. We discussed there as well that this is a strong assumption but for the simplicity of methodology following Gollin et al (2014), we continued with that assumption. In this section, we relax this assumption and allow for the heterogeneous rate of return on levels or years of education.

Tushar Agarwal (2012) calculates heterogeneous private rate of returns on levels of education using IHDS 2004-05 data. We are doing our analysis for the year 2004-05, therefore the rate of returns in the paper perfectly fits for our purpose of calculation of human capital. The following figure is a table from the paper that states the numbers we are interested in.

Figure 2: Tushar Agarwal (Journal of Quantitative Economics, July 2012)

Table 3. Private Rates of Return to Education (%)

Educational Level	*OLS*			*Heckman*		
	All	*Rural*	*Urban*	*All*	*Rural*	*Urban*
Primary	5.75	5.07	6.87	5.47	4.64	6.59
Middle	6.11	5.69	6.25	6.15	5.80	6.20
Secondary	11.40	10.41	12.76	11.38	10.29	12.73
Higher Secondary	12.00	9.50	14.33	12.21	9.60	14.67
Graduate	15.38	15.80	14.52	15.87	16.43	15.12

Notes: The results are computed using Table 2. For example, private rate of return for middle level (using the Heckman) can be computed as: $r_{middle} = (\beta_{middle} - \beta_{primary})/\Delta n_{middle}$ = (0.349-0.164)/3= 0.061 or 6.15%. For primary level of education, Δn is taken as three years instead of five years.

We use the rate of returns with Heckman correction given in the table though it is hardly different from the OLS values. We use education as a categorical variable i.e. levels of education in this subsection because the rate of return is available as categorical values. Our formula for human capital takes a slightly modified form as given below:

$$\text{Human Capital } = e^{\sum_{k=1}^{K} I(k) R_k Y_k} \tag{14}$$

Where : k is a categorical variable which takes values:- Illiterate, Informal Schooling, Primary, Middle, Secondary, Higher Secondary, Diploma, Graduation, Post-graduation. R_k and Y_k are the returns and number of years in particular category of education. I(k) is an indicator function. We assume rate of returns equal to zero for the below-primary education levels.

Using the new formula given in equation (14), we estimate human capital in three sectors under analysis for the year 2004-05. The estimates are tabulated as given below:

Table 21: Sectorwise Average Human Capital per Worker and Adjustment Factors for the Year 2004-05

Sector	Human Capital	H-Cap Adjust Factor
Agriculture(a)	1.30	-
Unorganized Non-Agri(u)	1.73	1.33
Organized Non-Agri(o)	2.46	1.89

Source: NSS.

Using our new estimates for human capital adjustment factors we rewrite the table for total adjustment factors and the table for adjusted APG. Note that the adjustment factors for the labor hour differences remain the same.

Table 22: Total Adjustment Factors for APG for the Year 2004-05 Using Heterogeneous Returns to Education

Sector	Labor-Hours	Human-Capital	Total
Unorganized Non-Agri(u)	1.53	1.33	2.03
Organized Non-Agri(o)	1.94	1.89	3.67

Table 23: Adjusted APG for the Year 2004-05 Using Heterogeneous Returns to Education

Sector	RawAPG	AdjFac	AdjAPG	Benchmark
Unorg. Non-Agri	2.21	2.03	**1.09**	1.56
Org. Non-Agri	14.48	3.67	**3.95**	2.97

Using heterogeneous returns to education, we find that residual APG for organized non-agriculture is around 3.95 against the benchmark level 2.97. This result says that the residual productivity gap between the organized non-agriculture sector and the agriculture sector is not large as claimed by Gollin et al (2014).

We can observe that adjusted APG for the unorganized non-agriculture sector becomes 1.09 which was 1.18 before and both numbers are below the benchmark level which is 1.56. Therefore, we can say that this robustness check doesn't change our conclusion. In fact, it confirms that there is no productivity gap between the unorganized non-agriculture and agriculture sectors. Note that in our discussion in this paper, we use the productivity gap in the context of a sector being more productive than the agriculture sector. Also, after allowing for heterogeneous returns to education, APG for organized non-agriculture sector becomes 3.95 which is still more than the benchmark level 2.97, therefore we can say that this robustness check doesn't change our conclusion that there is a productivity gap between organized non-agriculture and agriculture sectors. Though it changes the magnitude which can be interpreted as APG between organized non-agriculture and agriculture sector is of smaller magnitude than before.

In sum, this robustness check gives results in support to our story of the productivity gap and doesn't overturn any conclusions.

9 Conclusion and Future Scope of Work

According to national accounts data, value added per worker is much higher in the non-agricultural sector than in agriculture in most countries. This suggests that labor in the agricultural sector is less productive than the non-agriculture sector, which can be interpreted as evidence of labor misallocation across sectors. Literature attempts to explain this as a productivity gap between agriculture and non-agriculture i.e using the two-sector model of the productivity gap. In this paper, we question the standard literature view of the two-sector model in the context of developing countries. We are attempting to look at the productivity gap relative to the agriculture sector in a more general setting. We allow the non-agriculture sector to be heterogeneous and labor intensity to differ across sectors. Our analysis suggests that a large part of the non-agriculture sector is unorganized and is not more productive than the agriculture sector. Therefore the lower productivity of the unorganized non-agriculture sector is an important factor that is limiting labor movement out of the agriculture sector. This has important implications calling policies to focus on increasing the productivity of unorganized firms in non-agriculture sectors. The main policy implication of the standard two-sector model of productivity gap i.e. the labor misallocation across agriculture and non-agriculture sectors looks like secondary importance according to our findings.

Accounting for labor input differences, the two divisions of non-agriculture show opposite productivity characteristics relative to the agriculture sector. After adjusting for labor input differences, the unorganized non-agriculture sector is less and organized non-agriculture sector is more productive than the agriculture sector. The findings hold when we repeat the analysis using wage as an alternative measure of labor productivity, in other words, robust to the measures of productivity. The conclusion is consistent with the second robustness check which allows for a flexible form of human capital to adjust for the human capital differences across sectors. These findings has different implications in contrast to the standard two-sector model of the agriculture productivity gap. We conclude that the simply moving labor out of the agriculture to the non-agriculture sector may not result in a better reallocation of labor. Moreover, it even can get worse as there is evidence that a large division of non-agriculture i.e. unorganized is less productive than the agriculture sector. For better reallocation of labor, it should the case that labor is moved to the organized non-agriculture sector from the agriculture sector to reduce the productivity gap.

We conclude that if one wants to say that there is a productivity gap between two sectors then these sectors are organized and unorganized. The statement "There is a productivity gap between agriculture and non-agriculture sectors" is a sentence with limited information. Also, "There is a productivity gap between organized and unorganized sectors" is an informed and nuanced sentence. We motivated our view of the three-sector model with the evidence of the presence of large unorganized sectors in developing countries, therefore we do not claim that the results of our paper as it is can hold in developed countries. But one can think of this view in developed countries by replacing our unorganized non-agriculture sector with a sector containing daily wage labor or minimum wage labor. Our findings are likely to be true in the context of developing countries because there typically a large portion of the non-agriculture sector is unorganized.

In sum, we say that what literature view as the agriculture productivity gap, vanishes for a large portion of the labor market when we allow the non-agriculture sector to be heterogeneous. Though the productivity gap is still there between organized non-agriculture and agriculture, therefore, between these two sectors, the labor is misallocated. But, more importantly, one should look at lower productivity of the unorganized non-agriculture sector which limits options for movement of labor out of the agriculture sector.

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