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A New Look at the Measurement Problem

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(revised)

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Abstract

The Agricultural Productivity Gap (APG) - the ratio of the average labor productivity in non-agriculture to that in agriculture - tends to be very large in developing countries and potentially represents misallocation of resources. This paper makes three contributions to the literature on APG. First, it shows that APG steadily and substantially increased for an extended period of time in a majority of countries in recent past. Given the inverse correlation between APG and the level of income, it is contrary to expectations, especially for developing countries. Moreover, such an increase happened while the Agricultural Wage Gap (AWG) - the ratio of the average wage in non-agriculture to that in agriculture - remained more or less stable. Second, this paper provides an explanation for the puzzling breakdown of the accounting identity that the ratio of APG to AWG must be equal to the ratio of the labor share in agriculture to that in non-agriculture. It shows that inconsistency in estimating the labor income of the self-employed in the process of measuring the average wage and the labor share plays a crucial role. Third, this paper demonstrates that the puzzle is indeed resolved to a large extent, once the labor shares are calculated in ways that are consistent with the measurement of the average wage.

JEL: E24 E25 J31 O13 O41

1. Introduction

Large differences in labor productivity between agriculture and non-agriculture have long been a central issue in the economic development literature (Lewis, 1955; Kuznets, 1971; Gollin, Parente, and Rogerson, 2002). According to the national accounts data, during 1995~2015 the Agricultural Productivity Gap (APG) – the ratio of the average labor productivity in non-agriculture to that in agriculture – stood at 3.4 for developing countries as a whole. Since the agricultural sector employs large proportions of workers in developing countries, huge APGs are responsible for the low aggregate productivity to a considerable extent and suggest possibility of significant misallocation of resources (Vollrath, 2009; McMillan and Rodrik, 2011; Gollin, Lagakos, and Waugh, 2014).

Most of the attention in the literature has been centered on the labor market factors such as differences in observed and unobserved human capital (Young, 2013; Lagakos and Waugh, 2013; Gollin, Lagakos, and Waugh, 2014; Herrendorf and Schoellman, 2017) and the barriers to labor mobility that give rise to the non-agricultural wage premium (Caselli and Coleman 2001; Restuccia, Yang, and Zhu 2008; Adamopoulos and Restuccia 2011; Tombe 2011; and Herrendorf and Teixeira 2011; Munshi and Rosenzweig, 2016; Morten, 2016).

However, labor market factors generate productivity gaps only through wage gaps, and it is well known that productivity gaps are typically much larger than wage gaps. That is, APG is typically much larger than the Agricultural Wage Gap (AWG) - the ratio of the average wage in non-agriculture to that in agriculture. It may be because factors outside the labor market play important roles in generating productivity gaps. Nonetheless, this possibility has been more or less ignored. The reason is that the gap between the productivity gap and the wage gap, APG/AWG, should be equal to the ratio of the labor share of income in agriculture to that in non-agriculture by an accounting identity, and therefore the common belief that the labor share is smaller in agriculture than in non-agriculture (Gollin, Lagakos, and Waugh, 2014; Herrendorf and Schoellman, 2015) casts doubts on productivity gaps exceeding wage gaps. If we accept the findings on productivity gaps and wage gaps on the one hand and the sectoral labor shares on the other, the accounting identity breaks down. The only logical explanation for the breakdown of the accounting identity is mismeasurement. In fact, Herrendorf and Schoellman (2015) argue that productivity gaps are exaggerated as a result of mismeasurement. They claim that the agricultural value added is underestimated and hence APG is overestimated in the case of the US, and suggest that the same must be the case in developing countries.

We do not believe that matters are so simple, and suggest that we need to go beyond the labor market and investigate the role of factors outside the labor market in trying to understand APG. For one thing, Gollin, Lagakos, and Waugh (2014), after carefully examining household survey data from 10 developing countries, find that APGs calculated from these micro data are quite similar to those calculated from the national accounts data. They conclude that large productivity gaps in developing countries are not a figment of measurement errors. Our own conclusion is based on the following findings and arguments.

First, our calculations below add two more reasons to doubt that mismeasurement of APG alone can explain the breakdown of the accounting identity. To begin with, according to our calculations, overestimation of APG by more than two times is required to resolve the problem. It is hard to believe that measurement errors of such magnitude exist. More importantly, we find that the average APG increased steadily and substantially over an extended period time while the average AWG remained rather stable. We are able to show this because we analyze the data over an extended period instead of looking at snap-shot pictures: our data cover more than 100 countries over the 21-year period 1995-2015. This result is surprising, since APG in developing countries might be expected to decrease over time as their incomes grow, given the inverse correlation between APG and the level of income. At any rate, it means that the incongruence between the accounting identity and the measured gaps in productivity and wage got worse. It is difficult to believe that measurement of the agricultural value added became more and more inaccurate over time to such a large extent. The inevitable conclusion is that the measurement problem lies primarily in estimating wage gaps or the labor shares rather than productivity gaps, at least as far as developing countries are concerned.

Second, we point to the presence of the self-employed, who dominate agriculture almost everywhere, as a crucial source of the measurement problems. Applying different methods to estimating the labor income of the self-employed will necessarily lead to inconsistency between the measured average wage and the measured labor share. Calculation of the average labor productivity poses no serious difficulty. We simply divide value added by the number of workers, including both employees and the self-employed. Standard practice in measuring the average wage is to treat the self-employed as if they are receiving the same wage as employees. We call this the 'naive average wage' or the 'sophisticated average wage', depending on the method of imputation. When calculating the labor share, the presence of the self-employed requires us to figure out what portion of their income should be counted as labor income, and there are various alternative approaches to this problem. However, there is only one approach that is consistent with the average wage and will yield a measure of the labor share that satisfies the accounting identity. It is to impute the average wage of employees to the self-employed using the same method of imputation as in measuring the average wage.

Third, using the EU KLEMS dataset that adopts an imputation approach in estimating the labor shares, we demonstrate that the accounting identity in fact holds quite well. Thus, the problem of the incongruence between the gap between the productivity gap and the wage gap on the one hand and the gap in the labor shares on the other is effectively resolved. Needless to say, adopting any other approach to measuring the labor share, including direct estimation of the agricultural production functions, will necessarily give rise to the incongruence problem except by a fluke. Then, depending on one's viewpoint, either the wage gap or the gap in the labor shares could be considered as mismeasured.

The remainder of the paper is organized as follows. In section 2, we calculate the Agricultural Productivity Gap and the Agricultural Wage Gap for more than 100 countries over the period 1995-2015, and find that the average APG increased steadily and substantially during 1995-2010 while the average AWG remained rather stable for both developing and developed countries. In section 3, we discuss the meaning of the accounting identity mentioned above and the sources of the measurement problems that lead to its breakdown. We emphasize the role of the self-employed in creating mismeasurements. In section 4, using the labor shares calculated from the KLEMS database, we demonstrate that the accounting identity can be more or less satisfied once the labor shares are measured in a way that is consistent with measurement of the average wage. Section 5 concludes with a summary, a discussion of the implications of our findings and suggestions for future research.

2. Trends in the Agricultural Productivity Gap and the Agricultural Wage Gap

2.1. The Agricultural Productivity Gap

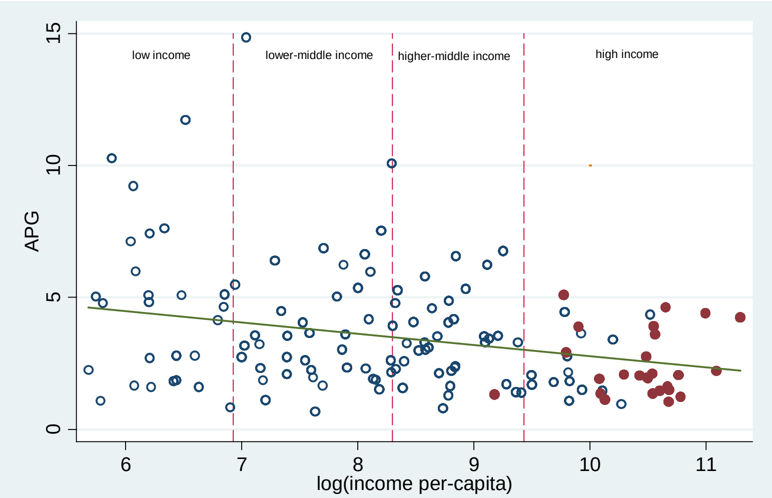
We calculate APG by dividing the ratio of the share of value added in non-agriculture to that in agriculture by the ratio of the share of employment in non-agriculture to that in agriculture as follows:

$$(1)\quad APG = \frac{VA_n / VA_a}{L_n / L_a}$$

where *VA* and *L* stand for value-added and employment, and the subscripts '*n*' and '*a*' refer to non-agriculture and agriculture.

We use the annual data on value added and share of employment from the World Development Indicators. Non-agriculture is the sum of industry and services. Since we can compute APGs only when the data on value added and the data on share of employment exist for the same year, a number of countries with many missing data had to be dropped from our sample. We still have a large sample, covering 153 countries for the period of 1995-2015. We also had to remove some observations on employment shares that exhibit inconsistencies and result in extremely biased APG, as explained in the Appendix I. We end up with 12 observations on average per country over the 21-year period.

Fig. 1. APG vs Income per-capita



Note: Country averages for 1995-2015. Hollow circles represent developing countries
Source: Authors' calculations based on WDI, 2017

While previous works on APG tend to provide only snap-shots, we examine APG over an extended period and present APG of countries or groups of countries as period averages. The advantage of this approach is that the period averages are free from short-term fluctuations, which can sometimes be quite large, and hence more robust.[1] Furthermore, we are able to evaluate the trend of APG over time.

Fig. 1 shows the results of our calculations of the average APGs of the individual countries over the sample period. It shows that, while APG is substantially greater than unity in most countries, the distribution of APG exhibits a great diversity, ranging from Zambia's 14.6 to Kosovo's 0.25. Furthermore, it clearly suggests an inverse relationship between the level of income and APG. In fact, the simple correlation coefficient is -0.30. Since agriculture employs a large share of the labor force in poor countries, a large APG may be considered an important cause of low aggregate productivity and per capita income in many such countries.

We divide the countries in our sample into two groups and calculate group averages so that we can find broad tendencies. We consider two ways of dividing the sample: low-and middle-income vs. high-income, and developing vs. developed. Even though high-income countries are often treated as developed countries, there is significant heterogeneity in quality of economic development among high-income countries. We classify as developed countries only those countries that are members of the OECD and at the same time rank within the top quarter in terms of 2015 PPP-adjusted per-capita income. In Fig 1, we can see that many high-income countries are classified as developing countries, represented by hollow circles.[2]

Table 1 presents the average APG over the sample period for each group of countries. It shows that an average worker in non-agriculture is 3.8 times more productive than her counterpart in agriculture in low and middle-income countries, and 3.6 times more productive in developing countries. In high-income countries, the productivity difference is 2.7 times, and it is 2.5 times in developed countries. Our numbers are generally consistent with those from Gollin, Lagakos, and

[1] For instance, for Cambodia, APG is 1.6 in 2004 and 2.3 in 2010. Similarly, for China APG is 6.2 in 2006 and 4.0 in 2015. Since we are looking at nominal value added per worker in each sector, fluctuations in relative prices may bring about substantial changes in APG in the short term.

[2] Developed: Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Iceland, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand, Portugal, Sweden, the United States. High-income but not developed: Antigua and Barbuda, Aruba, Bahamas, Bahrain, Barbados, Bermuda, Brunei Darussalam, Chile, Croatia, Cyprus, Czech Rep., Estonia, Hong Kong SAR, Latvia, Lithuania, Malta, New Caledonia, Oman, Poland, Puerto Rico, Qatar, Saudi Arabia, Seychelles, Singapore, Slovak Republic, Slovenia, Trinidad and Tobago, Venezuela, United Arab Emirates, Uruguay.

Waugh (2014) for developing countries, Cai and Pandey (2013) for European economies and Herrendorf and Schoellman (2015) for the US.

Table 1. Average APG over 1995-2015		
	APG	*Number of countries*
Low and middle income	3.79	98
High income	2.66	55
Developing	3.58	127
Developed	2.45	26

From now on, we present calculations for the developing and developed groups only. As can be seen in Table 1, the results of our analysis do not change much when we divide the sample simply by the level of income. The average APGs for the developing group and developed group are somewhat lower than those for the low-and middle-income group and the high-income group, since many high-income countries that are not classified as developed exhibit APGs in between the low- and middle-income group and the developed group. The reason why we prefer dividing the sample into the developing group and the developed group is that we have very few data on the labor share for the low-income and middle-income countries. We can increase the number of observations substantially by looking at the developing countries rather than the low-and middle-income group when we later examine the data available on labor shares.

Next, we look at the movement of yearly APG over time. For this purpose, it is necessary to exclude countries with too many missing data. Consider a country with a high APG, say, Botswana, for which we have 1995 data but lack 2014 data. The inclusion of Botswana in the sample would then lead to underestimation of the average APG in 2014. In order to avoid pitfalls like this, we calculate the yearly average APG for each group of countries using a reduced sample consisting of only those countries for which we have a complete set of observations. We also exclude 2015 from the sample period, since data for 2015 are missing in too many developing countries. The reduced sample comprises 34 developing and 25 developed countries, each of them with all 20 possible yearly observations from 1995 to 2014.[3] Since only 34 out of 127 developing countries are included in the reduced sample, there is a need to test whether the reduced sample is representative of the full sample. Our estimations presented in the Appendix II show that there are no systematic differences in the computed level of APG between the reduced and the full samples of developing countries. This conclusion holds for both country-average APG's as well as APG's over time.

Fig. 2. Trend of Average APG

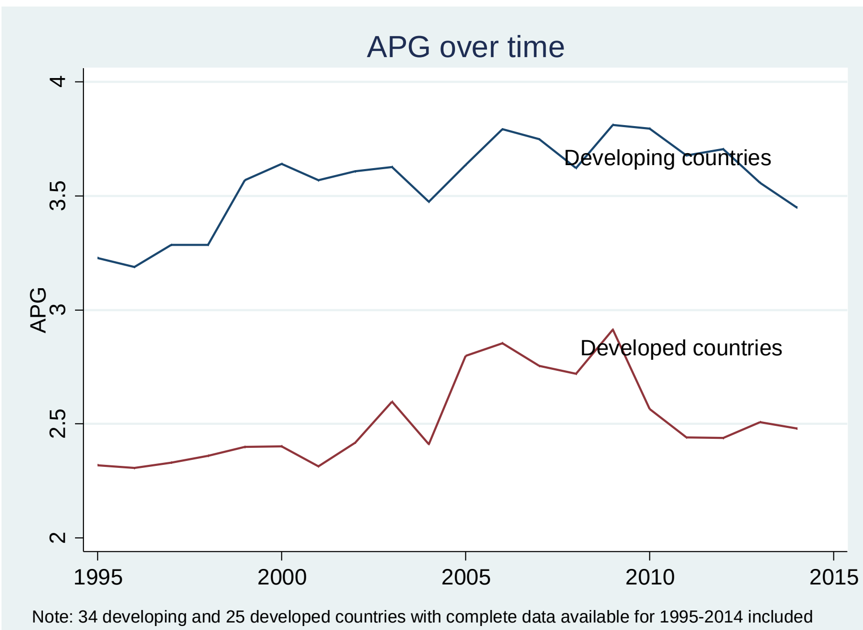


Figure 2 depicts the movement of average yearly APG over time for each group of countries, and we find that the average APG of developing countries increased significantly over the sample period, at least until 2010. The average APG for the group of developed countries also increased until 2009 before coming down rather sharply. The sustained and substantial increase of the average APG for a decade and a half is surprising, especially for the developing countries that experienced significant

[3] Developing countries: Azerbaijan, Barbados, Brazil, Bulgaria, Chile, Chine, Costa Rica, Croatia, Cuba, Czech Republic, Dominican Republic, Egypt, Estonia, Indonesia, Jamaica, Kyrgyz Republic, Latvia, Lithuania, Malaysia, Mexico, Moldova, Mongolia, Panama, Philippines, Poland, Romania, Russia, Slovak Republic, Slovenia, Sri Lanka, Thailand, Turkey, Ukraine, Venezuela. Developed countries: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.

growth of income during that period. Given the inverse correlation between the level of income and APG shown in Fig. 1, APG in developing countries might be expected to decrease over time as their incomes grow. If persistence of large APGs in developing countries poses a challenge, a steady and substantial increase of the average APG over a sustained period of time borders on a mystery.

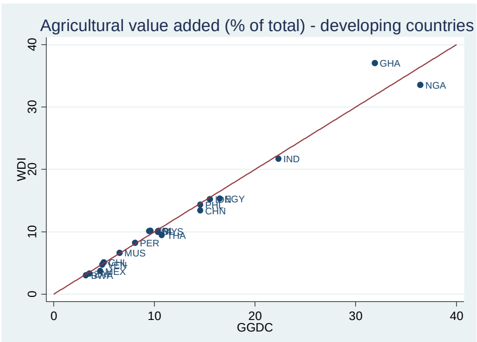
2.2. An Alternative Measurement

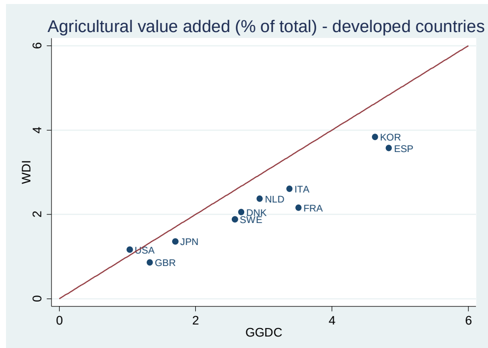
The WDI dataset has the great advantage of covering most of the countries around the world. However, there are serious concerns about the quality of the data. Labor data in the WDI dataset originate from the national labor force surveys. However, the labor force surveys vary widely among countries and within countries over time with regard to sampling and definition of concepts. As Timmer, de Vries, and de Vries (2015) point out, a key problem with labor data in the WDI is their inconsistency with value added data in national accounts as they stem from surveys of small samples. This inconsistency undermines reliability of productivity measures based on the WDI data. The national accounts data in the WDI dataset are also deficient in consistency.

The Groningen Growth and Development Centre (GGDC) database addresses these concerns by correcting employment and value added data for periodic changes in coverage of economic activities, prices, and calculation methods to ensure inter-temporal consistency of series over time. It tries to maximize overlap in coverage of the employment statistics and value added from the national accounts by using persons employed rather than employees as its employment concept and basing its employment numbers on large-scale population censuses, among others (Timmer, de Vries, and de Vries, 2015). We make use of the GGDC 10-sector database and recalculate APGs in order to check the robustness of our estimates based on the WDI dataset. The GGDC data are available for 29 developing countries and 10 developed countries for the period of 1995-2012. However, availability of common observations in WDI and GGDC database allows us to make comparisons for all 10 developed but only 18 developing countries.[4]

Fig. 3. Comparisons between WDI and GGDC Data

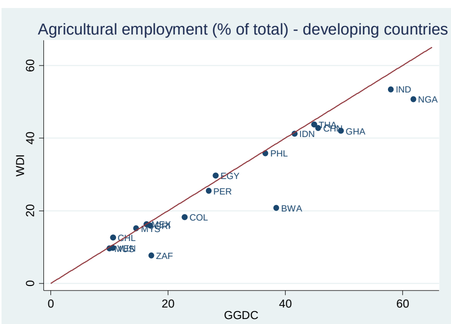
[4] Developing countries: Botswana, Chile, China, Colombia, Costa Rica, Egypt, Ghana, India, Indonesia, Malaysia, Mauritius, Mexico, Nigeria, Peru, Philippines, South Africa, Thailand, and Venezuela. Developed countries: Denmark, France, Italy, Japan, South Korea, Netherlands, Spain, Sweden, United Kingdom, and the United States.

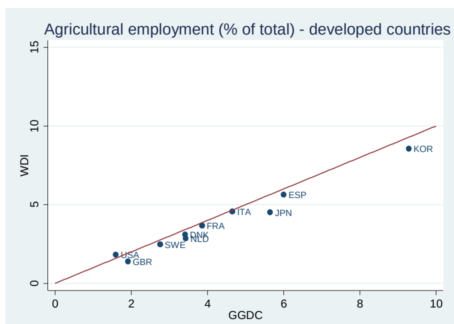

Agricultural value added (% of total) - developing countries
WDI
GGDC
GHA
NGA
IND
EGY
CHN
PER
MUS
THA


Agricultural value added (% of total) - developed countries
WDI
GGDC
KOR
ESP
ITA
NLD
FRA
DNK
SWE
JPN
USA
GBR

(a)

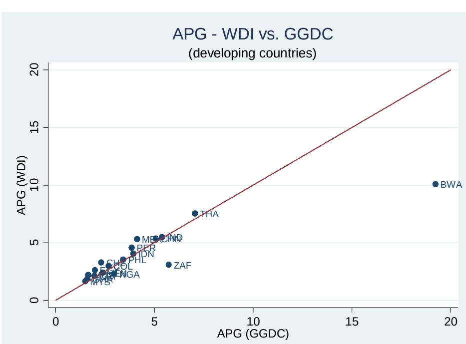
(b)

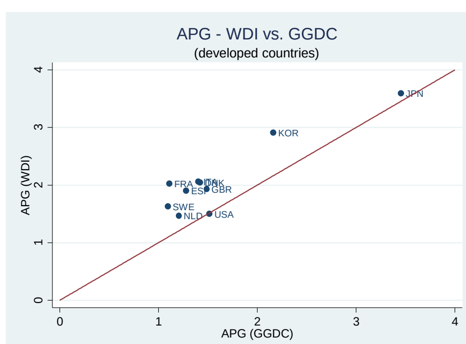

Agricultural employment (% of total) - developing countries
WDI
GGDC
IND
NGA
THA
IDN
GHA
PHL
EGY
PER
BWA
COL
CHL
ZAF


Agricultural employment (% of total) - developed countries
WDI
GGDC
KOR
ESP
ITA
JPN
FRA
DNK
NLD
SWE
USA
GBR

(c)

(d)


APG - WDI vs. GGDC
(developing countries)
APG (WDI)
APG (GGDC)
BWA
THA
ZAF
PER
PHL
IDN
NGA


APG - WDI vs. GGDC
(developed countries)
APG (WDI)
APG (GGDC)
JPN
KOR
FRA
GBR
SWE
NLD
USA

(e)

(f)

Figure 3 contrasts between the WDI data and the GGDC data in terms of the share of agricultural value added in total value added, the share of agricultural employment in total employment, and the Agricultural Productivity Gap for 18 developing and 10 developed countries in the sample. Fig. 3(b) shows that, when we use the GGDC data, the share of agricultural value added turns out greater than what we obtain from the WDI data in most developed countries, validating the mismeasurement hypothesis advanced by Herrendorf and Schoellman (2015). However, in the case of developing countries, Fig. 3(a) shows that there are hardly any differences between the shares of agricultural value added from the two data sets. On the other hand, as we can see from Fig. 3(c) and Fig. 3(d), the share of agricultural employment in the GGDC data is very close to that in the WDI dataset for most countries, except for some developing countries where the former is substantially greater than the latter and some developed countries where the former is slightly greater than the latter. As a result, compared to APG based on the WDI data, APG based on the GGDC data is practically the same for most developing countries, somewhat higher for a few developing countries, and somewhat smaller for most developed countries, as we can see in Fig. 3(e) and Fig. 3(f).

Table 2. Alternative Estimates of Average APG over 1995~2012

	APG (WDI)	APG (GGDC)	Number of Countries
Developing	3.91	4.30	18
Developed	2.11	1.61	10

Note: Only the observations commonly available in WDI and GGDC database are used.

Table 2 compares the average APG based on the GGDC data with that based on the WDI data for each group of countries, summarizing the information in Fig. 3(e) and Fig. 3(f). It turns out that, compared to the average APG based on the WDI data, the average APG based on the GGDC data is somewhat lower for developed countries and somewhat higher for developing countries. We conclude that the national accounts data provide a reasonably good picture of the productivity gaps. In particular, the problem of large productivity gaps in developing countries does not get diminished when we make corrections to the national accounts data. Gollin, Lagakos, and Waugh (2014) make a similar claim based on a meticulous analysis of household survey data from 10 developing countries. Therefore, we continue to use estimates from the WDI data that are much more advantageous in terms of the number of countries covered.

2.3. The Agricultural Wage Gap and the Adjusted Productivity Gap

We calculate the Agricultural Wage Gap by dividing the average wage in non-agriculture by that in agriculture, using the monthly wage data from the ILO. Note that we should use wages per worker instead of per hour when calculating the average wage, since we use the employment shares in terms of the number of workers rather than man-hours in computing APG. We apply to the wage data similar standards as we did to the employment data and remove grossly inconsistent data from the sample. After removing problematic data, we end up with 112 countries - 87 developing and 25 developed countries. Then, we drop 10 developing countries for which we do not have estimates of APG. Our sample, therefore, consists in 77 developing countries and 25 developed countries for which we have estimates of both APG and AWG. We calculate the average AWG over the period of 1995-2015 for each country first, and then find the group averages of those period averages for each group of countries.

메모 [유1]:

Table 3. Productivity Gaps and Wage Gaps over 1995-2015

	APG	*AWG*	*APG'*	*Number of Countries*
Developing	*3.81*	*2.30(61%)*	*1.66(39%)*	*77*
Developed	*2.45*	*1.76(62%)*	*1.39(38%)*	*25*

As shown in the second column of Table 3, while the wage gaps are significantly greater than unity in both developing and developed countries, they are much wider in developing countries than in developed countries. An average non-agricultural worker is paid 2.3 times more than an average agricultural worker in developing countries, and 1.8 times more in developed countries. Our results are largely consistent with Herrendorf and Schoellman (2015) who found AWG of 1.4 ~ 1.6 for the US, Israel and Canada, and AWG of 1.7 ~ 4.0 for less developed countries. Lagakos and Waugh (2013) also calculate AWG, using the same ILO data and producing similar results.

Table 3 also reports the average APGs recalculated for the reduced sample of 102 countries, which are essentially the same as those reported in Table 1. Table 3 reaffirms a well-known fact that, on average, APG is considerably greater than AWG in both developing and developed countries. The productivity gap divided by the wage gap, APG/AWG, is hence significantly greater than unity. We call this ratio the adjusted productivity gap, denoted by APG'. We may consider it to be that part of the productivity gap that originates from outside the labor market. For the 77 developing countries, the average APG' is 1.7 while it is 1.4 for the 25 developed countries. The numbers in parentheses indicate the proportions of APG that can be attributed to AWG and those that cannot. We can see that while the wage gaps account for the greater part of the productivity gaps in both developing and developed countries, close to 40% of the productivity gaps cannot be attributed to the wage gaps and therefore calls for an explanation based on factors outside of the labor market.

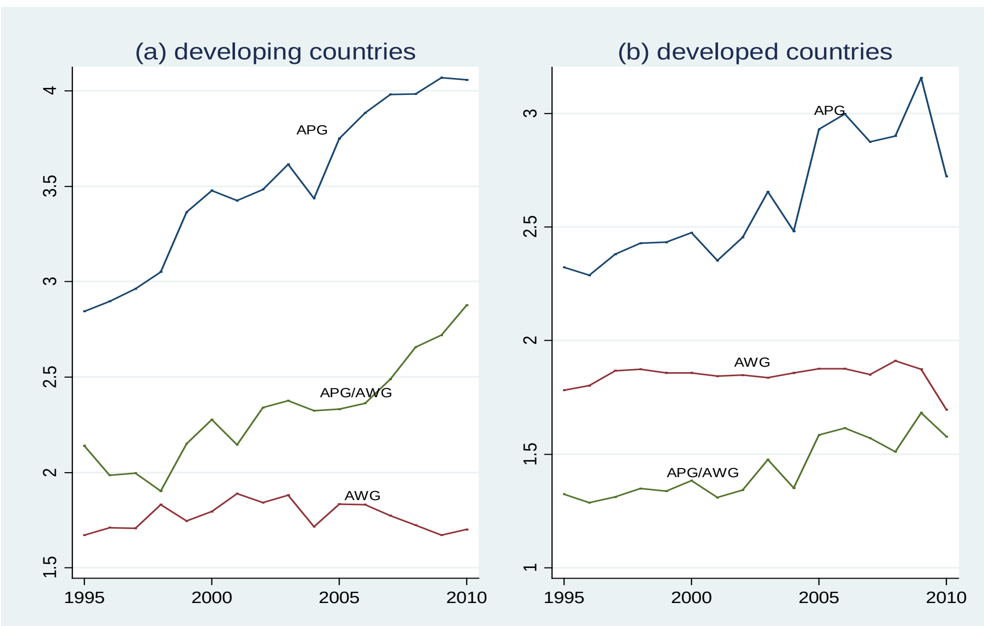
Given the fact that the wage gaps explain only about 60% of the productivity gaps, a natural question is the extent to which changes in the wage gaps can explain changes in the productivity gaps. As explained before, for this kind of trend analysis, the sample should include only those countries for which complete yearly data exist. If we try to cover the entire sample period, we are left with very few developing countries. By adjusting the sample period to 1995-2010, we can retain 19 developing countries and 20 developed countries with most complete APG and AWG data in the sample.[5]

메모 [유2]:

[5] Developing countries: Azerbaijan, Bulgaria, China, Croatia, Cuba, Czech Republic, Egypt, Estonia, Indonesia, Kyrgyz Republic, Mauritius, Moldova, Philippines, Poland, Romania, Slovakia, Slovenia, Turkey, Ukraine. Developed countries: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom

From Fig. 4, we can see that, for both developing and developed countries, the increase in the average APG during 1995-2010 had little to do with changes in the average AWG and was mostly due to changes in the adjusted productivity gap, APG'. This observation is one of the reasons why we believe that we need to pay more attention to factors outside the labor market in our quest to understand the APG problem.

Fig. 4. Trends in APG and AWG



3. Puzzling Breakdown of an Accounting Identity and the Measurement Problem

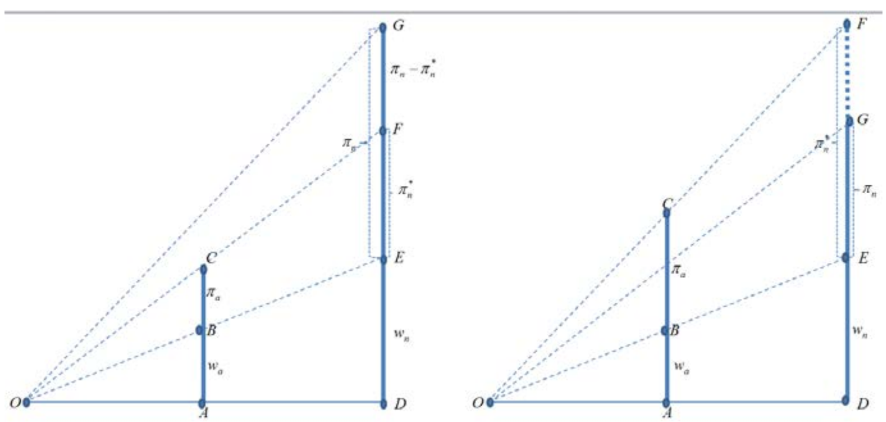
3.1. An Accounting Identity for the Agricultural Productivity Gap

There is a simple accounting identity involving the Agricultural Productivity Gap. Denoting the average wage and the share of labor income in value-added by w and θ, respectively, we have, by definition, $\theta = wL/VA$. Therefore, APG can be expressed as a product of the Agricultural Wage Gap (AWG) defined as w_n/w_a and the Labor Share Gap (LSG) defined as θ_a/θ_n as follows[6]:

$$(2)\quad APG = \frac{VA_n / L_n}{VA_a / L_a} = \frac{w_n / \theta_n}{w_a / \theta_a} = \frac{w_n}{w_a}\frac{\theta_a}{\theta_n} = AWG \bullet LSG$$

Different versions of the above accounting identity have been discussed in the literature (Vollrath, 2009; Gollin, Lagakos, and Waugh, 2014; Herrendorf and Schoellman, 2015). It is important to note that it does not depend at all on the market structure or technology, since it follows directly from the definition of the labor share as the ratio of the average wage to the average product of labor.

Fig. 5. Illustration of the Accounting Identity



(a) $APG'>1$ (b) $APG'<1$

Figure 5 illustrates how the accounting identity (2) may be used to understand various sources of the productivity gap. The thick bars represent per-worker value-added in agriculture and non-agriculture, with each of them divided into the wage income *(w_a, w_n)* and the capital income *(π_a, π_n)* per worker. Noting that APG = DG/AC, AWG = DE/AB and LSG = (AB/AC)/(DE/DG), we can easily confirm that APG = AWG·LSG. Define $\pi_n^* = \pi_a(w_n/w_a)$ so that it represents what the capital income per worker in non-agriculture would have been had the labor shares been the same ($\theta_a = \theta_n$). Fig. 5 shows the division of π_n into π_n^* and π_n-π_n^*. When APG > AWG, or APG' > 1, π_n is greater than π_n^* as

[6] Herrendorf and Schoellman (2015) define LSG as the ratio of the labor share in non-agriculture to that in agriculture. For our purposes, it is more convenient to define it in our way.

depicted in Fig. 5(a). When APG < AWG, or APG' < 1, on the other hand, π_n is smaller than π_n^* as depicted in Fig. 5(b). Rewriting (2) as

(2') *APG' = APG/AWG = LSG*,

we can see that the case (a) corresponds to a situation of LSG > 1 and the case (b) corresponds to a situation of LSG < 1.

We can tell from Fig. 5(a) that the productivity gap originates from the wage gap ($w_n > w_a$) and the Labor Share Gap ($\pi_n > \pi_n^*$). The wage gap arises either because human capital per worker is greater in non-agriculture than in agriculture and/or because labor market frictions lead to a wage premium in non-agriculture. We have LSG > 1 either because capital intensity in non-agriculture relative to that in agriculture is greater than is necessary to generate per-worker capital income of π_n^*[7] and/or because market imperfections create a wedge between the rate of return to capital in non-agriculture and that in agriculture. The literature has indeed explored these diverse sources of the productivity gap.

One line of inquiry has been the extent to which productivity gaps can be attributed to human capital gaps. Gollin, Lagakos, and Waugh (2014) find that the average worker in non-agriculture has greater human capital than his counterpart in agriculture, but that large productivity gaps remain even after taking the gaps in human capital into account in most countries. Parts of such remaining productivity gaps may reflect differences in unobserved human capital. It has been argued that, via selection mechanism, non-agricultural workers tend to possess greater unobserved human capital than agricultural workers (Young, 2013; Lagakos and Waugh, 2013). Gollin, Lagakos, and Waugh (2014) show that APG unexplained by the human capital gap tends to be greater in poorer countries and virtually disappears in rich countries. This finding makes sense to the extent that it represents misallocation of resources.

Noting that the wage gap is created by either the human capital gap and/or barriers to labor mobility, Herrendorf and Schoellman (2017) carry out such a decomposition for 13 countries and obtain results that bolster the above interpretation. They show that human capital gap, estimated carefully to incorporate differences in unobserved human capital via selection, can fully account for the wage gap in the US, where markets supposedly work efficiently, but leaves sizable portions of

[7] It can be shown that, in a standard model, the relative capital intensity that meets this condition is equal to APG.

the wage gap unexplained in developing countries. The literature offers various examples of barriers to labor mobility that give rise to a non-agricultural wage premium in developing countries (Caselli and Coleman 2001; Restuccia, Yang, and Zhu 2008; Adamopoulos and Restuccia 2011; Tombe 2011; and Herrendorf and Teixeira 2011). In particular, greater social risks in the urban areas are found to be important in some areas (Munshi and Rosenzweig, 2016; Morten, 2016).

Since APG is much larger, on average, than AWG in developing countries, we need to go beyond the labor market factors that can generate productivity gaps only through wage gaps. As suggested by Herrendorf and Schoellman (2017), productivity gaps may result from barriers that affect markets other than the labor market. Examples of such barriers include barriers to modern intermediate inputs in agriculture (Restuccia, Yang, and Zhu 2008; Donovan, 2014) and distortions to the land market (Adamopoulos and Restuccia, 2014). While these barriers have been identified primarily as sources of low TFP in agriculture, they can help explain the gap in value added productivity as well, since they enlarge LSG by suppressing the rate of return to capital in agriculture relative to that in non-agriculture. The wedge between the rates of return to capital across sectors may also be created by monopoly rents in non-agriculture. Herrendorf and Teixeira (2011) develop such a model. In their model of developing economies, there are barriers to entry into non-agriculture whereas entry into agriculture is free. While they use this model to explain the international income gaps, it can also help explain APG within developing countries.

Attempts to explain international differences in labor productivity have also touched on differences in capital intensity. Caselli (2005) finds that, for 65 developing countries with available data, capital-per-worker, including both physical capital and human capital, explains 15 percent of cross-country differences of labor productivity in agriculture, and 59 percent in non-agriculture. Lagakos and Waugh (2013), on the other hand, find that capital accounts for 22 percent of cross-country differences of labor productivity in agriculture, and 29 percent in non-agriculture for 28 countries from all income levels. While both of the above works emphasize that it is TFP rather than capital-per-worker that explains bulk of cross-country productivity differences, they do indicate that part of the reason why cross-country labor productivity differences are much larger in agriculture than in non- agriculture may be that "*developing countries use much less capital per worker in agriculture than in rich countries and use only modestly less capital per worker in non-agriculture*" (Lagakos and Waugh, 2013, p. 5).

While the above review of the literature has taken it for granted that APG > AWG, the opposite case is entirely possible as shown in Fig. 5(b). Indeed, the evidence on the sectoral labor shares seems to indicate that the labor share in agriculture is smaller than that in non-agriculture so that LSG < 1 (Gollin, Lagakos, and Waugh, 2014; Herrendorf and Schoellman, 2015). If this is true, the share of capital income in non-agriculture would be smaller than that in agriculture, i.e. $\pi_n < \pi_n^*$. In this case, the productivity gap will be smaller than the wage gap as the factors outside the labor market work to reduce the productivity gap.

To the extent that differences in human capital and capital intensity arise between agriculture and non-agriculture as a consequence of differences in the nature of technologies, such differences and the resultant productivity gap should not be necessarily considered as indications of resource misallocation. They could stem from misallocation, but may well be a result of human capital elasticity of output and capital elasticity of output in non-agriculture being greater than those in agriculture. Only that part of the productivity gap that cannot be traced back to efficient differences in human capital and capital intensity represents misallocation.

3.2. Breakdown of the Accounting Identity and Locating the Measurement Problem

As already hinted, a great difficulty arises surrounding the accounting identity (2). If we look at the adjusted productivity gap, the numbers - our estimates as well as others - unequivocally tell that we live in a world of Fig. 5(a). However, if we look at the Labor Share Gap, the other side of the identity, the opposite world of Fig. 5(b) seems to be the reality. Numerous independent estimates of the labor shares and other kinds of evidence suggest that the labor share in agriculture is smaller than that in non-agriculture, implying that the Labor Share Gap is less than unity (Herrendorf and Schoellman, 2015). While Gollin, Lagakos, and Waugh (2014) suggest that labor shares cannot differ very much between agriculture and non-agriculture, the evidence they invoke actually implies that the labor share in agriculture is likely to be smaller than in non-agriculture. Herrendorf and Schoellman (2015) claim that the labor share is 0.44 for agriculture and 0.67 for non-agriculture in the US and that similar numbers are applicable to developing countries as well. Indeed, a great many independent estimates of the labor share in agriculture support these claims. In a classic study, Hayami and Ruttan (1970) found, for a sample of 38 countries, that depending on the estimation method the average agricultural labor share falls into the range of 0.34 – 0.49. Fuglie (2010) provides a recent review of the estimates from around the world. His data imply that the average share of labor is 0.58 for China, India, Indonesia, Brazil, Mexico, and sub-Saharan Africa, while the corresponding figures for the U.S. and U.K. are 0.51 and 0.52.

We are faced with an utter breakdown of the accounting identity (2) or (2'). From the third column of Table 3, we have APG' of 1.4 ~ 1.7 on the left-hand side of the identity, while independent estimates of the sectoral labor shares suggest LSG of around 0.7 on the right-hand side of the identity. The difference is simply too large to be an outcome of minor statistical discrepancies. Herrendorf and Schoellman (2015) point out this puzzling beakdown of the identity and argue, correctly, that it must be a consequence of mismeasurement. They actually claim that APG is substantially overestimated in the US due to underestimation of agricultural productivity, which results from exclusion of land rents from agricultural value added and underreporting of proprietors' income in official statistics, among others. They suggest that similar underestimation of agricultural value added occurs in other countries too. Also, agricultural output may be underestimated due to home production, as suggested by Gollin, Parente, and Rogerson (2004).

We do not believe that overestimation of productivity gaps is the primary reason for the breakdown of the accounting identity. To begin with, the magnitude of overestimation required to resolve the puzzle is too large. The measured APG would have to be twice or more of its true value! However, Gollin, Lagakos, and Waugh (2014), who use household survey data to construct alternative measures of value added by sector for 10 developing countries, find "*surprisingly similar estimates of the size of the APGs*" to those computed from the national accounts. According to their calculations, the average APG from the micro data for the 10 countries is 2.2 compared to 2.6 from the macro data, and "*there are no countries for which micro and macro sources paint a substantially different picture of agriculture's share in aggregate value added*." (p. 29)

Next, even more importantly, the sustained and substantial increase of APG', the adjusted productivity gap, that we document in section 2 raises a difficult issue for the claim that overestimation of productivity gaps is the key to resolving the puzzle. It is difficult to believe that measurement of the agricultural value added became more and more inaccurate over time. If mismeasurement is caused by leaving out a certain portion of the agricultural value added, it is hard to imagine why the extent of mismeasurement would grow larger and larger. We think that the measurement problem lies primarily in measuring the average wage or the labor share rather than the value added in agriculture, at least as far as developing countries are concerned. This has to do with the fact that agricultural employment is dominated by the self-employed almost everywhere.

3.3. Measuring the Labor Income of the Self-employed

In measuring the labor shares, the presence of the self-employed and family workers poses a challenge. The income of the self-employed is classified as 'mixed income' in national accounts. 'Compensation of employees' includes only the labor income of those who work as employees, and omits the labor income of people who are not employees. Therefore, the common practice of measuring the labor share by the share of employee compensation as a fraction of GDP leads to underestimation of the labor share. The problem of underestimation will be serious for countries and sectors in which the self-employed make up significant fractions of the workforce.

Gollin (2002) offers three possible adjustments. The first approach is to count all mixed income as labor income. However, it leads to overestimation of labor income, since part of mixed income should be accrued to capital used by the self-employed (Feenstra, Inklaar, and Timmer, 2015). The second approach is to divide mixed income into labor income and capital income on the assumption that income shares in the self-employed sector are the same as the rest of the economy. While it makes sense to assume that mixed income includes some capital income as well as some labor income, it may not be sensible to assume implicitly that income shares are the same for establishments that differ significantly in size and structure. The third approach is to impute average employee compensation to the self-employed. The implicit assumption that, on average, employees and the self-employed possess the same earning ability will lead to a biased measure of the labor share if earning ability of the self-employed is systematically different from that of employees.

There are advantages and disadvantages in each of the three approaches, and we have to weigh them, along with the availability of data, before choosing one. However, there is only one approach that is consistent with the method of measuring the average wage. Suppose we measure the sectoral average wage by the average wage of employees only. It is a natural measure of the sectoral average wage, because we are, after all, measuring the average of wages received by people working in the sector and only employees receive wages. We call this the 'naive average wage', since it is based on the naive implicit assumption that the self-employed earn the same wage as employees. Obviously, the naive average wage is consistent with only the imputation approach to labor income - imputing the average wage of employees to the self-employed, as it is based on the same implicit assumption. When the relevant data are available, we may compute what may be called the 'sophisticated average wage' rather than the naive average wage by imputing to the self-employed the wage rate for employees with the same characteristics in terms of educational attainment, gender, experience and so on. It removes the bias in measuring the average labor income that may arise from systematic differences in the characteristics of workers between employees and the self-employed. Needless to say, if we use the sophisticated average wage, we must measure the labor share by the same sophisticated imputation. Obviously, the extent of sophistication depends on the availability of data, which is very limited for most developing countries.

The average wage data from the ILO that we use to calculate the Agricultural Wage Gap provide, we believe, something close to the naive sectoral average wages, so the accounting identity (2) or (2') will hold only when we plug in the Labor Share Gap calculated from the sectoral labor shares obtained by the same imputation approach. Indeed, below, we demonstrate that the accounting identity holds quite well and the incongruence between the adjusted productivity gap and the gap in the labor shares effectively disappears when we calculate the labor shares from the EU KLEMS dataset that have been constructed on the basis of the imputation approach.

4. Aspects of Measuring the Labor Share in Agriculture

4.1. Resolving the Puzzle with Alternative Labor Shares

The EU KLEMS Growth and Productivity Accounts provide internationally comparable data on measures of output and input, labor compensation and capital compensation as well as derived variables such as multi-factor productivity at aggregate and industry levels for 34 countries. In the KLEMS database, labor compensation of self-employed is calculated with an imputation by assuming that the compensation per hour of self-employed is equal to the compensation per hour of employees. It is a sophisticated imputation since hours worked are classified by educational attainment, gender and age, although the level of sophistication is limited and varies across countries due to data availability. When information on labor characteristics is missing, it resorts to the naive imputation (O'Mahony and Timmer, 2009).

From the KLEMS database, we exclude 2 countries, Argentina and Poland, in constructing our sample. Labor and capital compensation data at the sectoral level are missing for Argentina, while such data for Poland are highly unreliable. Our sample thus consists in 11 developing countries and 21 developed countries. Although the sample period is 1995~2014, for many countries, the annual data do not exist for more recent years of the sample period. The labor share of income in agriculture is calculated as ratio of labor compensation to value added in agriculture, which includes Agriculture, Forestry, and Fishing. Non-agricultural labor compensation and value added is derived by subtracting the agricultural labor compensation and value added from total labor compensation and value added in the economy. The labor share is then calculated as in the case of agriculture. Table 4 reports, for all individual countries in the sample, the labor shares for the aggregate economy, the agricultural sector and the non-agricultural sector. It also shows APG and AWG that we obtain from calculations in section 2. The derived gaps it shows include LSG, which is θ_a/θ_n, the adjusted productivity gap APG', which is APG/AWG, and the fully adjusted productivity gap APG", which is APG'/LSG. The accounting identity (2') implies that the fully adjusted productivity gap APG" should be equal to unity.

Table 4. Alternative Labor Shares and Adjusted Productivity Gaps

Years	countries	θ	θ_a	θ_n	LSG	APG	AWG	APG'	APG"
1995-2007	Australia	0.61	0.53	0.62	0.86	1.42	1.52	0.93	1.09
1995-2014	Austria	0.67	1.76	0.65	2.75	3.92	2.12	1.85	0.67
1995-2014	Belgium	0.63	0.69	0.63	1.11	1.96	1.7	1.15	1.04
1995-2010	Canada	0.58	0.42	0.58	0.73	1.23	1.28	0.96	1.31
1995-2012	China	0.50	0.89	0.41	2.18	5.36	2.26	2.37	1.08
1995-2012	India	0.49	0.54	0.48	1.12	5.49	5.40	1.02	0.92
1995-2007	Cyprus	0.59	0.52	0.59	0.88	1.82	1.98	0.92	1.03
1995-2007	Czech Republic	0.59	0.63	0.59	1.07	1.68	1.36	1.24	1.15
1995-2014	Germany	0.67	0.99	0.67	1.48	2.75	1.89	1.45	0.98
1995-2007	Denmark	0.68	0.70	0.68	1.03	1.93	1.62	1.19	1.16
1995-2014	Spain	0.65	0.38	0.66	0.58	1.90	2.38	0.80	1.37
1995-2007	Estonia	0.57	0.55	0.57	0.97	1.74	1.54	1.13	1.17
1995-2014	Finland	0.66	0.92	0.65	1.42	2.12	1.54	1.38	0.98

1995-2014	France	0.67	0.99	0.66	1.51	2.10	1.74	1.21	0.80
1995-2014	Great Britain	0.63	0.71	0.63	1.08	1.94	1.77	1.09	1.01
1995-2007	Greece	0.56	0.81	0.55	1.48	3.51	2.34	1.50	1.01
1995-2007	Hungary	0.60	0.55	0.61	0.94	1.31	1.61	0.81	0.87
1995-2007	Ireland	0.56	0.93	0.55	1.70	4.02	1.67	2.41	1.42
1995-2014	Italy	0.64	0.84	0.64	1.31	2.11	1.94	1.09	0.84
1995-2009	Japan	0.61	0.49	0.61	0.81	3.63	3.28	1.11	1.36
1995-2007	Korea	0.52	0.64	0.51	1.23	2.93	1.38	2.12	1.72
1995-2007	Lithuania	0.53	0.73	0.51	1.44	3.57	1.81	1.97	1.37
1995-2007	Luxembourg	0.56	1.03	0.55	1.86	3.87	1.74	2.14	1.15
1995-2007	Latvia	0.53	0.88	0.52	1.70	3.51	2.03	1.73	1.02
1995-2007	Malta	0.57	0.41	0.58	0.71	1.07	1.56	0.69	0.98
1995-2014	Netherlands	0.69	0.71	0.69	1.02	1.49	1.42	1.05	1.03
1995-2006	Portugal	0.66	1.20	0.64	1.86	4.58	1.99	2.30	1.23
1995-2009	Russia	0.55	0.80	0.53	1.61	2.46	1.43	1.72	1.07
1995-2007	Slovakia	0.50	0.46	0.50	0.91	1.4	1.38	1.01	1.09
1995-2006	Slovenia	0.75	2.83	0.68	4.11	3.96	1.23	3.22	0.78
1995-2014	Sweden	0.56	0.69	0.55	1.26	1.65	1.16	1.42	1.12
1997-2009	USA	0.62	0.75	0.62	1.21	1.61	1.79	0.89	0.74

Notes: θ = labor share in GDP; $\theta_{\mathbf{a}}$ = labor share in agriculture; $\theta_{\mathbf{n}}$ = labor share in non-agriculture; LSG = $\theta_{\mathbf{a}} / \theta_{\mathbf{n}}$; APG' = APG/AWG; APG" = APG'/LSG. Labor shares are calculated from EU-KLEMS; APG from WDI; AWG from ILO. Labor shares exceeding 1 are marked in red; Countries where less than 20% of agricultural employment is self-employed are marked by shade.

Since Table 4 contains a large amount of information, let us first take a look at the group averages for developing and developed countries that are reported in Table 5. The striking feature is that the labor share in agriculture is significantly greater than in non-agriculture, much more so in developing countries than in developed countries. As a result, the fully adjusted productivity gap, APG", turns out to be quite close to unity, as seen in the right-most column of the table. This is the key result, restoring the accounting identity. It shows that, once we measure labor shares with an approach that is consistent with the method of measuring the average wage, the inconsistency between the adjusted productivity gap, APG’, and the gap in the labor shares, LSG, effectively disappears and no puzzle remains at the level of group averages.

Table 5. Summary of Alternative Labor Shares and Adjusted Productivity Gaps						
	$\theta_{\mathbf{a}}$	$\theta_{\mathbf{a}}$	LSG	APG’	APG”	Number of countries
Developing	0.84	0.54	1.56	1.63	1.05	11
Developed	0.79	0.62	1.27	1.43	1.13	21

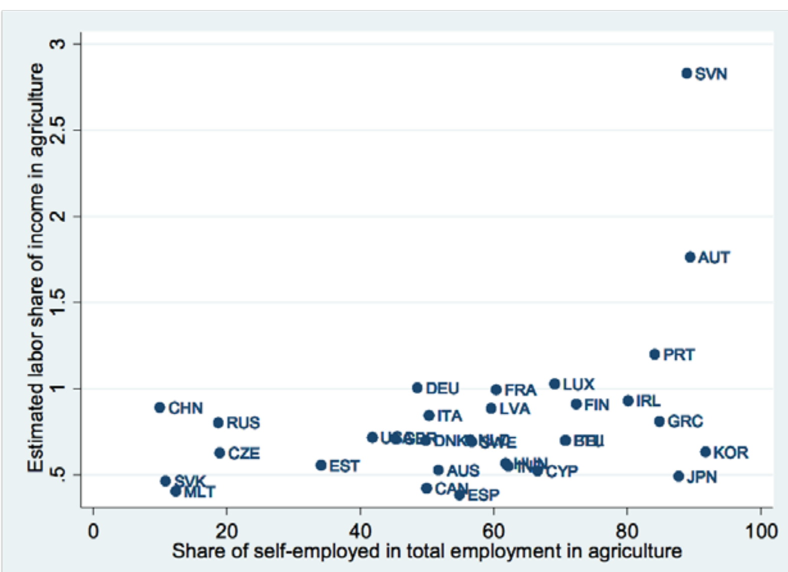
However, devils may be hiding behind the averages. Let us now examine the right-most column of Table 4. We can actually see that the puzzle still remains at the individual country level for some countries. It is true that the fully adjusted productivity gap falls within a reasonably tight range around unity for a majority of the sample countries. It falls within the range of [0.9, 1.1] in 14, and [0.8, 1.2] in 22 out of 32 countries. Except for two countries, Korea and Ireland, it falls within [0.67, 1.37]. Some discrepancies are to be expected for at least three reasons. First, there may be some mismeasurement of agricultural value-added and consequently APG. Even though we argue that overestimation of APG cannot be the primary reason for the breakdown of the identity, we are not claiming that there is absolutely no mismeasurement there. In fact, the fact that the average value of the fully adjusted productivity gap is slightly greater than unity for both developing and developed countries may be a consequence of such mismeasurements. Second, there are differences in labor data between the WDI database from which the sectoral average wage is calculated and the KLEMS database from which the sectoral labor share is calculated. Third, the imputation methods are not exactly the same. Given these considerations, it seems fair to say that the results reported in Table 4 resolve the puzzle to a large degree even at the individual country level.

4.2. Overestimation of the Labor Share in Agriculture

There is a big problem in Table 4, however. The labor share in agriculture is greater than 1 in four countries - Austria, Luxemburg, Portugal and Slovenia. This is definitely a nonsensical result. It is in between 0.9 and 1 for another four countries – Germany, Finland, France and Ireland. Given these numbers, it is natural to suspect that the agricultural labor shares reported in Table 4 may be exaggerated. When the imputation approach to measuring the labor income of the self-employed harbors an overestimation bias and the self-employed constitute a large fraction of the workforce, it is possible that we end up with measures of the labor share that are greater than 1 (Gollin, 2002). The agricultural labor shares reported in Table 4 are, however, not necessarily high for all countries. For instance, they fall between 0.38 and 0.42 for countries such as Canada, Malta and Spain.

The great variability and extreme exaggeration, at least in some countries, of the measured labor share that we find in agriculture do not arise for the non-agricultural sector or the aggregate economy. While the labor share in agriculture ranges from 0.38 in Spain to 2.83 in Slovenia, for non-agriculture, the labor share falls within a rather tight range of [0.5, 0.7] except for China and India. For the aggregate economy, the same is true except for India and Slovenia.[8] The above difference between agriculture and non-agriculture seems to be related to the fact that the share of the self-employed in total employment (employees+self-employed) is much larger in agriculture than in non-agriculture almost everywhere and much more variable across countries. The errors

Fig. 6. The Share of the Self-employed and the Labor Share in Agriculture



[8] The labor share differs little between non-agriculture and the aggregate economy, since agriculture's share of value added is relatively small almost everywhere.

produced by the imputation approach in estimating the labor income of the self-employed will be magnified as the share of the self-employed increases.

Fig. 6 is a scatter plot of 32 countries in our sample, with the horizontal axis representing the share of the self-employed in total employment in agriculture and the vertical axis representing the measured labor share in agriculture.[9] We can see that, in all of the four countries for which the labor share in agriculture is greater than unity, the self-employed make up very large factions of the agricultural workforce. Also, the same is true for Korea and Ireland, the two countries for which the adjusted productivity gap is wildly different from unity. In all these countries, the share of the self-employed in agriculture is over 80% except for Luxembourg where it is around 70%.

Then, why would the imputation approach overestimate the labor income of the self-employed? One potential reason is imperfect imputation due to limitations in data availability. Suppose we are forced to use the naive approach of imputing the average wage of employees to the self-employed. If the self-employed, on average, have lower schooling and experience than employees, the naive imputation will overestimate the labor income of the self-employed.[10] Another potential reason for overestimation is 'selection'. Even when we use the sophisticated imputation that perfectly takes into account systematic differences in observed characteristics of workers between employees and the self-employed, there may be systematic differences in unobserved characteristics of workers due to selection. Selection seems to play a significant role in generating productivity gaps between agriculture and non-agriculture (Young, 2013; Lagakos and Waugh, 2013). Selection may arise within each sector: Among the workers with the same observed characteristics, those with higher productivity or earning power may opt to work as employees and those with lower abilities may stay as self-employed. In this case, even a very sophisticated imputation will result in overestimation of the labor share.

Two observations are in order. First, while the above discussion points to the possibility of overestimation when we measure the labor share in agriculture by the imputation approach, it does not mean that overestimation is inevitable. If selection occurs in the opposite direction, for instance, it will lead to underestimation. If we have very good data and selection effect is unimportant, using a sophisticated imputation will produce unbiased estimate of the labor income of the self-employed.

[9] We use data on sectoral self-employment from Socio-Economic Accounts (SEA) in World Input-Output Database. The self-employed include family workers. We include the same 32 countries in the sample for the period from 1995 to 2009.

[10] This seems likely in developing countries. However, Herrendorf and Schoellman (2015) report that the self-employed have higher schooling and experience than employees in the US, especially so in agriculture.

This may be the case for countries such as the US, as claimed by Herrendorf and Schoellman (2017). At any rate, in Table 4, there are countries such as Canada, Malta and Spain for which the labor share in agriculture is only around 0.4.

Second, the puzzle of inconsistency between the adjusted productivity gap and the labor share gap is totally separate from the overestimation problem. If we compare the list of the countries with serious inconsistency with that of the countries with serious overestimation (the agricultural labor share greater than unity), there is no overlap. As long as we use the same imputation method in calculating the labor income of the self-employed in our measurement of both the average wage and the labor share, the inconsistency problem will not arise. If the labor share in agriculture is overestimated due to selection, for example, the average wage in agriculture will be overestimated just as much, leading to the same proportional underestimation of the wage gap. As a result, the adjusted productivity gap will be overestimated just as much as the labor share gap. The inconsistency problem will arise when differences in the data and imputation methods lead to *different biases* in the measurement of the average wage and the labor share. For example, suppose we use the naive average wage, but the labor share is measured by a sophisticated imputation method. Then, if the observable characteristics of the self-employed are inferior to employees, the the average wage will be overestimated *proportionately more* than the labor share. In this case, the fully adjusted productivity gap will be biased upward. If the observable characteristics of the self-employed are superior to employees, it will be biased downward. Differences in the data may also cause biases, with upward biases as likely as downward biases.

4.3. Further Discussion on the Agricultural Labor Share

It should be clear by now that inconsistent treatment of the self-employed in calculating the average wage and the labor share plays a major role in causing the inconsistency between the adjusted productivity gap and the labor share gap. The inconsistency largely disappears, therefore, when we adopt the imputation approach in measuring the labor share as we do in measuring the average wage. It does not mean, however, that the imputation approach yields measures of the agricultural labor share that are closer to the true value than other estimates, cited by Gollin, Lagakos, and Waugh (2014) and Herrendorf and Schoellman (2015) for example, on the basis of which it is claimed that the labor share in agriculture is smaller than in non-agriculture. We know that estimates obtained by the imputation approach can easily be biased upward and certainly so for at least some countries, and that is probably why we have the labor share in agriculture greater than in non-agriculture in a majority of the sample countries. Can we then trust the much lower estimates found by others?

One way to attemp answering the above question is to focus on countries where employees make up an overwhelming majority of the total employment, since the imputation approach should provide reliable estimates in such countries (Feenstra, Inklaar, and Timmer, 2015). From Fig. 6, we can see that the self-employed make up large fractions of the total employment in agriculture almost everywhere, and that there are only five countries - China, Czech, Malta, Russia and Slovakia - where the self-employed are rare and the share of employees exceeds 80% of the total employment. This contrasts with the fact that, in non-agriculture, the share of employees easily exceeds 80% in most of the sample countries, including the above five countries. From Table 4, we can see that, in all of the above five countries, the accounting identity (2) holds almost exactly, with the fully adjusted productivity gap ranging from 0.98 to 1.15. This observation assures us that the labor share measures obtained by the imputation approach are quite reliable in these countries.

Fig. 7. Labor Shares in Agriculture and Non-agriculture in Five Countries

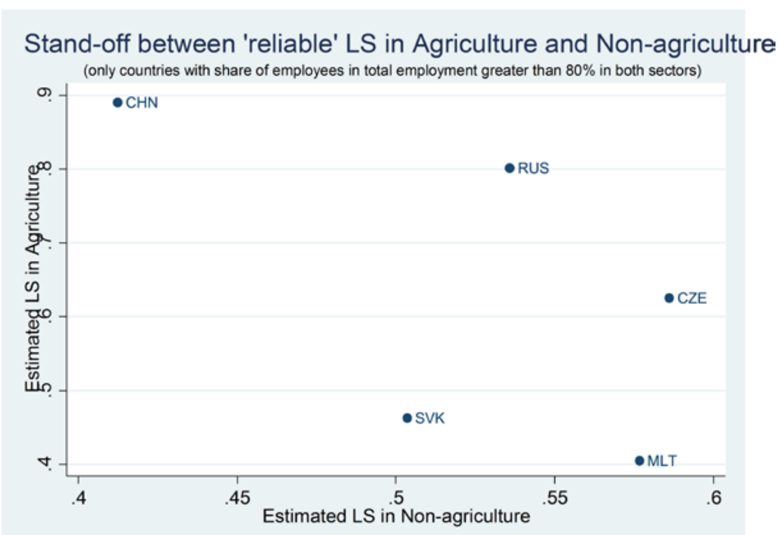


Fig. 7 compares the labor shares in agriculture with that in non-agriculture in the five countries with the share of employees greater than 80% in both agriculture and non-agriculture. We make two observations. First, the agricultural labor shares exhibit a very wide range – from 0.41 in Malta and 0.46 in Slovakia to 0.80 in Russia and 0.89 in China. In contrast, the labor shares in non-agriculture vary much less, ranging from 0.41 in China to 0.59 in Czech Republic. This observation suggests that the large variability of the agricultural labor shares that we find in Table 4 is not simply driven by measurement errors due to the often large but highly variegated share of the self-employed in agriculture. It probably has also to do with huge variations in environments, technologies and production organizations in agriculture across countries. Second, in three of the five countries the labor share in agriculture is greater than in non-agriculture, while it is smaller in two countries. That is, even when the overestimation bias is not a serious concern, the labor share in agriculture can be greater than in non-agriculture. This observation casts some doubt on the often-made claim based on approaches other than the imputation approach that the true labor share in agriculture is universally smaller than in non-agriculture. In many developing countries, the actual labor share in agriculture may be quite high.

A few comments are in order on the last point. First, while Herrendorf and Schoellman (2015, p. 10) suggest "*that agriculture is less labor intensive than non-agriculture, in part because agriculture is more land intensive*", it may apply only to countries like the US where the farm size is large. As Adamopoulous and Restuccia (2014) point out, the average farm size is very small in most developing countries. Also, as Lagakos and Waugh (2013, p. 5) observe, "*developing countries use much less capital per worker in agriculture than in rich countries and use only modestly less capital per worker in non-agriculture*." Indeed, Feenstra, Inklaar, and Timmer (2015, p. 22) report that "[*the*] *agricultural sector also uses very few fixed assets in these countries as, according to the SEA, the agricultural labor share (accounting for the self-employed) is over 90 percent of value added, on average*." The presumption that agriculture is less labor intensive than non-agriculture everywhere seems unwarranted.

Second, the low estimates of the labor share in agriculture reported by others may not be accurate. Many of them are based on the cost shares of inputs, "*[but] for most countries of the world we lack representative data on input prices and therefore cost shares. This is especially true for developing countries where the most important inputs are farm-supplied, like land and labor, but where wage labor and land rental markets are thin, thus making it difficult to assess the share of these inputs in total costs*" (Fuglie, 2010, p.65). In measuring the cost share of labor, then, one still needs to utilize some version of the imputation method that may be highly imperfect.[11] Another approach to measuring the labor share is to use the labor elasticity of output obtained by estimating the agricultural production function. It rests on many assumptions about technology and the market structure that may be far-fetched, however. For example, it assumes that markets are in long-run competitive equilibrium, and that the same technology is used by the self-employed sector and the incorporated sector within agriculture.

Consider, in this context, the case of China for which the imputation approach is supposed to yield a reliable estimate of the agricultural labor share. Our estimate, 0.89, is far higher than most existing estimates. For instance, Hayami and Rutten (1985) found 0.53, and Chow (1993) found 0.4, both based on estimations of the agricultural production function using data from the pre-reform period. The numbers change somewhat when the cost share approach is applied to the more recent post-reform period data. Dekle and Vandenbroucke (2012) find that the average labor share in agriculture was 0.76 for the period 1978 to 2003, and Fan and Zhang (2002), cited in Fuglie (2010), find 0.59 for the period 1961 to 1997 using the Chinese National Bureau of Statistics (NBS) data. But the NBS data, as Wu and Ito (2015) point out, suffer from serious mismeasurement problems. Bai and Qian (2010), who make several adjustments to the NBS data using Input-Output Tables, Flow of Funds Accounts and provincial income estimates, find that the share of labor income in agriculture ranges from 0.86 to 0.92. Our estimate is vindicated, after all.

Finally, predominance of the 50-50 split in share tenancy output sharing arrangements has also been cited as an evidence of a relatively low labor share in agriculture (Mundlak, 2005; Gollin, Lagakos, and Waugh, 2014; Herrendorf and Schoellman, 2015). However, it may be difficult to arrive at precise calculations from share tenancy arrangements, because relationships between land owners and operators may be quite complicated (Jacoby and Mansuri, 2009). Otsuka, Chuma, and Hayami (1992, p. 1969) explicitly warn against inferring the labor share from the output sharing rule of share tenancy: "*A major puzzle unexplained by existing contract theories is the stylized fact of share tenancy that output is almost universally shared between the tenant and landlord at a 50:50 ratio with no explicit fixed payments, despite obvious differences in the relative contributions of land and labor to agricultural production among different production environments and technologies*." Important in this context is the prevalence of interlinked contracts in rural

[11] Then, why do these estimates tend to be lower than those we obtain from the KLEMS data for most countries? It is probably because of the inclusion of land rental costs in the cost share approach, whereas the rental income for land that is not owned by farmers does not get counted as part of the agricultural value added in national accounts (Herrendorf and Schoellman, 2015).

communities (Bardhan, 1984). Due to underdevelopment of markets, there is a strong tendency for various transactions to be interlinked in highly personalized relationships. Typically, the landlord provides consumption credit and *de facto* production loans (through cost-sharing arrangements) to his tenants at subsidized interest rates, and also insures them against unexpected hazards. The 50-50 rule is most likely a sociological phenomenon rather than an efficient economic choice.

5. Conclusion

The main findings of this paper are as follows. First, APG steadily and substantially increased for an extended period of time in a majority of countries in recent past, while AWG remained more or less stable. Second, the puzzling breakdown of the accounting identity that the productivity gap adjusted by the wage gap must be equal to the gap in the agricultural labor share owes much to inconsistency in estimating the labor income of the self-employed in the process of measuring the average wage and the labor share, and is effectively resolved once we adopt a consistent approach.

These findings imply that productivity gaps over and above wage gaps are real and therefore we need to pay attention to factors outside the labor market in trying to understand large productivity gaps in developing countries. Furthermore, the sustained and substantial increase in the adjusted productivity gaps in recent past imply a similar increase in the gaps between the labor shares, either by a rise in the agricultural labor share and/or a fall in the non-agricultural labor share.

In fact, the decline of the labor share of income since the 1980s has been widely noticed and extensively discussed. To cite just one source, the most recent issue of the *World Economic Outlook* by the IMF documents this phenomenon for both advanced countries and emerging market and developing countries, and point to technology and financial integration as the two main reasons (IMF, 2017). Since the agricultural value added is a relatively small part of GDP almost everywhere, the decline of the labor share in GDP probably comes mostly from the decline of the labor share in non-agriculture. However, little is known about the trends of the labor share in agriculture.

In order to advance our understanding of APG, we need to dig deeper into the functional distribution of income at the sectoral level and investigate how it is influenced by barriers outside the labor market. In this connection, one idea that we are pursuing is the role of technology transfers from advanced countries to developing countries in enlarging the productivity gaps (You and Sirojiddin, 2017).

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Appendix I

Employment shares in the WDI database originate from the ILO that reports observations from labor force surveys, official estimates, household surveys, population censuses and their own estimations. Some observations are highly implausible. For instance, ILO reports that 9.5% of labor force work in agriculture in Ethiopia in 2011. Actually, over 70% are engaged in agricultural activities. We went through the data for each year, each country and removed the following data.

Singapore 1997-2006: Agricultural employment includes mining, quarrying, electricity, water and gas supply as well as activities not classified elsewhere (inconsistent with years 1995-1996)

Peru 1995-2008: for 1995 – ILO survey conducted in Metropolitan Lima (not-representative for whole country), 1996 to 2008 – ILO survey for urban areas only (inconsistent)

Morocco 1995-2001: Household Survey conducted in urban areas only (inconsistent)

Ethiopia 2004, 2006, 2011-2012: Urban areas only (inconsistent)

Ecuador 1995-1999: urban areas only (inconsistent)

Colombia 1995-2000: ILO survey conducted in 7 main cities only (inconsistent)

Bolivia 1995-1997: 1995 – ILO survey in main towns only, 1996-1997 – ILO survey in urban areas only

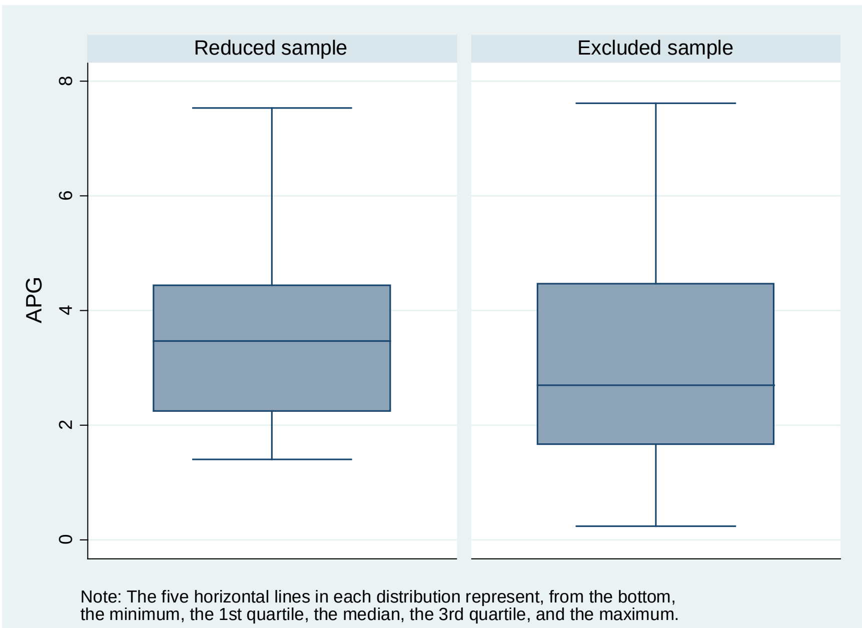
Argentina – 1995-2015 labor force surveys conducted in urban areas only

Lesotho – inconsistent estimates of agricultural share of employment for all years

Albania – 1995-2006, 2008, 2010, official estimates of agricultural employment not consistent with labor force survey data

Appendix II

Fig. A1. Distributions of APGs for the reduced sample and the excluded sample



The figure describes the distribution of country-average APG's of the reduced sample and that of the excluded sample (countries excluded from the reduced sample). Out of 127 countries, 34 are in the reduced sample and 93 are in the excluded sample. Key descriptive statistics (Minimum, 1st quartile, 3rd quartile, and Maximum) of the observed APG's in the reduced sample lay within the boundaries of those of the observed APG's in the excluded sample. The median APG in the reduced sample is slightly higher than that in the excluded sample, but the difference is statistically insignificant.

Table A.1. Testing for systematic differences between the reduced and the full sample

	(1)	(2)	(3)	(4)
VARIABLES	(1)	(2)	(3)	(4)
Reduced	-0.03	-0.03		
	(0.39)	(0.39)		
Year			0.02***	0.02***
			(0.01)	(0.01)

	(1)	(2)	(3)	(4)
Reduced*Year				-0.00
				(0.00)
Constant	3.59***	3.58***	-31.59***	-31.59***
	(0.28)	(0.28)	(11.53)	(11.53)
Observations	127	1,276	1,276	1,276
R-squared	0.00			
F-stat [Wald chi2]	0.93	[0.00]	[0.002]	[0.009]
Number of countries		127	127	127

Notes: The sample includes 127 developing countries. In column (1), the dependent variable is the average APG over 1995-2015 for each country. Columns (2)-(4) are estimated for all available observations. Variable 'Reduced' is 1 for 34 developing countries included in the reduced sample, and 0 for the rest. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In order to test whether there are any systematic differences between the reduced sample and the full sample, we estimate the following three equations:

$$APG_i = \beta_0 + \beta_1 \mathrm{Re}\,duced_i \qquad (1)$$

$$APG_{i,t} = \beta_0 + \beta_1 \mathrm{Re}\,duced_{i,t} \qquad (2)$$

$$APG_{i,t} = \chi_0 + \chi_1 Year_t \qquad (3)$$

$$APG_{i,t} = \alpha_0 + \alpha_1 Year_t + \alpha_2 \mathrm{Re}\,duced_{i,t} * Year_t \qquad (4)$$

The result of the estimation of equation (1) is presented in column (1) of Table A1. The dependent variable is the APGs in 127 developing countries averaged over 1995-2015 for each country. The variable of interest is the dummy variable *'Reduced'*, which takes the value of 1 if the countries are included in the reduced sample, 0 if not. Should there be any systematic difference in the average APGs of the reduced sample in comparison with those of the full sample, the estimated coefficient should be statistically different from zero. We find that it is not. We may also observe that the mean of the average APGs in the full sample of developing countries is 3.59 (as in Table 1), whereas it is lower by 0.03 in the reduced sample. This difference is statistically insignificant.

Column (2) shows the result of estimating equation (2), which is identical to estimating equation (1) except that it uses the full panel data. That is, the dependent variable is now simply the APGs observed in all sample countries over the period 1995-2015, with each data point for each set of a country and a year, rather than country averages for the period. Conclusions are, naturally, identical to those in the case of column (1). Equation (1) and (2), however, tell us nothing about the trend of APG over time, and therefore we estimate equations (3) and (4).

Equation (3) adds *Year* as an explanatory variable to equation (2) in order to pick up the time trend of APG. The result in Column (3) reaffirm our proposition that APG tended to increase in the developing countries from 1995-2015. Estimated coefficient of the *Year* variable is statistically significant at 1% critical level. The beauty of this estimation is that we have included all developing countries – not only the ones in the reduced sample.

Finally, equation (4) includes the product of *Year* and *Reduced* in addition to *Year* in the explanatory variables. It allows us examine whether the trend of APG in the reduced sample is different from that in the full sample. If it is the case, the coefficient of the *Year*Reduced* variable should be statistically different from zero. Column (4) shows that it is not.