Agricultural Productivity Gap in Developing Countries

By

Sirojiddin Salomovich Juraev

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF DEVELOPMENT POLICY

2017

Agricultural Productivity Gap in Developing Countries

By

Sirojiddin Salomovich Juraev

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF DEVELOPMENT POLICY

2017

Professor Jong-Il, YOU

Agricultural Productivity Gap in Developing Countries

By

Sirojiddin Salomovich Juraev

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF DEVELOPMENT POLICY

Committee in charge:

Professor Jong-Il, YOU, Supervisor __________

Professor TaeJong, KIM __________

Professor Siwook, LEE __________

Professor Jisun, BAEK __________

Professor Wang, Shun __________

Approval as of May, 2017

Abstract

Labor is substantially less productive in agriculture than that in non-agricultural sectors in poor countries. The gap has tended to increase over time. Conclusions from the existing literature, which mainly trace the factors related to labor market frictions and statistical discrepancies, are inconclusive in explaining the magnitude and pattern of the gap. The phenomenon has remained puzzling. In this work, we intend to show that the unexplained portion of the gap and its trend over time can fully be attributed to differences in capital intensities and relative technical change. In formal framework with two sectors, two factors, and exogenous prices, we show that in equilibrium with constant labor supply agricultural productivity gap is related to relative cross-sector technical change through skill-premium and division of, heterogeneous in skills, labor. Under plausible empirical assumptions and stylized facts, resulting propositions imply that technology imports from abroad stimulate the productivity gap between agriculture and non-agriculture in developing countries.

The theory developed is substantiated with two sets of empirical estimations on cross-country longitudinal data. Results imply that technology imports have positive, statistically significant, and robust impact on the sectoral productivity gaps in developing countries. Key findings reinstate the debate regarding appropriateness of technologies transferred into poor economies and corroborate longstanding views that without technological change traditional agricultural productions deliver decreasing returns at increasing rate. High and increasing productivity disparities in developing countries suggest that proper development policies should be implemented to induce more balance and sustainable development. Particularly, in the short run, policies ought to emphasize on the elimination of barriers to free labor mobility between agriculture and non-agriculture, or equally, rural and urban areas. In the long-run, governments should pay greater attention to technical change in the agricultural productions, whether through domestic development or adoption of appropriate technologies from more advanced countries. Accumulation of human capital in the economy, overall, would make more skilled labor available for both traditional and modern sectors to embrace technical changes more smoothly and consistently.

Dedicated to my Family

ANCKNOWLEDGEMENTS

I am thankful to KDI School of Public Policy and Management for providing me the opportunity to further explore the field of Development Economics that I have always been fascinated by.

I would like to extend my deepest gratitude to Professor You Jong-il for his guidance, encouragement, and support. This work would not be possible without his motivations. Also, my sincere appreciations to Professor Baek Ji Sun, Professor Kim Taejong, Professor Lee Siwook, and Professor Wang Shun for their valuable comments and useful discussions.

No words can describe the love, care, and inspiration I have received from my Parents and my Family on the path to become who I am today. Thank you for the being there.

Contents

List of Tables

List of Figures

List of Key Abbreviations

APG – Agricultural Productivity Gap

CEPII – Centre d'Etudes Prospectives et d'Informations Internationales

CES – Constant Elasticity of Substitution

FAO - Food and Agriculture Organization

GGDC - Groningen Growth and Development Center

ISICV - International Standard Industry Classification

KLEMS - Capital, Labor, Energy, Materials, and purchased Services

OECD - Organization for Economic Co-operation and Development

SITC – Standard International Trade Classification

SNA - System of National Accounts

TFP – Total Factor Productivity

UNCTAD – United Nations Conference on Trade and Development

WDI - World Development Indicators

Introduction

As of 2013 average per-person income difference between the richest and the poorest 25% countries is recorded roughly 20-fold[1] . This gap is largely reflected on sectoral labor productivities. Comparing to the rich group agriculture is 35-times less productive in the poor group, and the analogous gap constitutes the factor of 12 for non-agricultural sectors. Almost half of workers in the poor nations are engaged into agricultural production. These numbers blindly imply to the presence of significant cross-sector productivity disparities in developing countries, and more importantly, to the large portion of labor stuck in relatively unproductive sector. Other things being equal, there is nontrivial incentive for relocation of workers from agriculture into non-agriculture, which, in turn, should greatly lessen the income gap across nations.

Data from the National Accounts suggest that agricultural productivity gap (APG), measured as the ratio of per-worker value added in non-agriculture to that in agriculture, stands over the factor of 4 in developing countries with increasing trend over the last two decades. If they can earn more income in other sectors, why are the agricultural laborers not simply moving out of agriculture? Why are the significant potentials for income gains not being realized? This work intends to provide a complementary standpoint in addressing these questions that have been rigorously discussed in development economics literature.

[1]Calculated based on National Accounts Data, PPP-based.

In founding theories, relatively large productivity gaps in agriculture is attributed to differences in land quality, climate, and capital intensity (Clark, 1940), the 'food problem' (Schultz, 1953), as well as stagnant production technologies and human capital (Schultz, 1964; Hayami, 1969). Recent streams of literature have explored the role of capital market distortions, and resulting statistical discrepancies due to home production (Parente *et al*, 2000; Gollin *et al*, 2004; Herrendorf and Schoellman, 2012; Gollin *et al*, 2014); human capital differences across sectors due to skill-constraints and skill-intensiveness of production technologies (Caselli and Coleman, 2001), self-selection of labor based on observed abilities (Lagakos and Waugh, 2013), and on unobserved skills (Young, 2014); frictions distorting the labor markets (Restuccia et al, 2008; Au and Henderson, 2006; Munshi and Rosenzweig, 2016) as well as aggregate productivity inefficiencies (Caselli, 2005; Vollrath, 2009), and barriers for using intermediate inputs (Restuccia *et al*, 2008) to explain the sectoral productivity discrepancies in poor countries.

However, the half of the observed magnitude of APG as well as its increasing trend in developing countries has remained unexplained (Gollin *et al*, 2014; You and Juraev, 2017a; Juraev and You, 2017b).

This work proposes an alternative theory that complies with the observed magnitude and pattern of APG both over time and across countries. Specifically, we argue that puzzlingly large portion of the productivity gap in developing countries can only, and fully, be attributed to ratio of labor shares of income in agricultural to that in non-agricultural production. After using the data on labor shares corrected for self-employment, we show that the puzzle profoundly disappears! More importantly, given unchanged pattern of wage gaps, moderately increasing trend of APG implies that labor shares are decreasing (increasing) in non-agriculture (agriculture) due to increasing (decreasing) shares of capital and technologies. In a simple accounting exercise, we demonstrate that relative sectoral capital intensities in the developing countries have remained constant, and thus, the changes in the productivity gaps unequivocally result from relative technical changes – more intense in non-agriculture comparing to agricultural sector.

In a simple formal framework with two sectors, two factors, and exogenous prices, we also show that in equilibrium, with constant labor supply, APG can be related to relative cross-sector technical change through skill-premium and division of, heterogeneous in skills, labor. Relationship is not positive *per se* without three empirically substantiated stipulations from literature. The first is the technology-skill complementarity hypothesis originating from Hicks (1932), which warrants a positive relationship between technical change, demand for skilled labor, and the skill premium. The second is the technical change that is sector biased resulting from demand driven profit incentives of producers. And finally, it is the aggregate technical change in developing countries that take place primarily through adoption of technologies from more advanced economies.

In our theoretical proposition, the skill-biased sector-specific technical change in developing countries via technology transfers increases the skill premium and allocates relatively more skilled labor into non-agriculture. Concentration of skilled labor further induces the technical change and the transformation of production technologies in the modern sectors. Agricultural production, on the contrary, remains relatively sluggish and unproductive.

We test our hypothesis through two specifications of empirical estimations using the data for the sample of 153 developing countries for the period of 1995-2014. In the panel instrumental variable estimations, technology transfers are proxied by the imports of machinery and equipment classified under the Section 7 of the Standard International Trade Classification (SITC7) of the United Nation's Conference on Trade and Development (UNCTAD). In order to overcome the issue of endogeneity, the imports are instrumented by the cumulative sum of bilateral trade of technologies predicted based on geographical factors and proximities among countries, and the innovative intensity of the technology exporters. The key exclusion restriction is the innovative intensity of the technology producers, measured as the ratio of aggregated R&D spending to GDP. Controlling for country specific fixed factors, panel instrumental variable estimation results provide plausible support for the proposition that technology imports are an important determinant of APG in developing countries. Findings are robust to inclusion of related covariates, sample restrictions, as well as factors representing alternative channels of technology transfers. In this first set of estimation specification, it is assumed that the R&D intensity of partner countries does not affect APG in developing countries except through technologies imported. The validity of this exclusion restriction is tested using the data on direct investment flows. However, due to paucity of complete data on other factors through which R&D intensity of the technology exporters may affect the sectoral productivities in developing countries, and because the panel instrumental variable estimations do not take the possible dynamic prevalence of APG over time, estimation results may well be subject to debate.

To provide alternative evidence on the theory developed and account for the likely dynamic persistence of APG, the impact of technology transfers is also estimated using Arellano-Bond system dynamic panel two-step specifications, where all variables-in-levels are instrumented by lagged differences and variables-in-differences are instrumented by lagged variables in levels as in Arellano and Bover (1995) and Arellano and Bond (1998). Moreover, in order to directly control for the sectoral bias in technology transfers, the key variable of interest in the dynamic panel specification is measured as the ratio of non-agriculture specialized machinery imports to those specialized for agricultural production. Overall, the results from dynamic modifications suggest that 1% increase in the ratio of non-agricultural-to-agricultural technology imports tends to increase the productivity gap by 0.18 units. Entailing tests provide plausible support for the validity of the instruments used and the inferences derived.

This work fits into existing literature in number of ways. First, we demonstrate that intersectoral allocation of skilled labor is determined by relative technical change in non-agriculture and agriculture. In existing models *e.g.* Lagakos and Laugh (2013) and Young (2014) distribution of skills is solely a supply side decision, where the skilled self-select into sectors based on their observed and unobserved characteristics. Additionally, the formal framework in this paper distinguishes the aggregate productivity parameter from sector-specific ones by formulating the production functions with skill-augmenting technical change in each sector. This formulation explains the relevance of the aggregate efficiency debated in Gollin *et al* (2004), Vollrath (2009), and Caselli (2005).

Using alternative sources of data, we also explore the relevance of statistical discrepancies and mismeasurement in calculation of productivity gaps for much larger samples than those in Gollin et al (2014) and Herrendorf and Schoellman (2012). Our findings reinstate that, while the magnitudes of APG's in the sample of developed countries seems slightly overestimated than those implied by national accounts data, productivity gaps in developing countries cannot simply be attributed to the measurement issues. Contrarily, the measurement problems seem to be relevant in the empirical estimations of labor shares of income, which consistently assign lower values onto agricultural comparing to non-agricultural production functions.

Furthermore, this work presents a unique comparative analysis of economic transformation of the advanced countries from a historical perspective, which helps understand why the developed countries have exhibited low and relatively constant APG's for over hundred years until now. The conclusions from the analysis imply that the historical development path of the advanced countries today did not necessarily embody large sectoral productivity disparities. Accumulated knowledge and human capital development triggered productivity growth, primitively, in the agricultural sector. Sufficiently high agricultural productivity enabled the reallocation factors of production and excess resources into non-agricultural sectors. The agricultural productivity revolution preceded the industrialization stage in the case of the advanced economies. The sequence of transformation, however, seems to be reversed for the developing countries today due to the availability of the technologies readily available in the world markets.

Another important novelty of this work is the establishment of empirical link between technology transfers and the productivity gaps in developing countries. To the best of our knowledge, this is the first attempt to do so. The closest in context research to this work by Wang and Wandschneider (2014) presents two-sector small economy endogenous growth model and concludes that increase in product-varieties' share in manufacturing imports increases the sectoral productivity in favor of modern productions. Their underlying intuition originates from Schumpeterian models of endogenous growth that increasing varieties in manufacturing imports induce the creation of more product varieties in the domestic manufacturing sector and increase labor productivities. They, however, assume that trade does not result in reallocation of labor, neither do they take the heterogeneity in skills of labor into account. Moreover, in their framework similar reasoning in case of varieties in agricultural imports would also give symmetric conclusions in favor of decreasing APG. In this work, we allow for technical change to be neutral, or non-agriculture biased, or agriculture biased. Should technical change favor agriculture relative to non-agriculture, skill premium would increase, and APG would decline due to relatively more skilled labor moving into agriculture.

Key findings from this work corroborate longstanding views that without technical change traditional agricultural production technologies deliver decreasing returns at increasing rate

(Theodore Schultz, 1953, 1964; Arthur Mosher 1966; Yujiro Hayami and Vernon Ruttan, 1985; Peter Timmer, 1988). High and increasing APG in developing countries suggest that the central importance of agriculture in development, at least in terms of the existence of large pools of less productive workers, seems yet to be tackled with proper development policies. Instead, surplus resources are directed to the productions in the non-agricultural sectors at the cost of delaying agricultural, perhaps aggregate, development.

Particularly, our analysis and results suggest that, in the short run, development policies ought to emphasize on the elimination of barriers to free labor mobility between agriculture and non-agriculture, or equally, rural and urban areas. In the long-run, governments should pay greater attention to technical change in the agricultural productions, whether through domestic development or adoption of appropriate technologies from more advanced countries. Accumulation of human capital in the economy, overall, would make more skilled labor available for both traditional and modern sectors to embrace technical changes more easily and consistently.

Chapter I. Agricultural Productivity Gap: Theory vs. Data

1.1. Preliminary Analysis

In this section, we start off by presenting the analytical discussion of labor productivity gaps implied by national accounts data. By definition, APG is measured as the ratio of value added per worker in non-agriculture to that in agriculture:

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

Where, VA and L are value added and labor, subscripts 'n' and 'a' refer to non-agriculture and agriculture, respectively. 'Agriculture' includes agricultural production, hunting, forestry, and fishing in accordance with the International Standard Industry Classification (ISIC) Rev.2 of the United Nations[2]. Non-agricultural sector is composed of all other economic activities. Value-added is the difference between gross value of output and intermediate inputs, and available from the World Development Indicators (WDI). Labor is derived from share of employment in each sector and total employment in the economy. Data on the share of employment is available from Food and Agriculture Organization (FAO) of the United Nations[3]. Total employment is measured by the total number of persons of 15 years of age or older engaged in any economic activity for a given year. Number of persons engaged is obtained from the World Penn Tables. Sample ranges from

[2] Equally refers to Sections A and B in ISIC Rev.3 and Section A in ISIC Rev.4.

[3] FAO employment shares data originate from the International Labor Organization's (ILO) household survey data. Surveys that are concentrated on non-representative geographical coverage such as urban areas, towns, major cities, and state-owned enterprises are excluded.

1995 to 2014 and includes 176 countries with relevant data available. Summary statistics of the variables presented in appendices Table A1.

Countries are classified into low income, lower-middle income, higher-middle income, and high-income categories in compliance with the 2016 December review by the World Bank. It is important to acknowledge that there is no precise definition of the 'developing' and 'developed' countries. Frequently, 'high-income' is interchangeably used to represent the 'developed' group despite there is significant heterogeneity in quality of economic development[4]. To tackle this issue, economies that became OECD member in or before 1995 are conditionally referred to 'developed' countries[5]. Table 1 summarizes the APG's computed[6].

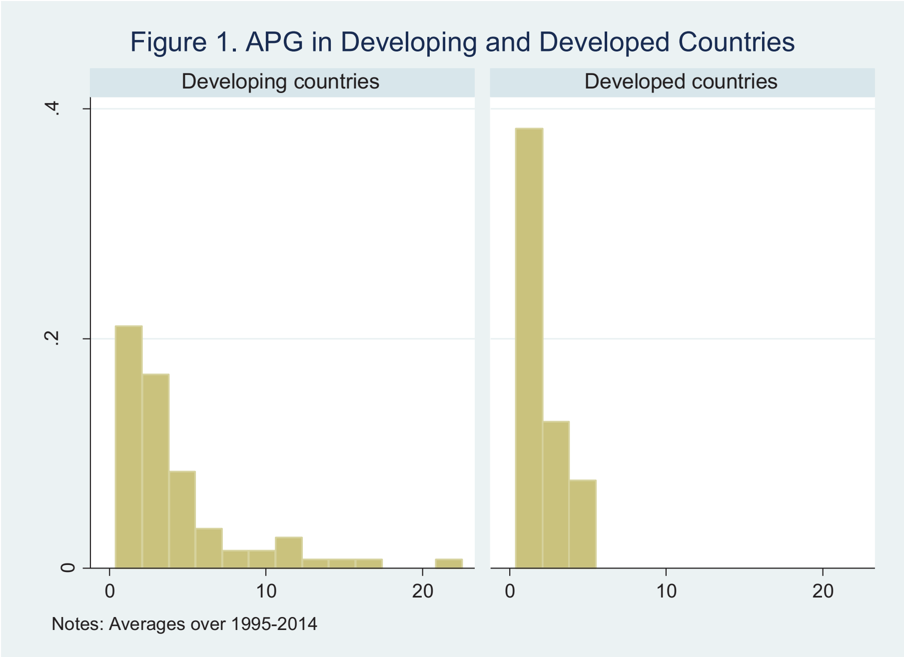
Results imply that an average worker in non-agriculture is over four times more productive than her counterpart in agricultural sector in developing countries. The calculated gap is two-fold in the developed countries. When population weights are applied, gap further increases in the sample of low and middle income or, in general, developing countries. This implies that APG is relatively larger in countries with more population. On the contrary, weighting decreases the gap in both high-income and developed countries.

[4]For example, it would be implausible to treat Saudi Arabia and Sweden, or Croatia and Canada under one level of development.
[5]Following countries are classified into the 'developed' group: 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, and the United States.
[6] Summary of APG's by income categories are illustrated in Figure A2 in Appendices.

Table 1. Implied APG			
Country groups	*APG*	*Weighted APG*	*Number of countries*
Low and middle income	4.03	4.5	121
High income	3.01	2.8	55
Developing	4.2	4.3	153
Developed	2.2	2.1	23
Notes: The second column is APG simply averaged over 1995-2014. The third column is the average of population weighted APG over 1995-2014.			

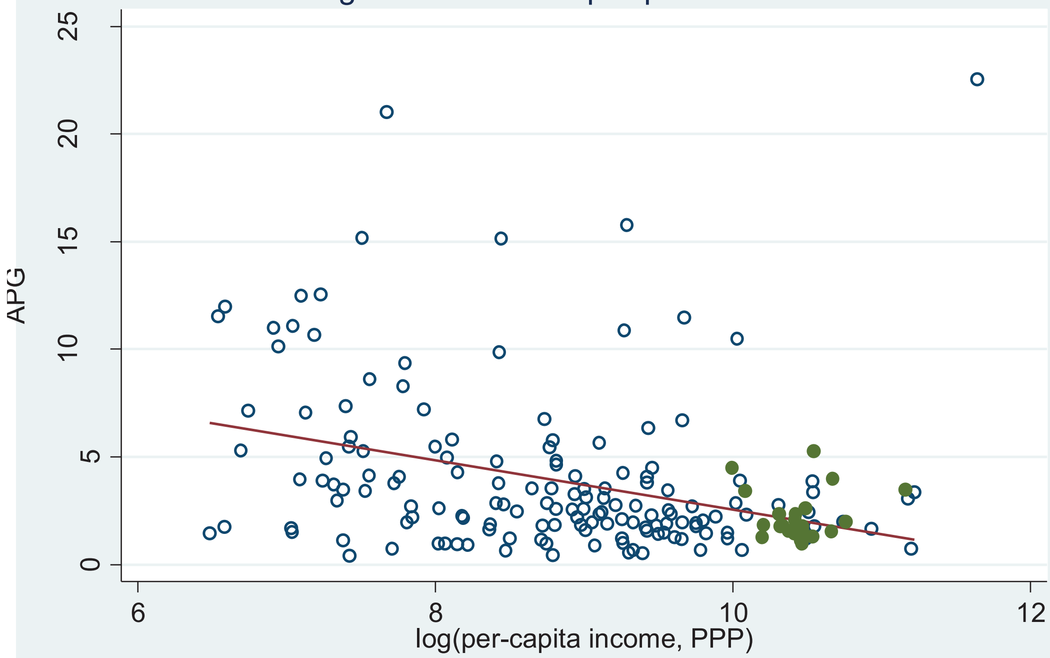
Among the developing countries the largest in magnitude productivity gaps are recorded in Bhutan (15.1), Botswana (15.8), Qatar (22.5), Kenya (21), and Senegal (15.2). Calculated APG's in developed countries are, roughly, in the range of one to five. Median APG is 3.1 and 1.8 in the 'developing' and the 'developed' samples, respectively. Distributions are illustrated in Figure 1.

Is high APG associated with low income? The answer seems to be mixed. Figure 2 illustrates the raw APG and purchasing power adjusted income per-capita. The observations from the figure has two important implications: that for same or similar levels of income, APG varies significantly, and that for same or similar levels of APG, income differences can be enormous. For example, both Tanzania and Senegal have per-person income of roughly 1700 USD. The productivity gap is 7.4 in Tanzania whereas it is 15.2 in Senegal – the difference is twofold! On the contrary, comparison between Guinea and Trinidad and Tobago shows that both have APG's slightly over 10 whereas the income difference between the two is 22-fold! However, in general, higher income is associated with lower APG's.



Negative, yet blurred, relationship between APG and income can be observed due to two reasons: 1) because a nontrivial part of income is determined by other factors; 2) because APG by itself does not necessarily imply to having a low level of income. By no means we neglect the importance of other factors, yet, continue with the second reason to keep the scope of this work as focused as possible. Since APG measures the relative productivity in two sectors, a country with high APG can have high income if: a) both agricultural and non-agricultural labor productivity is high relative to other countries; or b) unproductive agriculture employs small portion of labor force; or c) both. Opposite notion holds for countries with low implied APG and low income. High APG in countries with large share of employment in agriculture, however, implies to substantial potential gains in reallocation of labor from the less productive to the more productive sectors. In order to provide more substantiated explanation to the importance of sectoral productivity disparities it is of crucial importance to look at the share of employment in agriculture as well as labor productivity in both sectors relative to an arbitrary cross-country threshold level.

Figure 2. APG and per-person income



Note: Empty and filled circles represent developing and developed countries, respectively. Averages over 1995-2014.

As a threshold level, we choose the labor productivity in the US, without the loss of generality. Figure 3 compares the labor productivity gap in non-agriculture and agriculture in different groups of developing countries. Specifically, vertical axis represents the ratio of non-agricultural labor productivity in the US to that in each country. It, therefore, measures how unproductive an average non-agricultural labor is comparing to her counterpart in the US. Horizontal axis represents the ratio of agricultural labor productivity in the US to that in each country. For example, factor of 10 on horizontal axis means that average agricultural labor is 10 times more productive in the US comparing to average agricultural worker in the country of interest. Measures of labor productivity are adjusted for Purchasing Power Parities (PPP) in each country and represent face values.

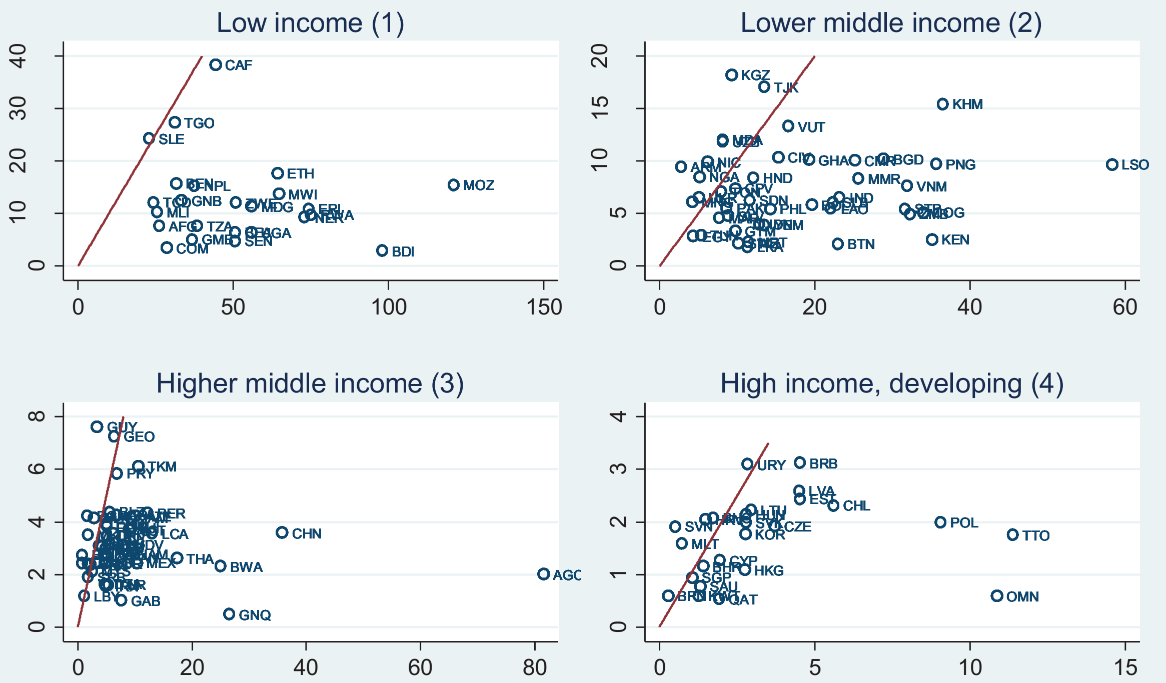
Conclusions from the Figure 3 are striking[7]! In almost all developing countries, labor productivity gap relative to the US is greater in agriculture than non-agriculture. For example, in Ethiopia, agricultural labor is 64 times less productive than that in the US, whereas the gap is 18-fold in non-agriculture. The relative gap in agriculture reaches shockingly large level of 121 for Mozambique, while the same gap in non-agriculture stands at the factor of 15.

Similar picture is observed in case of middle-income countries. In China, for example, labor is 36-fold less productive in agriculture, whereas the gap is 3.6 for non-agriculture relative to the US. The gaps are 2.8 and 1.8 in agriculture and non-agriculture in Korea, respectively, and 23-fold and 6.5-fold for India.

All these numbers imply that high agricultural productivity gap is due to very low labor productivity in agricultural production rather than very high non-agricultural productivity in the developing countries.

[7] The same picture for developed countries is presented in Figure A1 in appendices. I let that case speak for itself.

Figure 3. Labor productivity gap relative to US: non-agriculture vs. agriculture

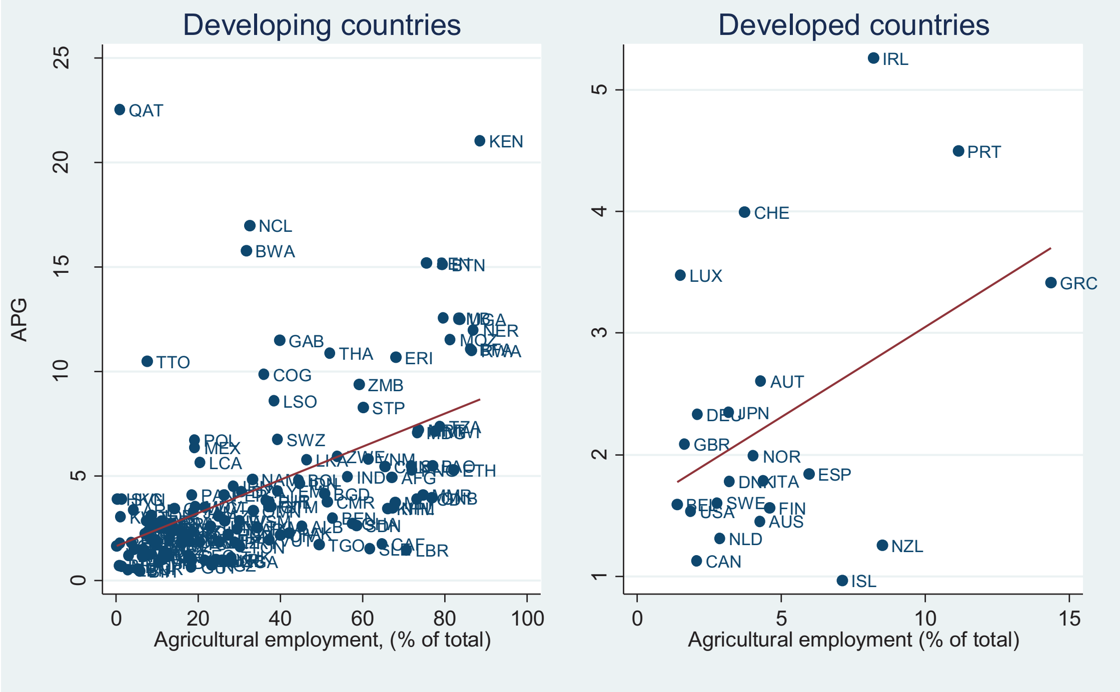


Note: Vertical axis=non-agriculture, horizontal axis=Agriculture.
Straight line from the origin represents the gap in two sectors being equal.

Now, let us return to the motion about the relationship between APG and per-person income and present two extreme cases. Consider Central African Republic (CAF). CAF is one of the poorest nations in the world with per capita income being around 800 USD. However, APG in CAF averages to 1.8 over 1995-2014, which is even lower than the average corresponding to the developed countries in Table 1. Coexistence of low income and low APG means that in both agriculture and non-agriculture labor productivity is proportionately low. Indeed, referring to the low-income group (3) in Figure 3, relative to the US, labor productivity gap in agriculture and non-agriculture is 44 and 39 – equally low. Consider, now, Qatar. In Figure 1, Qatar is the obvious outlier with APG over 20 and per-capita income being higher than that in all developed countries. What the case of group (4) in Figure 3 implies is that while Qatari agricultural labor is twice less productive than that in the US, non-agricultural labor is twice more productive than that in the US. In what we discuss next, less than 1% of the workers in Qatar are employed in agriculture, which allows for the existence of high APG and high-income (Figure 4).

Is there significant misallocation of labor? To address this question let me start off with the case of developed countries. In the ‘developed’ group, on average, non-agriculture is 2.2 times more productive than agriculture, and merely 4.7% of the employed are engaged into agricultural work. Without any assumptions, basic reasoning implies that even if some of the labor moved out of agriculture into non-agriculture the potential gain in aggregate productivity, or equally income-per-worker, would be negligible. On the contrary, in the case of developing countries, over one-third of the workers are in agriculture when the non-agriculture is over four times more productive. It is, therefore, plausible to expect that, holding everything else constant, reallocation of labor from less-productive sector to more productive sector should result in substantial improvement in per-person income in developing countries.

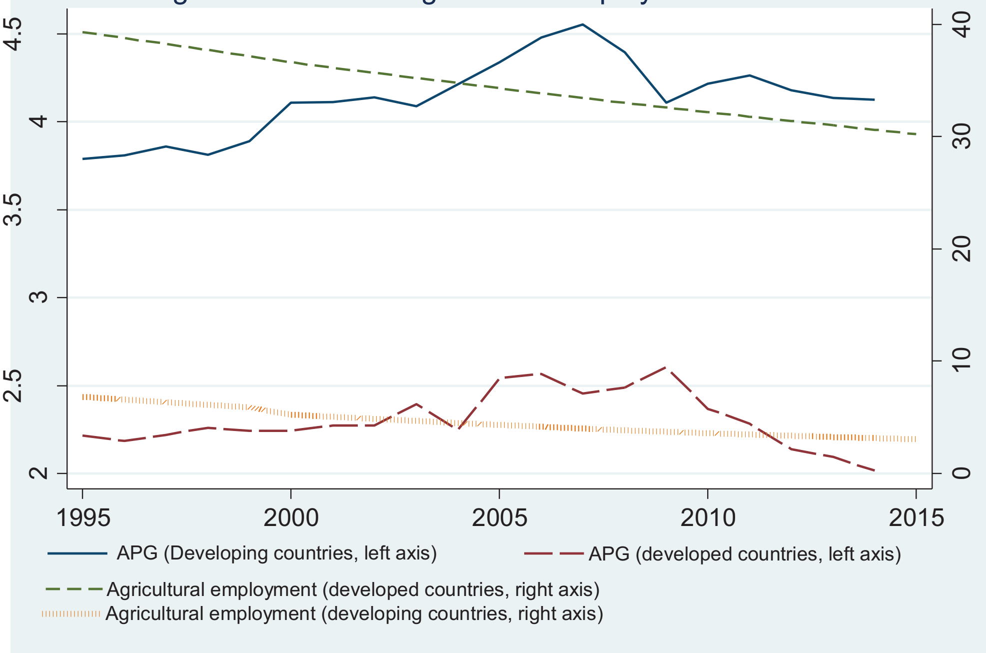
Figure 4.APG and Agricultural employment
(averages over 1995-2014)



In fact, potential gain should be higher, the higher the implied APG and the higher the share of employment in agriculture. For majority of developing countries data displayed in Figure 4 show that higher productivity disparities across sectors are associated with higher shares of employment in agriculture. When the sample of 40 poorest countries is considered, share of employment averages to 70% in agriculture, and APG surpasses the factor of 7!

Have countries realized such potentials for income-gains? What stylized facts in Figure 5 imply is astonishing: despite the share of employment in relatively less productive sector – agriculture, has steadily declined over time, APG has increased in developing countries over the last two decades! On the contrary, there is no viable trend of APG observed in developed countries[8].

Figure 5. APG and Agricultural employment over time



What causes such a large magnitude of productivity disparities in developing countries? As countries develop, why have the potential gains implied by APG increased instead of decreasing? Why should we see APG even in developed countries at all? These are some, but not all, of the important questions that have not found complete answers in development economics research. This work is obviously not the first one to pose these inquiries. Related

[8] In construction of the Figure 5, only those countries with complete data available from 1995 to 2014 are considered. Therefore, 'developing' and 'developed' samples include 116 and 19 countries respectively.

literature can be traced back over a half a century. Yet, this paper intends to provide a complementary explanation to the puzzle.

1.2. Existing Literature

Before we move onto exploring the literature related to productivity differences in agriculture and non-agriculture, introduction of some basic accounting identities would be plausible. Referring to equation (1), labor productivity in each sector is as the ratio of value added (*VA*) and labor (*L*). As defined in System of National Accounts (SNA) of the UN, value added is the value of output less the consumption of intermediate inputs. When considered from the income approach, *VA* is the sum of labor's and capital's compensation:

$$VA = wL + rK \qquad (2)$$

Where, *'w'* and *'r'* are wage-per-worker and rent-per-capital, respectively. *'L'* and *'K'* stand for labor and capital, as commonly expressed. Straightforward reformulation of (1) using (2) gives another representation of APG:

$$APG = \frac{w_n + rk_n}{w_a + rk_a} \qquad (3)$$

Where, *k=K/L* is the capital per worker in each sector.

Equation (3) implies that relative labor productivity in non-agriculture can be higher if wages and/or capital-per-labor are higher in non-agriculture, given that return to capital is identical in both sectors. Existing literature can be precisely summarized around the equation (3).

Large productivity differences between agriculture and non-agriculture, both within and across countries, were first discussed by Colin Clark in his *'The Conditions of Economic Progress'* in 1940[9]. Clark, by analyzing extensive raw data, concludes that per-worker cereal production *i.e.* agricultural productivity was surprisingly lower in poor countries, and that low agricultural productivity was one of the key reasons for their high poverty rates. Holding the terms of trade between cereals and dairy products constant at 1925-1934 prices, he finds that merely 6.4 percent of the labor force in New Zealand would be enough to produce the dairy food requirements in the country. On the contrary, agricultural productivity was so low in former USSR that it would take twice the size of all labor force to meet the same limits. Clark suggests that differences in agricultural labor productivity can be, mainly, explained by land quality, climate, and relative capital intensities. Some of the views of Clark (1940) oppose those from later works such as Theodore Schultz (1964). Schultz neglects the importance of factor endowments and land quality, and asserts the role played by innovations, fertilizers, and machinery in explaining the productivity differences in agricultural sector between poor and rich countries.

Yujiro Hayami (1969) made one of the early attempts to quantify the Schultz propositions. Hayami, as in Clark (1940), also presents that for 1957-1962 years, India's labor

[9] Colin Clark is, in fact, one of the co-founders of division of economic activities into sectors: agriculture, industry, and services.

productivity in agriculture was substantially lower than that in the US and Japan. More precisely, the gap was almost 50-fold between India and US, and 5-fold between India and Japan, when agricultural value added per male worker was considered. To decompose the gap, he estimates the world aggregate agricultural production function using data for 38 countries. Hayami finds that factor endowments *i.e.* land/labor ratio and fertilizers each explain 20% of the gap, whereas education, and research and development account for the remaining portion[10]. In case of India vs. Japan, human capital accounts for 40% of the labor productivity gap in agriculture. Hayami (1969) points out that India's agricultural output would double if the level of education improved to Japanese level[11].

Early analyses by Clark (1940), Schultz (1964), and Hayami (1969), among many others, are of absolute importance in terms of setting the cornerstones in APG literature. However, they are raw in a sense that the quality of data used is low, that scope of samples is limited, and that available theories and analytical techniques used are primitive.

---

[10]Hayami measures education as literary ratios and school enrollment ratios for the first and second levels of education. The variable 'research and development, and extensions' is measured as average number of graduates from agricultural faculties in third level of education during 1958-1962 per 10.000 farm workers. (Hayami, 1969.p.3).

[11]Hayami's (1969) conclusions are strictly based on the factors of elasticity estimated in aggregate production function. Without doubt his work is of high importance in APG literature, however, certain assumptions and measurement issues in his calculations create grounds for flaw. For example, he measures the labor in agriculture as number of male workers in agricultural production. He also excludes the number of workers in forestry and fishing as he estimates the production function for crop-production only. Because of data unavailability, measure of agricultural output does not take the capital formation and capital stock into account, which may result in biased results. Such restrictions impose some critical doubts on estimated factor elasticities of production, hence, his concluding findings.

Subsequent works explaining the magnitude and importance of APG can be classified into three *mutually nonexclusive* categories. The first category includes the literature dealing with statistical discrepancies and measurement issues in computing the APG. There is a rationale doubt in development economics about the quality of data reported in SNAs. Agricultural sector is especially vulnerable to such measurement errors because significant portion of the labor force are self-employed and nontrivial part of output is home-produced. Any understatement of value added in agriculture or overestimation of agricultural employment may result in illusionary high magnitude of APG implied by the National Accounts data. Stephen Parente, Richard Rogerson, and Randall Wright (2000), Douglas Gollin, Stephen Parente, and Richard Rogerson (2004), Berthold Herrendorf and Todd Schoellman (2012), and Douglas Gollin, David Lagakos, and Michael Waugh (2014) fall into this category. Parente *et al* (2000) and Gollin *et al* (2004) present a model where capital distortions induce home production and less labor participation in market activities. The relevance and significance of the home-production induced mismeasurement issues with respect to the observed magnitudes of productivity disparities across countries are explored in Herrendorf and Schoellman (2012) and Gollin *et al* (2014).

The second stream of literature traces the factors impeding the competitive mechanisms in labor markets while exploring the sources of APG. Predominant part of the literature in this context, on the grounds of the 'dual economy' concept of Arthur Lewis (1954), has dealt with the wage differences between non-agriculture and agriculture. Intuitively, because non-agricultural production is more skill intensive than agriculture, workers in the former tend to have more human capital as well as skills, both observed and unobserved. Francesco Caselli and Wilbur Coleman (2001), David Lagakos and Michael Waugh (2013), and Alwyn Young (2013) are some of the critical works in this category. Conclusions from Caselli and Coleman (2001) imply that, because less developed countries are typically constrained by the number of skilled labor force, agricultural production faces relatively more shortage of educated workers. According to Lagakos and Waugh (2013), on the other hand, low skilled workers sort themselves into agriculture while high-skilled into non-agriculture. Similar sorting mechanism dominates in Young (2013) based on unobserved skills and abilities.

Human capital is not the idle factor that may create differences in labor compensations between agriculture and non-agriculture. Besides skills, sectoral wage differences may emerge if labor mobility across sectors is limited or restricted. Several papers highlight the barriers to labor mobility in explaining urban-rural wage gaps. For example, Chun-Chung Au and Vernon Henderson (2006) show how *'hukou'* system restricts the rural-to-urban migration and prevents substantial income gains in China. Kaivan Munshi and Mark Rosenzweig (2016) explore the role of social insurance networks within '*castes'* in India that are found to discourage rural-to-urban migration and encourage the persistence of high urban-rural wage gaps.

The last, but not the least in importance, category includes the literature that emphasize output market imperfections, capital intensity, technology, and aggregate economic efficiency in generating labor productivity gap between non-agriculture and agriculture.

Francesco Caselli (2005), by growth account exercises, shows that total factor productivity and capital-per-worker is an important determinant of labor productivity differences in agriculture among countries. Diego Restuccia, Dennis Yang and Xiaodong Zhu (2008) argue that barriers for employing intermediate inputs seriously hamper the productivity in agricultural production in less developed economies. In Dietrich Vollrath (2009) low productivity in agriculture is associated with low aggregate productivity in economies. In Jong-il You and Sirojiddin Juraev (2017a, 2017b), capital income and output market imperfections explain the puzzlingly large residuals in APG.

As pointed out, these categories of literature are arbitrary and mutually non-exclusive. Many of them share significant commonalities, and sometimes, controversial views. In what follows, I review them in detail and elaborate more on their findings.

Both Parente *et al* (2000) and Gollin *et al* (2004) incorporate agricultural sector into neoclassical growth framework of Robert Solow (1956) to explain the cross-country productivity gap that is much larger in agriculture comparing to in non-agriculture. By doing so they demonstrate that neoclassical framework is incapable of explaining the large APG's observed across countries. They show that in neoclassical framework APG in equation (3) is reformulated into a basic accounting identity given as:

$$APG = \frac{w_n}{w_a}\frac{LS_a}{LS_n} \qquad (4)$$

Where, *LS* – stands for labor share of income and, subscripts *'a'* and *'n'* denote agriculture and non-agriculture as above[12]. Identity (4) must explain the APG since in equilibrium wages are equalized across agriculture and non-agriculture. Typically, income differences in neoclassical growth model are attributed to policies distorting capital accumulation and exogenous productivity differences *i.e.* total factor productivity (TFP) or *the Solow residual*. Parente *et al* (2000) and Gollin *et al* (2004) argue that TFP differences should have no impact on APG's observed in countries. Therefore, they conclude that neoclassical model, with the agricultural sector explicitly represented, cannot explain the existing sectoral productivity disparities. Because, TFP is assumed to change exogenously in Solow (1956), they continue by considering policies that distort capital accumulation in the sectors. To account for the role of capital distortions they incorporate home production into their models. While, in Parente *et al* (2000) capital distortions push labor participation from market activities into home production, same effect in Gollin *et al* (2004), additionally, induce labor to stay in rural area and engage more into home production. In both cases, since home production is not readily reported in SNA data, observed low agricultural productivity may be biased downward, which results in high APG's recorded for poorer countries, typically, with higher capital distortions.

Caselli and Coleman (2001) take alternative path in explaining the productivity gap between non-agriculture and agriculture. They focus on the wage premium in favor of non-

[12]Since labor share of income is *wL/VA*, equation (4) is easily derived by substituting LS into equation (3).

agriculture in equations (3) and (4). By analyzing the empirical data in the US, they show that wage in the agriculture has gradually converged towards the wage in non-agriculture. In their model, regions with less-skilled labor specialize in agriculture, whereas regions with more skilled labor produce nonfarm goods[13]. Decreasing costs of obtaining education ultimately makes it optimal for farm workers to acquire more skills and, thus, move into non-agriculture. In case of the United States, reduction in transportation costs, changes in schooling curricula, as well as the end of *'white vs. black'* segregation scheme in schools are some factors that have induced the farm workers obtain more and better schooling. Caselli and Colemen (2001), in calibration of their model, find that barriers to labor mobility have negligible impact on wage differences between non-agriculture and agriculture. One important implication of their propositions is that, since non-agriculture is more skill-intensive, the skill requirements might be one factor impeding the movement of labor from agriculture to non-agriculture.

Some of the most interesting findings regarding APG are presented in Caselli (2005). Besides evidencing on substantial differences in labor productivity gaps, Caselli undertakes number of exercises to question how significant these gaps are in explaining the income differences across 80 countries using data from 1996. In his first exercise, Caselli makes number of counterfactual assumptions on sectoral productivity and labor shares. Under one counterfactual, every country is assumed to have the US level of

[13]In fact, Caselli and Coleman (2001) show that when 120 industries are classified by the share of workers with elementary or less schooling in US Census of Population, agriculture was in bottom 10 group for each year from 1940 to 1990.

agricultural productivity, own non-agricultural productivity and own labor share of employment. Under another counterfactual, all countries are assumed to have the US agricultural share of employment and own agricultural and non-agricultural labor productivity levels. Results he obtains are amazing! In the first case, income inequality across countries basically disappears! In the second, it declines by roughly threefold! Caselli's (2005) another counterfactual analysis decomposes the differences in agricultural labor productivity for a sample of 65 countries. By accounting for observable factors of production, namely, labor, capital, land, and human capital, he concludes that per-worker capital explains 15 percent of cross-country productivity differences in agriculture. By contrast, capital can explain 59 percent differences in non-agriculture. Similar exercise is done in Lagakos and Waugh (2013) using more recent data but for a smaller sample of 28 countries from various income levels. Their results assign 22 and 29 percent variations in agricultural and non-agricultural productivity to capital intensities, in that order. Findings from Caselli (2005) and Lagakos and Waugh (2013) imply that, while capital does play a significant role, it is the productivity parameter *i.e.* TFP that captures large portion of existing gaps in agriculture.

Numerous papers in APG literature relate the low agricultural productivity in poor countries to, so called, *'the food problem*[14]*'* and *'the stagnant agricultural productivity*

[14]Schultz discusses number of reasons for persistence of low agricultural productivity in poor countries. The food deficit is one of them. According to his proposition, agriculture produces necessity for living – the food. Despite low productivity, poor people spend such a large portion of their income on food that they are not able to simply move out of agriculture. He also discusses number of demand side factors, which profoundly neglects the possibility that sluggish

trap[15]' introduced by Theodore Schultz in 1953 and 1964, respectively. For example, Restuccia *et al* (2008), in two-sector general equilibrium model, demonstrate that the low aggregate productivity and barriers for employing the intermediate inputs account for roughly half of the cross-country sectoral productivity gaps in agriculture. They argue that the barriers can be in two forms: direct barriers – when cost of intermediate inputs such as fertilizers are high, for example, due to trade policies protecting domestic industries; and indirect – when free mobility of labor is restricted or limited so that the wages in agriculture remain low, which induce farmers employ more labor than intermediate inputs in production. Similarly, Gottlieb and Grobovsek (2015) find that restrictive communal land arrangements in Sub Saharan Africa substantially dampen the agricultural labor productivity relative to that in non-agricultural sectors.

The 'food problem', which is reflected in low aggregate productivity in poor countries, drives relatively unproductive workers to self-select into agriculture in Lagakos and Waugh

---

agriculture is a self-resolving issue. It is a common wisdom that high demand for a good induces its production as well as productivity. Although demand for agricultural goods are mostly determined by population and income in the long run, according to Schultz, however, population growth in countries tends to decline over time, which means there is marginally diminishing change in demand for agricultural output. On the other side, demand of agricultural goods with respect to income is inelastic and declines as income increases. This, further, implies that potentials for demand-induced agricultural productivity improvements are negligible even in the long-run. He argues that rapid and successful economic transformation of countries depends on, mainly, supply side changes, specifically, implication of new production techniques in agricultural production. Schultz presents that technological advancements increased the US agricultural production by 1.6% annually for 27 years prior to 1953.

[15] With half of the population residing in rural areas and earning income from, mainly, agricultural work, poor countries seem to be trapped into, what Schultz (1964) defined as special long-term agricultural equilibrium, characterized with detrimental productivity growth and accumulation of unskilled labor, as well as barriers distorting any incentives for further improvements.

(2013). Because in the advanced economies aggregate productivity is typically high, only those workers with most comparative advantage in agricultural production self-select into agriculture. In the quantitative experiment of their model, Lagakos and Waugh find that selection captures 29 out of 45 factor differences in agricultural productivity between the richest and the poorest 10 percent of the countries. In Young's (2013) model, which conceptually shares similarities with Lagakos and Waugh, similar sorting of workers between urban and rural areas takes place due to unobserved skills and abilities. Young postulates that education and unobserved skills are correlated, although imperfectly, and that, urban production is characterized with relatively higher skill intensity. Migration of better educated rural workers into urban production represents their higher unobserved skills, and by the same token, migration of urban workers into rural areas is due to their lower unobserved skills. Young's conclusions imply that urban-rural wage gaps are completely explained by the observable education and unobserved skills. Unlike Lagakos and Waugh, this scheme of sorting does not leave any unexplained gap in relative wages.

Herrendorf and Schoellman (2012) calculate the APG for the US states using Bureau of Economic Analysis data for the period of 1980-2009. They find that, on average, labor is twice productive in non-agriculture than in agriculture. By adjusting the implied APG to ratio of wages and estimated labor shares of income, they conclude that accounting identity given by equation (4) does not hold. They show that the identity can be reestablished once agricultural value added is corrected for underreported proprietors' income. Herrendorf and Schoellman repeat the similar exercise for a sample of 12 countries and conclude that mis-measurement problems are universal[16]. Their conclusions contradict those by Gollin *et al* (2014) when it comes to the measurement concerns. To check whether APG is overstated by SNA data, Gollin *et al* (2014) employ micro household data from Living Standards Measurement Surveys for 10 countries[17]. Their results show that there is no evidence of mis-measurement in APG from the macro data provided in the National Accounts. Same conclusions hold even when APG is contrasted to the ratios of income-per-worker and expenditure-per-worker in the micro data[18].

Gollin *et al* (2014) find non-agriculture to be, roughly, four times more productive than agriculture for a sample of 113 developing countries. In addition to 'data-checking' exercises, they compute the differences in human capital and working hours between the sectors as well ratio of urban-to-rural living costs. Using country specific estimations of return to schooling, they find that human capital per-worker in non-agriculture is, on average, 1.5 times of that in agriculture for a sample of 90 developing countries. Their calculations remain relatively robust even when lower rates of return to schooling are applied in case of poorer countries. It implies that human capital differences cannot account for large APG, which to some extent undermine the importance of Lagakor and Waugh

---

[16]Following countries are examined by Herrendorf and Schoellman (2012) in their alternative sample: Brazil (1991,2000); Canada (1991,2001); India (1993,1999); Indonesia (1995); Israel (1995); Jamaica (1991,2001); Mexico (1990,2000); Panama (1990,2000); Puerto Rico (1990,2000); Uruguay (2006); United States (1990,2000); Venezuela (1990,2001).

[17]Gollin *et al* (2014) provide micro evidence for Armenia (1996), Bulgaria (2003), Cote D'Ivore 1988), Guatemala (2000), Ghana (1998), Kyrgyz Republic (1998), Pakistan (2001), Panama (2003), South Africa (1993), and Tajikistan (2009).

[18]Contradiction is purely conceptual since sample of Herrendorf and Schoellman (2012) does not have common countries with that of Gollin *et al* (2014)'s sample using micro-data.

(2013) and Young (2013) in explaining APG's[19]. On average, half of the productivity gap between agriculture and non-agriculture remains unexplained even when the differences in human capital, working hours and urban –rural living costs are taken into account[20] (Gollin *et al*, 2014, p.36).

The recent pieces of related literature, that we are aware of, are You and Juraev (2017a) and Juraev and You (2017b). In our first paper, we show that even after adjusting for non-agriculture – agriculture wage differences, significant part of APG remains unexplained. Since the wage ratio captures all labor market frictions related to human capital differences *e.g.* sorting on skills and education as well as barriers for cross-sector labor mobility, the remaining gap in labor productivity must be attributed to the differences in the capital share of income. By evidencing on empirical and estimated labor shares of income, we demonstrate that no puzzle in the observed magnitude of APG remains unexplained. In Juraev and You (2017b), we proceed with findings in our first work and amplify the inadequacy of neoclassical models under the assumption of perfect competition as in Parente *et al* (2000) and Gollin *et al* (2004). We emphasize the importance of output market imperfections in generating the large productivity gaps in agriculture and non-agriculture. While Parente *et al* (2000) and Gollin *et al* (2004) diverge into home-production, we

[19] Vollrath (2009) find even smaller ratio of human capital between non-agriculture and agriculture - around the factor of 1.2.

[20] Gollin *et al* (2014) find ratio of working hours between non-agriculture and agriculture constitute, average, 1.2, whereas urban-rural living costs account for the factor of 1.3.

incorporate monopoly powers in non-agriculture, instead, that give birth to substantial profit-per-worker, typically, accrued to capital owners.

Literature discussed in this section circles around the current issues related to cross-country income differences from the point of large sectoral productivity gaps implied by data. However, there is limited discussion of why APG is consistently low in developed countries, and whether APG is typical phenomenon of economic transformation, and if so, whether the developed countries also experienced similar productivity disparities when they were poor. The only piece of interest regarding this curiosity that we came across with is in Gollin *et al* (2004). In matching the historical per-capita-income of the US, UK, and Canada with per-capita-income of developing countries in 1990, they show that APG has been surprisingly small and relatively constant in all three countries since 1900. They, however, do not explain the reasons behind such differences in economic transformation between the poor countries today and the ‘poor’ countries of the past.

Since the poorness is closely associated with APG today, we find the phenomenon of great importance to be analyzed from the historical perspective. In the following sub-section, we intend to accomplish this task by providing basic theoretical insight into why developed countries might not have experienced the stage where large portion of labor are stuck in substantially unproductive production.

1.3. Additional Insights

Understanding the persistence of productivity differences between non-agriculture and agriculture in developing countries sets forth a complex task of synthesizing the theories explaining the economic transformation and growth from the historical perspective. Doing so takes us back to the period when today's rich countries were poor and helps us elaborate more on the relationship between APG and economic transformation. We intend to substantiate the proposition that transition from the 'poorness' to the 'richness' in the developed countries did not necessarily embody large productivity differences between traditional sector *i.e.* agriculture and modern sectors *i.e.* non-agriculture. Instead, high agricultural productivity preceded and created grounds for the industrialization.

1.3.1. Historical Perspective

Not that the rich countries were once poor, they were poor for prolonged periods of time until the early 19th century, when industrial revolution took off. Pre-industrialization period can well be described referring to the provocative work by Thomas Malthus in 1789 – *"An Essay on the Principle of Population."* There, Malthus presents one of the initial attempts to explain the relationship between agricultural production, population growth, and sustainable development. Up to the late 18th century agriculture was the main source of income and production in the Old Europe. Living standards did not improve and people lived at subsistence levels of income. Malthus advocated the idea that disproportionate rates of growth in population exceeding that in food production would give birth to a state, where consumption- and income-per-person remain stagnant[21]. In what later became known as "Malthusian trap", any gains in production surpluses resulting from increased agricultural productivity and/or inputs would be concomitantly dispersed off by population growth.

The theory lends itself to three basic assumptions: that human needs food to sustain, that land used for food production is fixed, and that population growth is an inevitable natural process[22]. In contrast to Adam Smith (1776) and David Ricardo (1817), Malthus paid limited attention to technical advancements. He argued that even increasing capital in agricultural production would result in per-capita income that is no more than the subsistence level in the long run. Higher capital intensity would increase the agricultural labor productivity and wages in the short run only, which would then induce higher population growth. Because land is fixed, however, decreasing returns would resettle the economy back into equilibrium with subsistence (or even lower) level of wages.

In its simplest possible form, Malthusian production would be given by:

$$Y = f(K, N, \bar{L})$$

[21] Thomas Malthus assumed that population tend to grow geometrically, whereas amount of food produced grows arithmetically.

[22] Malthus puts it holistically as: "*…the passion between sexes is necessary and will remain in its present state.*" (Ch1.p4).

Where, output (Y) is produced using capital (K), population[23] (N) and fixed land ($\bar{L}$).

Abiding by Malthusian propositions, population is, in turn, determined by output:

$$N = \phi(Y)$$

Per capital output would then be:

$$y = f(k, \bar{l})$$

Because the production was mainly agricultural and because the key input in agricultural production was land, fixed in amount, combined return to capital and population would be diminishing as:

$$aY > f(aK, aN, \bar{L}) > f(K, N, \bar{L}) \qquad \forall \;\; a > 1$$

An important assumption is that population grows 'geometrically', whereas output growths 'arithmetically.' As a result of increase in K, change in per capita income would be:

$$\dot{y} = \dot{Y} - \dot{N} \leq 0$$

Increase in Y would be less than that in N because $L = \bar{L}$.

[23] I use the term 'population' to infer to 'labor' in this section.

Malthusian theory well describes the Old European economies characterized by mostly agricultural production[24]. For example, Gary Hansen and Edward Prescott (2002) evidence that real farm wage – a rough proxy for living standards, was roughly constant in the English economy from 1275 to 1800. Returns to land were closely and positively correlated with the population: land rents increased when population increased and decreased when population shrank. Oded Galor and David Weil (2000) present that per-capita income in European economies did not grow from 500 to 1500, while the population growth was barely 0.1 percent per annum.

Can Malthusian theory be applied to European countries only? The answer is 'not necessarily.' Several papers also suggest that stagnancy in growth was present in China for almost two millenniums. For example, according to Kao Chang (1986) wages in China stayed constant from the first to early nineteenth century. Dwight Perkins (1969) also discusses how growth in agricultural output was sluggish just to keep up with population growth in China for almost thousand years.

Malthusian theory can no longer be fit to the development patterns of countries in present time. Hansen and Prescott (2002) observe that starting from 1800 Malthusian theory no longer holds in case of the English economy. They present historical data for the United

[24] This is an important reason why I refrain from presenting the discussion of other influential works in Malthusian period such as Adam Smith's "Wealth of Nations" (1776) and, later, David Ricardo's "Principles of Political Economy and Taxation" (1817).

Kingdom which show that for the last two centuries both high labor productivity and high population growth coexisted, the value of land in production decreased substantially[25].

Despite Malthus' view on later improvements in societies was rather far skeptic than optimistic or, even, correct in predicting the world we are living in today, we find the underlying philosophy intriguingly relevant for the scope of this work for two reasons. First, it helps understand the possible causes of low or stagnant agricultural productivity even in the presence of increasing physical capital. Second, the very reason why Malthusian theory fails to explain the transformation from traditional economy to modern one – the technological change[26], makes it more consistent with stagnant and low standards of living in the Old European countries largely based on agricultural production with no technological improvements.

In what follows, we present the discussion of the role played by technical change in escaping the stagnant agricultural production and the industrialization of the countries that are rich today and how it can be relevant for the issue being raised in this work.

[25]Specifically, Hansen and Prescott (2002) report 22-fold increase in UK's labor productivity from 1780 to 1989 and almost 10-fold reduction in value of land as share of GDP from 88% in 1870 to 9% in 1990.

[26] Reading through Malthus, there is not a single word of 'technology' or a phrase of 'technological change' that I came across with.

1.3.2 Pre- and Post-Malthusian Technical Change

An important feature of neo-classical growth models, developed by Trevor Swan (1956) and Robert Solow (1956), is that in steady state per-capita income stagnates without technological growth. However, because of two key assumptions in the model, it can explain neither why income-per-person remained constant in the Malthusian period nor how the economies jumped into the post-Malthusian growth stage. First, Solow (1956) assumes constant population growth rates. But as discussed earlier, population in the Malthusian period was strongly correlated with the level of income. Second, and more importantly, technological change is entirely exogenous to the model. If technological change is determined outside of the system, seven-fold difference in income-per-worker between the Great Britain and China today must entirely be attributed to fortunate luck in favor of the British[27].

Existing theories closely associate the transition of the developed countries from the Malthusian stagnation with technological development, primarily, in agriculture. In fact, technical change can precisely explain why British economy recorded successive growth starting from the late 18th century, but China remained poor, despite both nations experienced constant subsistence level of income up to the Malthusian period. As Dwight Perkins (1969) describes, for centuries Chinese subsistence income was sustained due to

[27] Difference in income per-worker is calculated from World Development Indicators; constant 2011 prices and adjusted for purchasing powers.

increasing physical capital *e.g.* cultivated land and labor in agricultural production with traditional technologies that generally remained unchanged. On the other hand, Patrick Wallis, Justin Colson, and David Chilosi (2016) by collecting and analyzing old probate and apprenticeship data, conclude that until the beginning of growth period England's agriculture demonstrated strong and sustained productivity growth starting from the mid-17th century. They emphasize that industrialization would not be possible without substantial improvements in agricultural production. Moreover, historical data in Oded Galor and Davil Weil (2000) suggest that it was the technological change that deluded the decreasing trend in per-capita income in European countries in post Malthusian period.

So, what triggered the technical change in European agriculture? As pointed out earlier, propositions from the neoclassical models of growth are, generally, inconclusive about this question[28]. It was only from the late 1980's that when new growth theories emerged[29], and technical change was perceived to be endogenous, the scholars were able to conceptualize the transition from Malthusian stagnation to the growth phase. The key forces behind the European agricultural revolution are discussed to be adaptive learning in production (Arifovic *et al*, 1997), increasing returns to knowledge and labor (Jones, 1999), and mutual human capital-technology stimulation and demographic changes (Galor and Moav, 2001).

---

[28] Hansen and Prescott (2002) assume exogenous technical change in agriculture prior to industrialization. I will return to this issue soon.
[29] See, for example, Robert Lucas (1988), Paul Romer (1990), and Gene Grossman and Elhanan Helpman (1994) among many important others.

Arifovic Jasmina, Bullard James, and Duffy John (1997) are among the first to formalize the transition from stagnation to growth. Their model is characterized with two steady states: one with low income and one with high income. Economies satiate around the low-income state and engage into adaptive learning. Long period of learning eventually shifts the economy towards high-income state. Arifovic *et al* (1997), therefore, suggest that transformation from agriculture-based economy to industrial system is a long-lasting process. Their approach resembles that in Charles Jones (1999) in a sense that land is assumed to be a fixed factor of production in agriculture. Jones' work, however, differs by incorporating the property rights which give rise to increasing returns to knowledge and labor. He suggests that increased scale of population increases the probability of creating more advanced technologies and innovations. It is that increasing returns inevitably enable the escape from stagnation.

Later, Galor and Weil (2000) present more comprehensive theory explaining how countries move out from low- to high- agricultural productivity, and industrialization afterwards. Their model generates pseudo - Malthusian stage where income per worker remains constant due to fixed land/labor ratio *i.e.* decreasing returns to labor. Shocks to land/labor ratio or any technical change induce only temporary gains in productivity. These temporary gains in per-worker-income vanish once population growth increases. Malthusian pseudo-stage eventually fades out as a result of acceleration in technology growth because of larger scale of population. An important feature of Galor and Weil's model is reflected on how demographic changes succeed the accelerated technology growth. As in Theodore Schultz

(1964), where swift technical improvements increase the return to human capital, Galor and Weil impose ‘quality-quantity trade-off’ for parents. Utility maximizing parents invest into fewer children with more human capital than more children with less human capital. The demographical change entails further technical change which eventually increases the return to human capital. This vicious cycle enables the transition from low- to high-agricultural productivity, and subsequently, to the industrialization stage characterized with high rates of growth in income per worker and technologies, and slow to moderate population growth.

Hansen and Prescott (2002) show that transition from stagnation to growth can take place even if the technical change is assumed exogenous as in Solow (1956). Their model consists of two sectors that produce one good under different technologies: the first is the Malthusian technology where labor, capital, and land are used, and the second is the Solow technology where only labor and capital are employed. Initially, economy operates under Malthusian technology because Solow system is not profitable. Over time, there comes a point where the total factor productivity is sufficiently high that agents gradually start producing using Solow technology. Conceptually, Hansen and Prescott’s rationale resembles the learning-by-doing framework discussed in Arifovic *et al* (1997).

Despite theories widely differ in assumptions, specification of production technologies, and sequence of stages in historical economic transformation, they all have one profound commonality: industrialization in the developed countries followed the significant technological improvement in agricultural production. Accumulated knowledge and human capital development triggered productivity growth, *primitively,* in agricultural sector. Sufficiently high agricultural productivity enabled the reallocation of surplus resources and the factors of production into non-agricultural sectors.

It is, therefore, substantiated to point out that, from the historical perspective, there was no significant productivity gap between agriculture and non-agriculture in advanced countries in the early stages of development. Even if any, productivity gap did not embody vast opportunities for income gains because agriculture had already been productive and only relatively small share of labor was involved in the sector.

1.4. The Ex-ante Results and The Remaining Puzzle

In this section we discuss the part of APG that has remained unexplained or largely controversial in the empirical literature.

1.4.1. Measurement Issues Revisited

As discussed earlier, the role of statistical discrepancies may be immense, especially, in measuring the inputs and output in agricultural production. Despite Gollin *et al* (2014) show that for the sample of 10 developing countries results from micro household data and SNA are 'surprisingly' similar, no research has been carried out to show whether similar conclusions hold in case of majority of other countries.

To examine whether statistical discrepancies create illusionary high APG, two alternative sources of data are employed. First data originate from KLEMS[30], which provide internationally comparable data corrected for self- and family- employment as well as output measurements based on various household survey data at detailed industry levels (Kirsten Jäger, 2016; Marcel Timmer, Ton van Moergastel, Edwin Stuivenwold, Gerard Ypma, Mary O'Mahony and Mari Kangasniemi, 2007). The second source is the 10-sector database from the Groningen Growth and Development Center (GGDC) (Timmer, de Vries, and de Vries, 2015). There are two major advantages of GGDC dataset over national accounts data: 1) labor data are collected from labor force surveys at household and firm levels, and composed of all paid employees as well as self-employed and family workers in all sectors; 2) GGDC database corrects for periodic changes in coverage of economic activities, prices, and calculation methods, where otherwise national accounts typically lack in consistency.

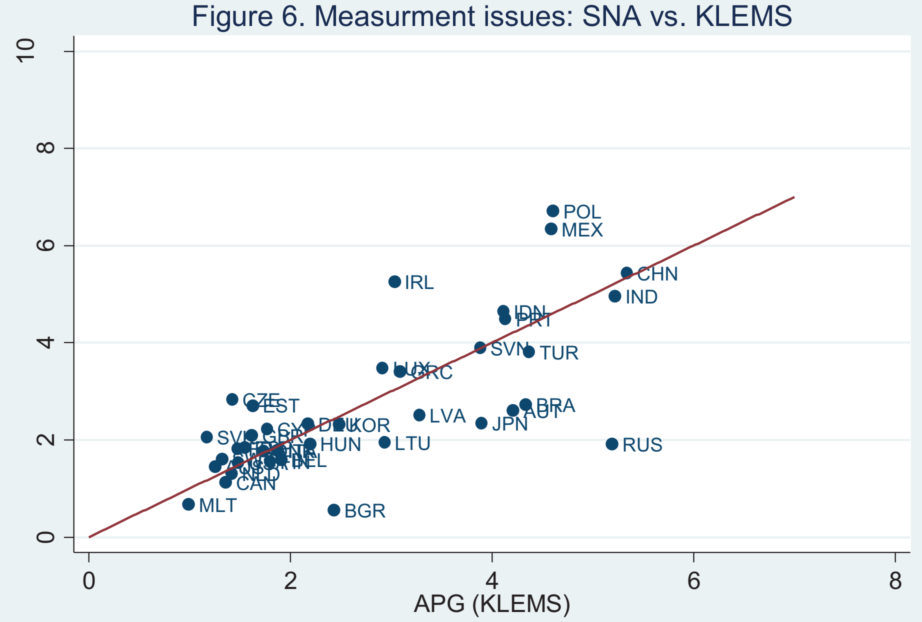
APG is measured as in equation (1). Using KLEMS data APG can be calculated for 38 countries. Data are available for 39 countries in the GGDC. The two samples overlap, and at the same time, differ in terms of countries' coverage. The results are presented in the Figures 5 and 6 below. Straight lines from the origin are drawn at 45-degree. APG (raw) implies to calculations from the National Accounts data.

---

[30] KLEMS project is intended to create a database on measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level for all European Union member states from 1970 onwards. A few countries from Asia have also joined the project under the Asia-KLEMS initiative.

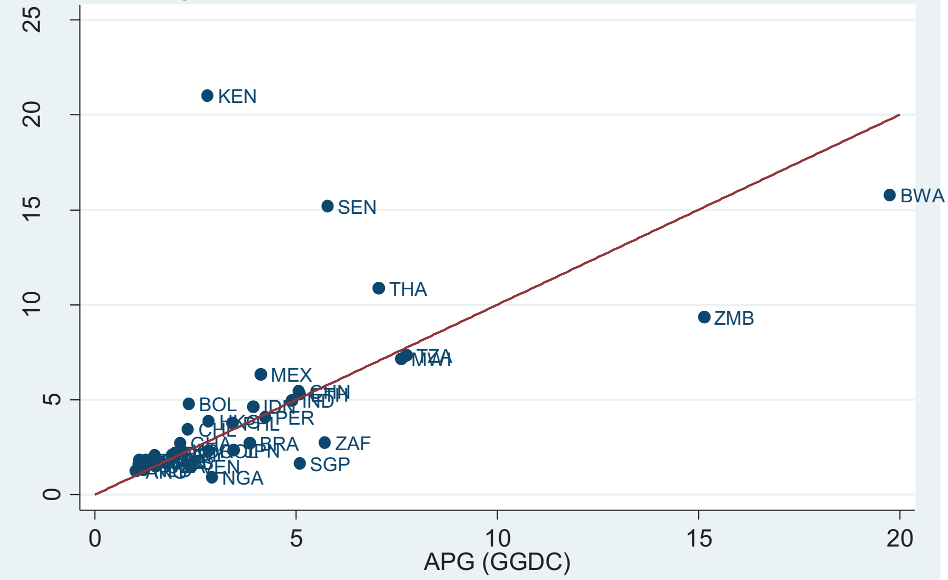
Pictures generally speak for themselves, but some points are worth emphasizing. For majority of countries, there is no significant divergence of APG calculated from the National Accounts and the alternative sources. In case of KLEMS, countries such as Russia, Japan, Austria, Brazil, and Bulgaria are assigned much higher APG's comparing to SNA. In contrast, raw APG seems to be overstated in case of Poland, Mexico, Ireland, and Czech Republic.

Figure 6. Measurment issues: SNA vs. KLEMS



Note: APG (raw) - implied APG by the National Accounts data; APG (KLEMS) - APG calculated from KLEMS data

Figure 7. Measurement Issues: SNA vs. GGDC



Notes: APG (raw) - implied by SNA data; APG (GGDC) - computed based on GGDC data

GGDC data expose noticeable divergences for four low income countries. For Kenya and Senegal APG reduces by, roughly, the factor of three. For Zambia and Botswana implied APG increases noticeably. These naïve country-wise comparisons imply that the problems related to statistics may seriously understate or overstate the APG. However, in aggregate terms, there are no large differences observed as summarized in the Tables 2 and 3.

Table 2. APG: National Accounts vs. KLEMS			
	APG (raw)	APG (KLEMS)	Number of Countries
Developing	3.17	3.32	18
Developed	2.28	2.22	20
Full sample	2.72	2.78	38
Non-weighted averages for 1995-2014.			

On average, APG slightly increases from 3.2 to 3.3 for the overlapping sample of 18 developing countries in the KLEMS data. Implied change is negative in case of GGDC dataset. For 30 developing countries that are common in SNA sample and GGDC sample, APG decreases by, average 0.6 units. However, productivity disparities are lower for developed countries when the alternative data are considered.

Results can be summarized as follows: a) APG implied by the National Accounts, on average, does not significantly differ from what is observed using alternative, more reliable, sources of data for the overlapping samples of developing countries. If any, the differences are negligible; b) APG calculated from SNA data seems to be slightly overestimated for the group of developed countries. However, again, the difference is small. These findings are consistent with Gollin *et al* (2014) for developing countries and Herrendorf and Schoellman (2012) for the US economy[31].

Hereafter, we continue by postulating that statistical discrepancies are much less important comparing to the observed magnitude of APG across countries. If the quality of data is not the main issue, what is next?

Table 3. APG: National Accounts vs. GGDC

	APG (raw)	APG (GGDC)	Number of Countries
Developing	5.31	4.65	30
Developed	1.8	1.6	9
Full sample	4.5	3.9	39

Non-weighted averages for 1995-2014.

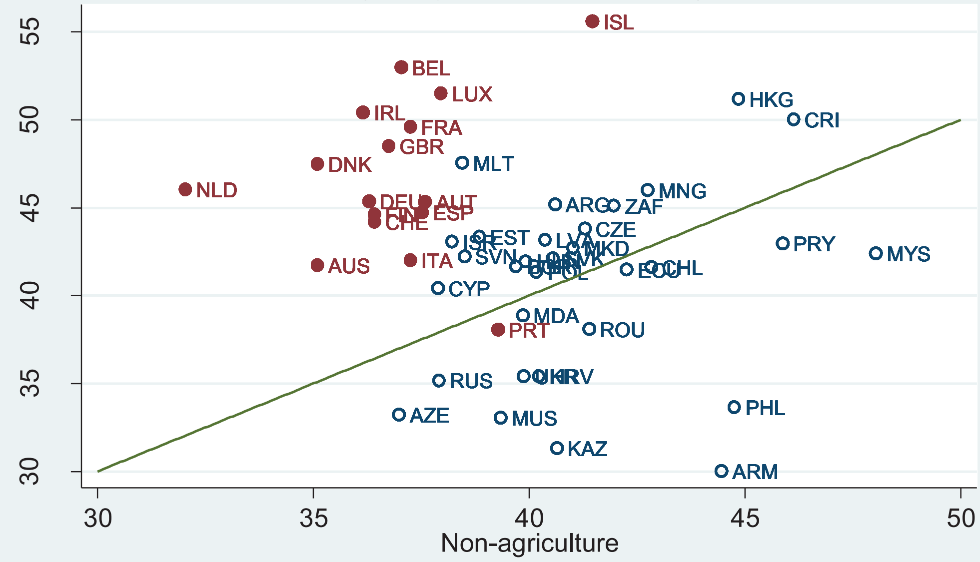
[31] One possible explanation for these conclusions can be, as mentioned in Gollin *et al* (2014), that the National Accounts data on employment and value added are largely based on household surveys.

1.4.2. Working Hours

In the 'home-production' models developed by Parente *et al* (2000) and Gollin *et al* (2004), because poor countries are typically characterized with large capital distortions, rural workers tend to switch from market activities to home production activities. In home productions despite a worker is classified into, for example, agricultural sector by her main job assigned, in fact, she may devote muss less time to agricultural production. So, are the working hours sufficiently high in non-agriculture that the differences can account for the APG?

To address this question, we collected data on average weekly working hours 'actually worked' per-employed in agriculture and non-agriculture. Data originate from household income and expenditure surveys, population censuses and labor force surveys from International Labor Organization. The sample consists of 47 countries from different income levels. The results are surprising.

Figure 8. Hours worked in Agriculture and Non-agriculture
(weekly, actual hours worked)



Source: calculated based on ILO data
Note: Developing countries are labeled with empty circles

Average weekly working hours in agriculture and non-agriculture are contrasted in Figure 8. The straight line from the origin represents the case when they are equal. Developing countries in the figure are labeled with empty circles.

Except Portugal, in all developed countries a typical person in agriculture works more hours weekly than her counterpart in industry and services. On average, employees in agriculture work around 45 hours a week. For almost half of the developing countries, hours worked in non-agriculture surpass that in agriculture. In some countries such as Azerbaijan and Russia, average working hours are less than 40 per week in both sectors.

When summarized, the ratio of working hours between non-agriculture and agriculture averages to 1.05 and 0.82 for the corresponding samples of developing and developed countries (Table 4). In the full sample, the difference is merely 5%. Overall, there seems to be no reason to believe that differences in working hours can be a significant factor for adjusting the APG's observed. If not the working hours and statistical discrepancies, where might such a huge labor productivity gap come from? This is where the most crucial, or perhaps intriguing, part of the story begins.

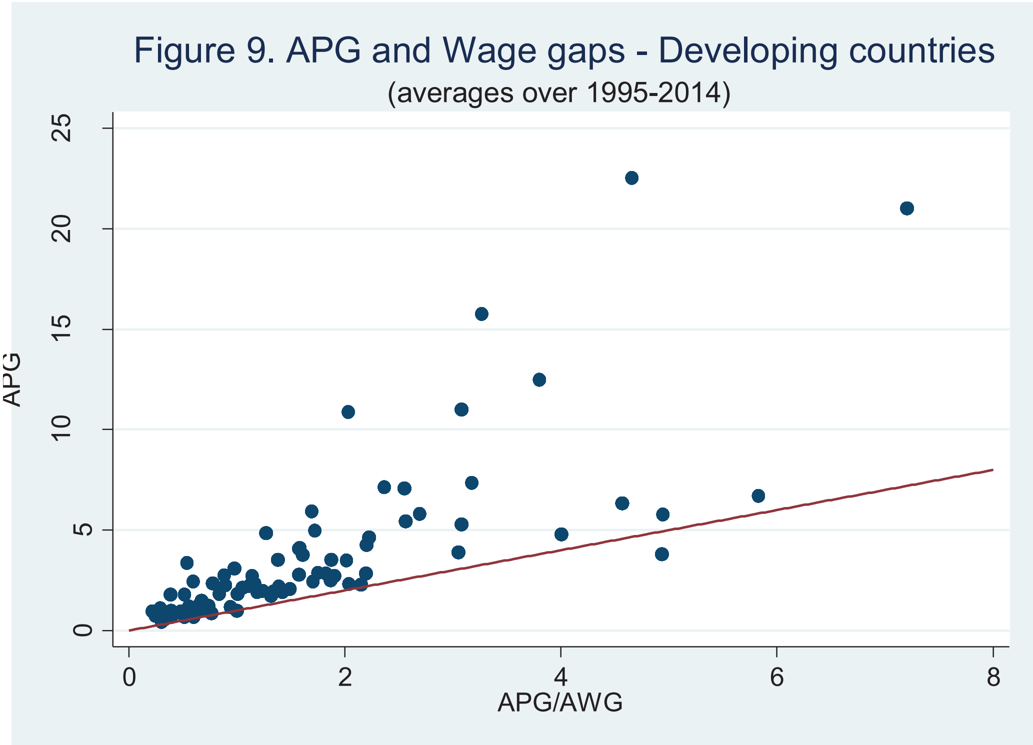
Table 4. Working hours		
	Ratio of working hours in non-agriculture to agriculture	Number of Countries
Developing	1.05	31
Developed	0.82	16
Full sample	0.95	47
Non-weighted averages for 1995-2014.		

1.4.3. Wage Gaps

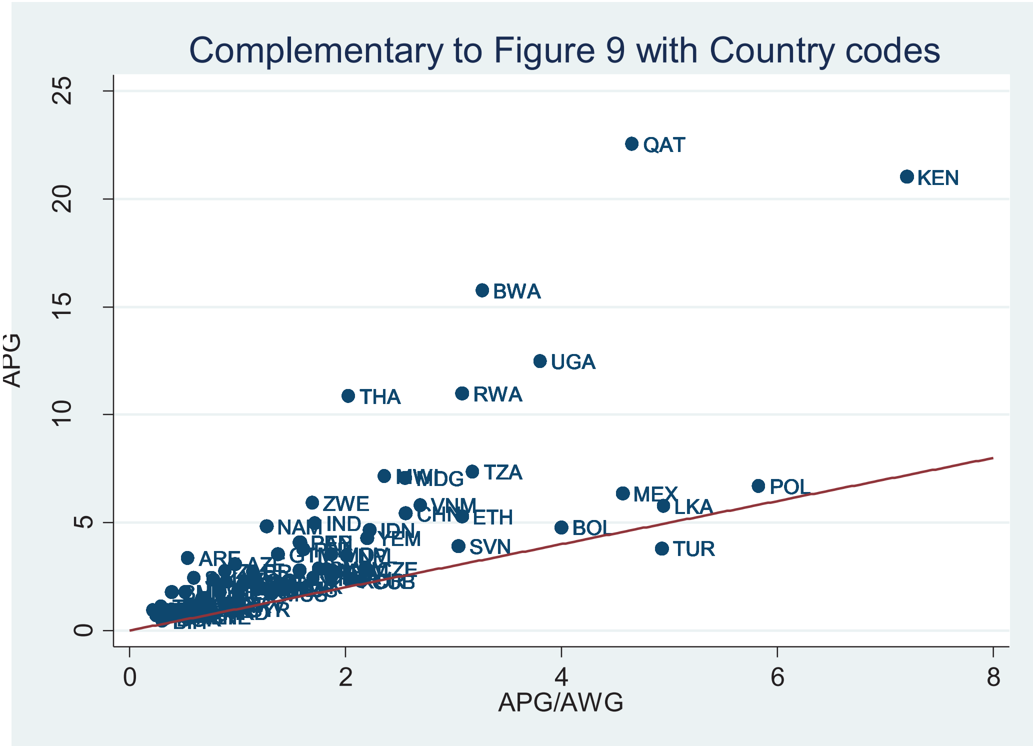
Can high ratio of labor productivities in developing countries be fully accrued to the ratio of human capital in non-agriculture to agriculture? Despite the conventional wisdom that the skill intensity of non-agricultural production is higher than that of agricultural sector, empirical data imply that differences in human capital can only account for a modest portion of the productivity gaps observed. In this section we discuss the wage gaps to elaborate more on the matter.

By theory, labor is paid its marginal product. Workers with high human capital receive higher wages. If no differences in human capital per worker exist, and if no barriers in factor markets prevent free mobility of labor, wages should be equal between non-agriculture and agriculture. In reality, the actual levels of human capital are different between the two sectors due to the nature of production, self-selection of workers based on observable and unobservable skills and traits (Caselli and Coleman, 2001; Lagakos and Waugh, 2013; and Young, 2013). Moreover, market frictions may also prevent the free labor movement between agriculture and non-agriculture or, similarly, rural and urban areas (Henderson, 2006; Munshi and Rosenzweig, 2016). The underlying message is that, the differences in human capital and all frictions can only explain the existing wage gaps between non-agriculture and agriculture, nothing more or nothing less.

Examining the observed wage gaps, therefore, delivers crucial insights into the contribution of skill differences and market frictions to the APG's implied by data. Should the average wage gap between non-agriculture and agriculture be sufficiently large to re-establish the accounting identity given by equation (4), there remains no more puzzle about the sectoral productivity disparities in the developing countries.

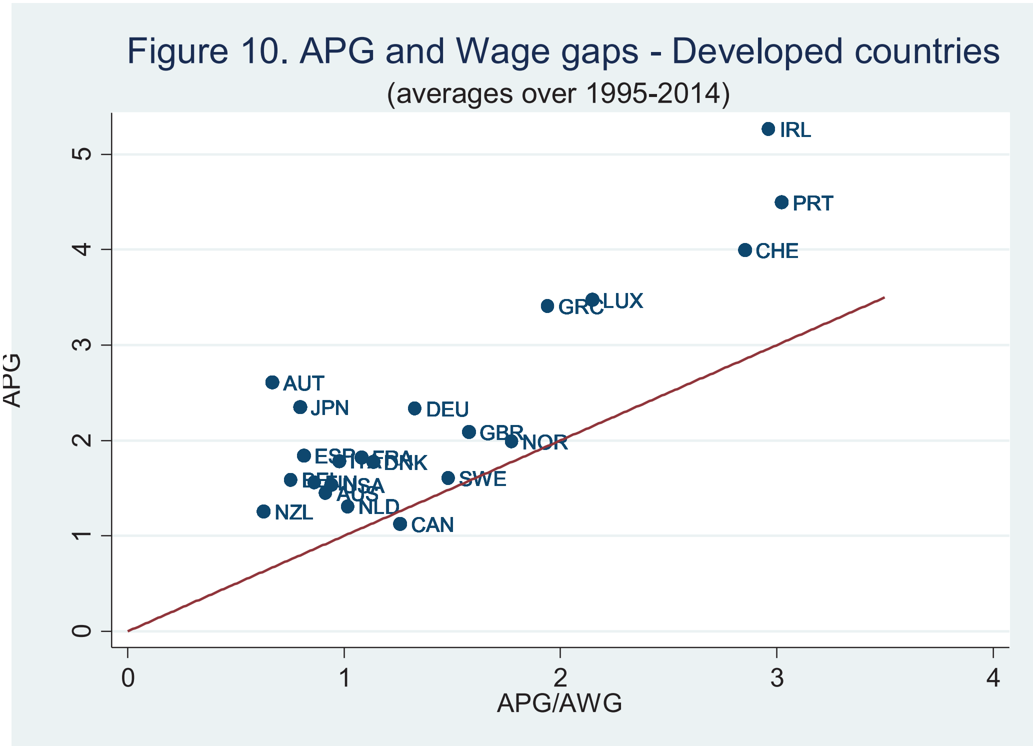


To perform this exercise, we collected the sectoral wage data available from ILO household surveys and KLEMS dataset. Wages are monthly, denominated in nominal terms, and represent the average earnings of employees. As in the computation of APG's, we categorize the activities related agricultural production, forestry, hunting, and fishing into 'agriculture', and the rest into 'non-agriculture.' Average wage gaps (AWG) are measured as ratio of average wages in non-agriculture to that in agriculture. Final wage sample includes 101 countries from all income levels. The stand-off between APG and wage-gap-adjusted APG's are shown in Figure 9 for developing countries and in Figure 10 for the developed. The straight lines from the origin represent the case when APG and wage-gap-adjusted APG are equal. In other words, in any given country on the straight line, the average earnings of employees are identical in agriculture and non-agricultural sectors.



Surprisingly, in all developing countries except Turkey, APG remains higher than that adjusted for wage gaps. Countries such as Qatar, Kenya, Botswana, Uganda, Rwanda, and Thailand with high APG's also exhibit high wage gaps. However, remaining productivity disparities are also high. In Botswana, for instance, wage gaps account for almost 80 percent of the APG, but labor productivity gap in non-agriculture/agriculture remains to be around 4-fold. For a few countries such as Poland, Bolivia, and Sri Lanka, large portion of APG can be explained by human capital differences and/or labor market frictions.

Similar conclusions can be derived for the case of developed countries. In Ireland, Switzerland, Greece, Luxembourg, and Portugal, on average, half of the APG can be accounted for the wage gaps. In Austria, Japan, Netherlands, and Belgium adjusted APG's are below one. It is only in Canada, as in Turkey, that average wages are higher in agriculture than in non-agriculture. In Norway and Sweden, among some others, average earnings are similar in the two sectors.



The summary of labor productivity gaps, wage gaps, and wage-gaps adjusted gaps are presented in Table 5. Speaking of the full sample, an average worker in industry and services are paid more than twice of the wage paid to an average agricultural worker. The wage ratio stands at the factor of 2.1 in developing countries. The gap constitutes a smaller factor of 1.9 in the advanced economies.

Table 5. APG and Wage Gaps					
	APG	Wage-gaps	APG/AWG	Number of Countries	Ratios of estimated human capital per-worker
Developing	3.9	2.1	1.9	79	1.3-1.5 (Gollin et al, 2014, Sample: 98 developing countries[32])
Developed	2.3	1.9	1.2	22	1.9 (Herrendorf and Schoellman, 2012: Sample: US)
Full sample	3.5	2.1	1.6	101	
Non-weighted averages for 1995-2014.					

Since the wage gap between agriculture and non-agriculture represents the combined effect of human capital differences as well as barriers to the migration of labor between the sectors, by comparing the wage-gaps in column 3 to the estimated human capital differences in Gollin *et al* (2014) for a sample of 98 developing countries and in Herrendorf and Schoellman (2012) for the United States in the last column of Table 5, two important conclusions can be reached. First, the barriers to free mobility of labor emphasized in number of papers such as Au and Henderson (2006) and Munshi and Rosenzweig (2016), can explain the anything between 1.5-1.7 differences in wage gaps, hence, only that portion of the productivity differences in the developing countries[33]. Second, there seems to be no

[32] Adjusting for schooling quality returns average 1.4 difference in human capital between non-agriculture and agriculture in Gollin *et al* (2014).

[33] Munshi and Rosenzweig (2016) studies the case of India, as discussed above, where rural-urban migration is especially high comparing to other developing countries of the same level of economic development and size. In my computations, estimated wage gap for India equals 3.2. This implies, information social insurance networks – 'castes' that are centralized in Munshi and Rozensweig can account for at most 47% of rural-urban gaps. Similarly, the internal migration restrictions in China as discussed in Au and Henderson (2006) can account for 68% of urban-rural wage gaps, at most.

barriers for labor mobility from agriculture to non-agriculture in the developed countries. Existing wage-gaps can be solely accounted for the differences in human capital.

1.4.4. The Remaining Puzzle

The accounting identity given by equation (4) above implies that any residual that remains after adjusting the APG to the average wage gaps should be accounted for by the ratio of labor shares of income in agriculture to that in non-agriculture. Calculations summarized in Table 5 reveal that even after adjusting for average wage gaps, there is a significant portion of APG that remains unexplained in the case of developing countries. In other words, the ratio of labor share of income in agriculture should be 1.9 times of that in non-agriculture.

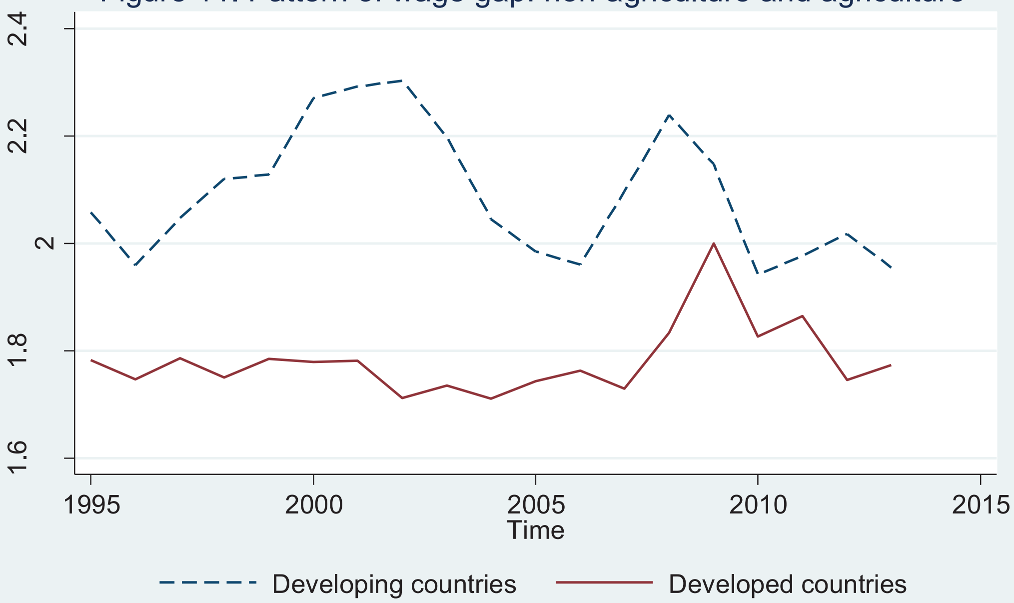
However, numerous independent estimates of the labor shares suggest that the labor share of income in agriculture is indeed smaller than that in non-agriculture, leaving the wage-gaps adjusted APGs puzzling. While Gollin *et al* (2014) suggest that labor shares cannot differ very much between agriculture 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. This claim is supported by, among others, a classic study by Hayami and Ruttan (1970) who 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.

Even if the labor shares are assumed to be equal, in the best scenario, the remaining 1.9 factor productivity gap in developing countries is simply too large to be an outcome of minor statistical discrepancies due to home production as suggested by Gollin, Parente, and Rogerson (2004) or exclusion of land rents from agricultural value-added and underreporting of proprietors' income in official statistics in the case of the US economy as in Herrendorf and Schoellman (2015).

It is hard to believe that overestimation of productivity gaps is the primary reason for the breakdown of the accounting identity in equation (4). Gollin *et al* (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 SNA data. According to their calculations, "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). More importantly, the puzzle is amplified by the pattern of APG over time. As illustrated in the Figure 5, the gap in the labor productivity between non-agriculture and agriculture has tended to increase in developing countries. Since the wage gap in the developing countries in Figure 11 has stayed relatively constant, even with little tendency to decline, over time, could it be that the statistical discrepancies worsened in the System of National Accounts? It is highly implausible to believe so.

Figure 11. Pattern of wage gap: non-agriculture and agriculture



Note: wage gap is measured as ratio of average nominal monthly earnings in non-agriculture to agriculture
Source: Calculated based on ILO data

Table 6 summarizes simple panel regressions of ratio of APG to wage gaps on time variable for the 'developing' and 'developed' samples. In case of the developing countries, since APG has increased and wage gaps have remained constant, the puzzling portion has increased over time. There is no statistically significant change in either APG or AWG in developed countries. Their ratio over time has remained relatively constant.

Table 6. APG/AWG over time

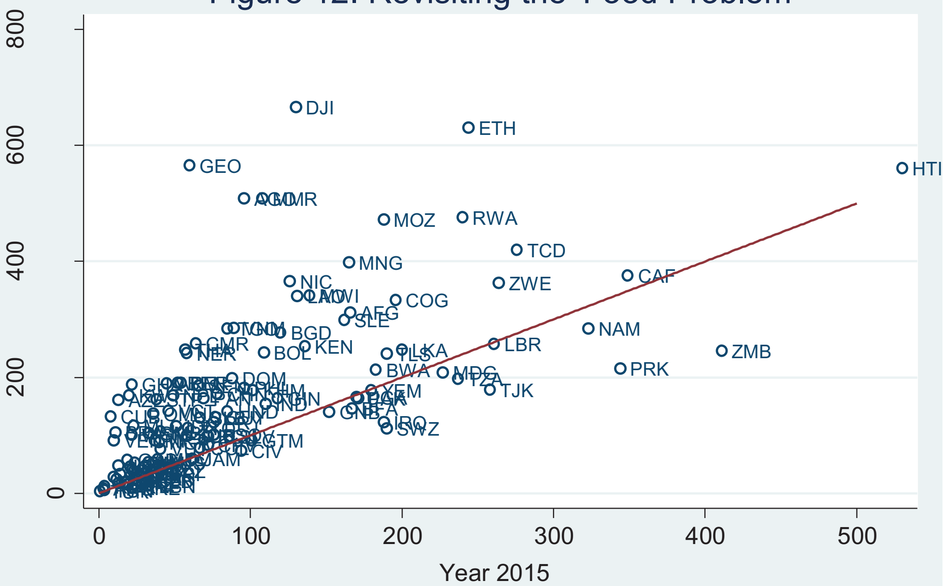
VARIABLES	Developing countries	Developed countries
Year	0.01***	-0.00
	(0.00)	(0.00)

	[0.00]	[0.93]
Constant	-16.37**	1.96
	(6.38)	(7.00)
Observations	743	206
Number of countries	79	22

Dependent variable is APG adjusted for wage gaps. Sample covers 1995-2014.
Standard errors in parentheses; p-values in square brackets
*** p<0.01, ** p<0.05, * p<0.1

Majority of models related to APG are built on the 'food problem' hypothesis by Schultz (1953). Is it possible that the 'food problem' has worsened? Figure 12 illustrates the change in the depth of food deficit, measured in kilocalories per day, in 106 developing countries from 1995 to 2015. Except some countries *e.g.* Tajikistan, Namibia, Zambia, Iraq, Swaziland, Tanzania, and few more, substantial improvements in the food deficiency can be observed in most of the developing countries. On average, the depth of food deficit has declined almost twice from 174 kilocalories in 1995 to 98 kilocalories per day in 2015.

Figure 12. Revisiting the 'Food Problem'



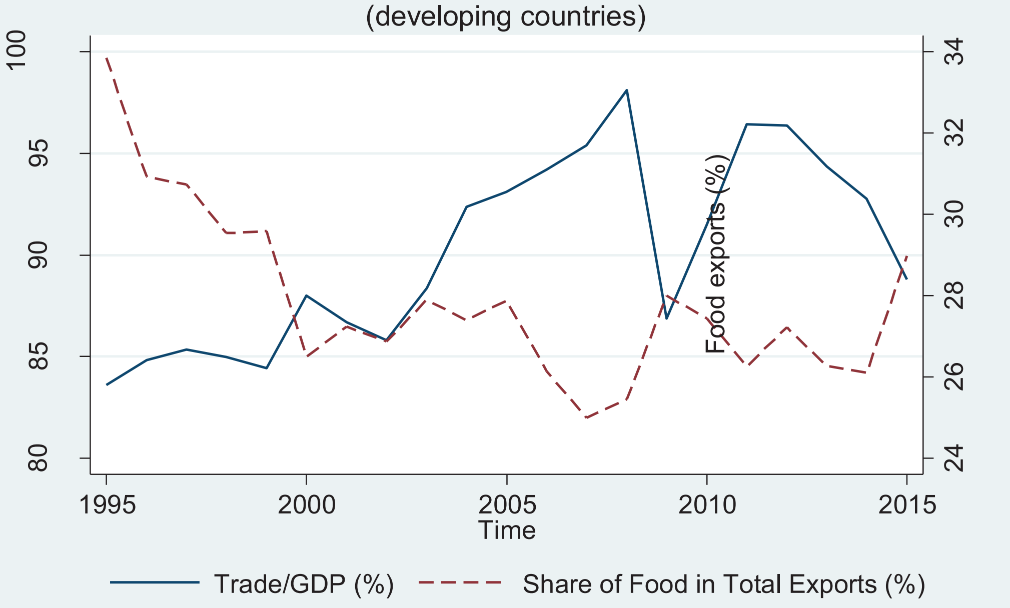
Note: Numbers represent the Depth of the food deficit (kilocalories per person per day)

Trade theories can also be related to the productivity differences in non-agriculture and agriculture. But data imply that incorporating the role of trade makes the puzzle even more intricate. Here is why: classical Hechscher-Ohlin trade theory in conjunction with Stolper-Samuelson theorem, suggests that agricultural productivity gap in emerging economies should decline as they get involved into more trade with the rest of the world. With relative abundance in unskilled labor and land, developing economies should export more agricultural goods. They should import more skill-intensive industrial products and services. Trade should increase the value of output and income-per-worker in agriculture. Countries tend to trade more over time, because trade increases income (see, for example, Jeffrey Frankel and David Romer, 1999). Demand induced increase in agricultural productivity should be followed by declining APG.

Indeed, participation of developing countries in global exchange of goods and services has intensified substantially for the last several decades. Economic borders have been greatly liberated from barriers to trade. From 1995 to 2013, applied tariff rates shrank almost threefold to 6.1% in developing countries. Share of trade in GDP has increased by average 10 percentage points during 1995-2015 (Figure 13). More importantly, the share of food in total exports of the developing countries has declined by 5 percentage points for the same period.

Figure 13. Trade and food exports

(developing countries)



Source: World development Indicators

In the case of developed countries wage gaps account for almost all the productivity differences across sectors, and that average wage gap itself is fully absorbed by the human capital differences without anything left for other frictions in labor markets. Slight residual in APG/wage gap ratio disappears when higher quality data from KLEMS and GGDC are considered, as shown above.

For developing countries, on the other hand, there is no way to explain the puzzle in APG except through labor shares of income in the sectors. Estimations from literature presented above that assign lower (or equal) labor shares in agriculture than (and) in non-agriculture seem highly susceptible. Many of them are based on the cost shares of inputs. However, as Fuglie (2010, p.65) points out, in case of most of the developing countries there is a lack of representative data on factor input prices, thus the estimated labor shares of income, since especially in agriculture, factor inputs are farm-supplied and date on labor wages and capital rents are not reliable. Estimating production functions and obtaining the elasticity of labor with respect to output is another typical method of measuring labor share of income. However, these estimates are not reliable due to some strict assumptions about production technologies and the underlaying market structures. Hayami and Ruttan (1970), for example, assumes that all 38 countries in their sample have same technologies and markets are perfectly competitive.

To comprehend how biased might the labor shares be depending on the estimation approach and type of data used, consider the example of China. When calculated using the KLEMS database, labor share of income in agriculture is 0.89. Since KLEMS data is corrected for home production and self-employment, and the share of the self-employed constitutes merely 10% in Chinese agriculture sector, there is less doubt on the reliability of the estimation. However, 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. However, Wu and Ito (2015) points out that the NBS data suffer from serious mismeasurement problems. Bai and Qian (2010), after making several adjustments to the NBS data, find that the share of labor income in agriculture ranges from 0.86 to 0.92, which roughly matches the estimate of 0.89 from the KLEMS data.

Lastly, Gollin *et al* (2014) argue that the ratio of labor share of income in the accounting identity given by equation (4) constitutes a unity based on the stylized fact about the '50-50 split' rule that is universally common in share tenancy output sharing arrangements in agriculture. However, Otsuka, Chuma, and Hayami (1992, p.1969) points out that the '50-50 split' rule has no rationale grounds representing optimal allocation of output since the contributions of land and labor are explicitly different within different production technologies. In developing countries, where contract institutions are typically weak, the arrangements on agricultural labor compensation are mostly based on social linking and negotiations. Therefore, the '50-50 split' rule is most likely a sociological phenomenon rather than an efficient economic arrangement that can be applied to the empirical puzzle in both the magnitude and the pattern of APG in developing countries.

In conclusion, except attributing the remaining 1.9 factor gap in the sectoral labor productivity levels in developing countries to the ratio of labor shares of income, there is no other viable way of solving the puzzle. In fact, calculating the labor shares using the KLEMS database for a feasible sample of countries leaves nothing unexplained in the APG's observed. The moderately increasing trend of APG can also be captured by the increase in the ratio of labor shares of income. Large and increasing labor shares ratio is, in turn, can be related to the technologies that are transferred into developing countries from abroad. All these are achieved in the Chapter II.

Chapter II

Comparative analysis of the historical transition of the developed countries from agriculture-based systems to industrialization revealed that APG is not just a matter of economic transformation. The advanced economies did not necessarily exhibit high productivity disparities between traditional and modern sectors at the early stages of development because agriculture was sufficiently productive before the industrialization stage thanks to the substantial improvements in production technologies associated with human capital development and innovations. Contrarily, due to the accessibility of technologies from more developed countries, less developed countries tend to jump into the industrialization stage at the cost of delaying any significant improvements in the agricultural production, where most of their unskilled labor is stuck.

This chapter aims to achieve three sequential objectives. The first is to demonstrate that wage-gaps adjusted APG's in developing countries can fully be attributed to the ratio of labor shares of income in agriculture and non-agriculture. Recalling that the pattern of wage-gaps is relatively constant (Figure 11), all of the puzzling portion of APG and its increasing trend must, therefore, be captured by the magnitude and the changes in labor shares ratio. By conducting a simple accounting exercise, it is also shown that, after controlling for capital intensities, the changes in the APG can only be accounted for by the relative technical changes in agricultural and non-agricultural productions. Second, based on empirical data on technology imports, it is argued that technical change in developing countries, which takes place primarily due to technology transfers from abroad, which is strongly biased in favor of non-agricultural sectors. Finally, in the last section, the relationship between relative technical change in the sectors and APG is formalized into a two-sector, two-goods model by incorporating the heterogeneity in skill levels of labor. Key proposition from this chapter implies that biased and increasing imports of technology imports is an important determinant of sectoral productivity disparities observed in the developing economies.

2.1. Reinstating the Technical Change

Labor productivity is a simple ratio of value added to the number of workers in a sector. Value added in each sector is the total income of labor, capital, and technologies employed. Controlling for wage-gaps, high and increasing APG, given by equations (3) and (4), imply that the portion of per-worker value added in non-agriculture that is not accrued to labor should be high and increasing relative to that in agriculture.

$$\frac{APG}{w_n / w_a} = \frac{LS_a}{LS_n} = \frac{1 - share\,of\,Value\,added\,accrued\,to\,Kapital\,and\,Techno\log y\;\;in\,Agriculture}{1 - share\,of\,Value\,added\,accrued\,to\,Kapital\,and\,Techno\log y\;\;in\,Non-Agriculture}$$

In our concomitant work, Jong-il You and Sirojiddin Juraev (2017a), we show that the unexplained part of the APG can be fully accounted for by the ratio of labor shares (LS_a/LS_n), when more alternative data from the KLEMS are used.

We compile internationally comparable data on sectoral value added, labor compensation and capital compensation for 32 countries from the KLEMS sources. Eleven countries fall into the 'developing' sample, whereas the rest are in the sample of developed countries. Comparing to the national accounts data, factor compensation measures in KLEMS are much more reliable as they make up for the compensation of the self-employed through imputations, where hourly wages of the self-employed are predicted based on the hourly wages of the employees by controlling for educational attainment, gender and age of the workers (O'Mahony and Timmer, 2009). Also, KLEMS data allow for the direct computation of the sectoral labor shares for individual countries without estimating production functions under strict and generalized assumptions.

Calculated APG's, aggregate labor shares, labor shares in agriculture and non-agriculture, estimated wage-gaps, as well as wage-gaps and labor shares adjusted APG's are reported in Table A4 in Appendices. For many countries the sample period varies depending on the availability of data. Agriculture labor shares are calculated as the ratio of labor compensation in Agriculture, Forestry, and Fishing to the total value added in those sectors. Labor shares in non-agriculture is calculated in the same way. Whereby, non-agricultural value-added and labor compensation are found by subtracting the agricultural labor compensation and value-added from total labor compensation and value-added in the economy.

By the accounting identity in equation (4), the APG adjusted for wage gaps and labor shares ratio should be unity for any country. At first sight, for 13 countries in Table A4, the identity seems to hold quite well when the accuracy is arbitrarily set at 10% level[34]. More importantly, in case of the remaining 19 countries in the sample residuals from the adjusted

[34] India, Finland, Malta, Germany, Great Britain, Greece, Latvia, Netherlands, Belgium, Cyprus, Russia, Australia, China.

APG exceeds the 10% critical level. The primary reason for the failure to establish the accounting identity for majority of the countries in Table A4 is related to the mismeasurement of the labor compensation data, as we show in You and Juraev (2017a). The measurement errors are found to be the direct consequence of presence of the self-employed in both agriculture and non-agriculture. When a predominant portion of labor in any sector is self-employed, the imputed wages in the KLEMS data cannot incorporate for all unobservable characteristics of the workers. As O'Mahony and Timmer (2009) point out, due to the absence of data on more comprehensive characteristics, the wage imputations in KLEMS should be considered cautiously. Labor shares being unrealistically high, exceeding unity, in some cases reported is a clear evidence of the very mismeasurement issue.

The lower the share of self-employed in a sector, the higher the accuracy of the wage-imputations, thus, the higher the reliability of computed labor share for that sector should be. To test this proposition, in You and Juraev (2017a), we select five countries (China, Czech Republic, Malta, Slovakia, and Russia) from the sample where the share of employees exceeds 80% of labor in both agriculture and non-agriculture. Indeed, we find striking evidence that these countries do not exhibit any significant divergences from unity in APG's adjusted for wage gaps and labor shares ratio. The fully adjusted productivity gaps range from 0.97 on the lower end to 1.16 on the higher[35]. It is equally important to

[35] Computed APG/Wag Gap/Labor share ratio constitutes 0.97 for Malta, 1.07 for Russia, 1.09 for China, 1.11 for Slovakia, and 1.16 for Czech Republic.

point out that for three of these countries, estimated labor shares in agriculture is higher than that in non-agriculture. This finding contradicts most of the empirical estimates that consistently assign relatively lower labor shares to agricultural sector as discussed in the previous chapter. No grounds, thereof, remain to believe that labor shares in agriculture is universally lower than in industry and services for all countries, where the differences in production technologies may be significant.

Sample averages of fully adjusted productivity gaps for developing and developed countries are reported in Table 7. Overall, when more reliable data on labor shares ratio are used, the puzzle in the wage-gaps adjusted APG's vanishes to a significant extent. It almost completely disappears for the sample of less developing economies.

Table 7. Summary of Labor Shares (KLEMS) and Adjusted Productivity Gaps

Sample	LS_a	LS_n	LSG (LS_a / LS_n)	$APG / wage\ gap$	$\frac{APG / wage\ gap}{LS_a / LS_n}$	Number of countries
Developing	0.84	0.54	1.56	1.63	1.04	11
Developed	0.79	0.62	1.27	1.43	1.12	21

Source: Jong-il You and Sirojiddin S. Juraev (2017a)

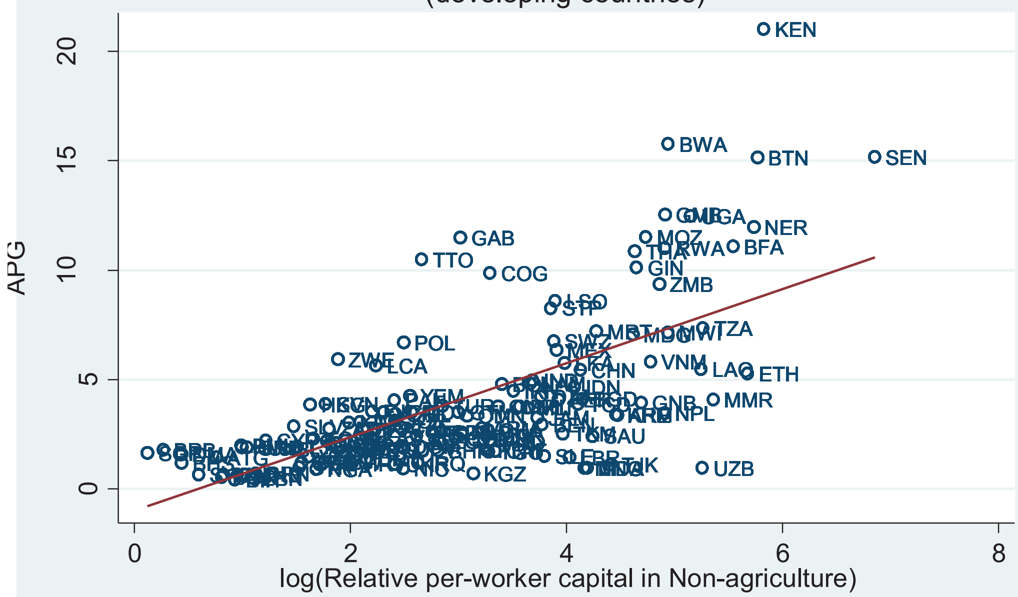
Increasing pattern of APG in developing countries imply that the ratio of labor shares (LS_a/LS_n) must be increasing. In other words, the share of labor compensation in agriculture must be increasing and/or that in non-agriculture must be decreasing. Earlier, in the beginning of this section, the difference between value added and labor compensation is decomposed into compensation for capital and compensation for technologies in each sector. To understand whether the increasing labor shares ratio (LS_a/LS_n) is a consequence of the increasing capital and/or technology intensity in non-agriculture relative to agricultural production, it is necessary isolate the per-worker-income of capital and technologies from each other and observe their pattern over time.

In practice, capital more freely moves across sectors comparing to labor. The return to each dollar value of capital can, therefore, be assumed equal between agriculture and non-agriculture. By calculating the per-worker-capital ratio between the sectors and analyzing its trend over time, one can roughly see whether labor shares ratio portion of APG has changed due to changes in the relative capital intensities, or not.

To undertake this raw accounting exercise, the data on the physical capital stocks for agriculture are obtained from the Food and Agriculture Organization's (FAO) databases. Agriculture is composed of agriculture, forestry, and fishing activities. Observations are made internationally comparable by reconciling them into ISIC Rev.3 classifications. Based on country characteristics and statistics from OECD and the UN, FAO provides calculations on the agricultural capital stock using traditional perpetual inventory method. Non-agricultural capital stock is computed by subtracting the agricultural capital stock from aggregate capital stock in the countries. The estimates of the aggregate capital stock are available from the World Penn Tables. As in FAO methodology, aggregate capitals are also calculated using perpetual inventory methods by applying relevant depreciation rates to the distinguished the types of assets (Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer, 2015). Sample with relevant capital stock data for the period of 1994-2014 consists of 164 countries from all income levels.

Calculated relative capital intensities are depicted against observed productivity gaps in Figure 14[36]. Straight line represents the linearly estimated best-fit estimation. There seems to be a weak, but positive relationship between capital and labor productivities. Countries represented by the largest magnitudes of APG's such as Senegal, Botswana, Kenya, Bhutan, and Burkina-Faso also exhibit largest gaps in per-worker capital in non-agriculture to agriculture. At the same time, in the countries where the productivity disparities are similar, for instance, Uzbekistan and Kyrgyzstan, significant variations are present in the ratios of per-worker-capital levels.

Figure 14. APG and Relative per-worker capital intensity
(developing countries)



Notes: averages over 1995-2014.

---

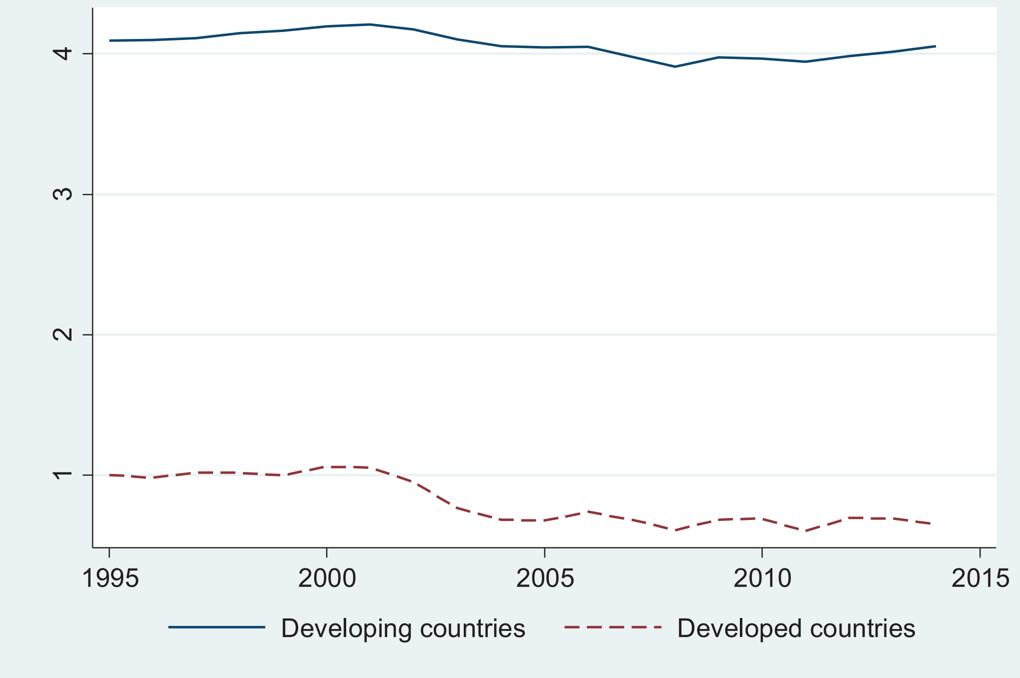
36 Illustrating the wage-gaps adjusted APG's instead does not alter the conclusions significantly.

Inferences from Figure 14 partially vindicate the findings in Caselli (2005) and Lagakos and Waugh (2013) in a sense that capital intensities cannot account for large portion of the productivity differences.

The pattern of the capital-per-worker ratios over the sample period is illustrated in Figure 15. The vertical axis measures the natural logarithm of the ratio of capital-per-worker in non-agriculture to that in agriculture.

The difference in relative capital intensity is overwhelmingly large in the developing countries. In fact, the difference translates into 55-fold! The gap is around the factor of 2.5 in the case of developed economies. More surprisingly, the relative capital intensities have remained relatively constant in both samples!

Figure 15. Ratio of per-worker-capital in non-agriculture to agriculture



In per-worker terms, the stable relative capital intensities imply that the changes in the labor shares ratio can only be explained by the relative technical changes in non-agricultural and agricultural production technologies. Controlling for physical capital, labor, and land, Caselli (2005) also demonstrates that a significant portion of labor productivity gap in agriculture can be accounted for by total factor productivity differences in developing countries. Restuccia *et al* (2008) show that the barriers to adoption of intermediate inputs can be an important determinant of sluggish labor productivity growth in agriculture. In Juraev and You (2017b), we highlight the role of output market imperfections defined by monopoly powers resulting from technical change in non-agricultural sectors to explain the changes in relative labor shares.

The key finding from the accounting exercise in this section is that the rate of technical change is more intense in non-agriculture comparing to that in agriculture. In what follows next, a brief implication of endogenous growth theory shows that technical change in developing countries take place, mostly, due to adoption of technologies from developed countries. Empirical data on imports of technologies and equipment present solid evidence on the bias observed in favor of non-agricultural sectors.

2.2. The Observed Bias

The importance of technologies for development has gained immense attention in the endogenous growth literature (Romer, 1993; Prescott, 1998, among many critical others). One important pillar of the endogenous growth theories distinguishes how technical change takes place in the rich and the poor states. Accordingly, extensive stock of available technologies and knowledge enables the rich states to produce most of the new technologies, whereas the technical change in the poor countries takes places, primarily, though the transfers from the more technologically advanced states. Acemoglu and Zilibotii (2001) observe that over 90% of world R&D expenditures came from the OECD countries in 1997. Similarly, according to World Development Indicators, as of 2011, over 65% of the total number of new patents, and two-third of global high-tech exports originate from the advanced states.

In empirical research, measuring the level of technologies or technology transfers remains to be a challenging task. Technologies are, generally, believed to move across countries through trade, foreign direct investments (FDI), licensing, franchising, and many other channels. The measurement problem is due to the abstractness or embodied nature of technologies. In this work, technology transfers are measured directly as imports of machineries and equipment, classified under SITC 7 of United Nations Conference on Trade and Development (UNCTAD)[37]. For the last two decades, imports of machineries and equipment constitute roughly one third of total imports by developing countries. One key advantage of using SITC 7 is that it provides detailed categorization of machineries and equipment imported. The subsection 72, for instance, distinguishes the technologies

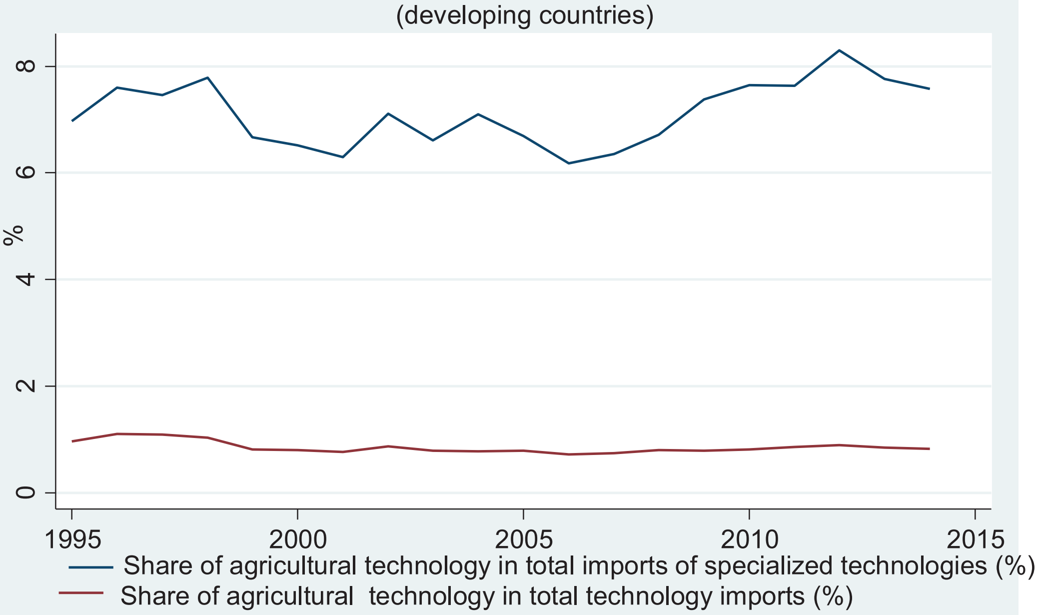
[37]More on the measurement issues are discussed in the third chapter.

imported for agricultural production from those for non-agricultural sectors. This allows to observe the relative intensity of technology transfers in the sectors.

Changes in the ratios of agriculture specialized technology imports to total sector-specialized (SITC 7, Subsection 72) as well as total machinery and equipment imports (SITC 7) are presented in Figure 16. Observations imply that, during the sample period, over 90% of the total sectors-specialized technology imports were specialized for non-agricultural production, whereas less than 10% was for agricultural use. Share of agriculture-specialized technologies make up mere 1% of the total imports of machineries and equipment by developing countries.

Figure 16. Bias in technology transfers implied by data

(developing countries)



Note: Calculated based on UNCTAD data

Investments into technologies, irrespective of whether into their development or adoption, are endogenous *i.e.* driven by profit-maximizing incentives for firms (Romer, 1990; Grossman and Helpman, 1994). More new technology adoptions in a sector imply that the share of income going to capital owners, rather than workers, tend to increase. Since relative capital intensities have remained constant, as shown above, any change in the portion of APG represented by the ratio of labor shares must be associated with relative technical change through technology transfers, which is found to be significantly biased in favor of non-agricultural production according to the empirical data.

The primary explanation to the observed bias originates from the technology-skill complementarity hypothesis, which claims that technical change tends to favor the more-skilled rather than the less-skilled workers. The earlier roots of the hypothesis can be traced back to 'The Theory of Wages' by John Hicks (1932). In the concept of elasticity of substitution between production factors, Hicks emphasized the increasing scale of 'labor saving' technologies developed. In response to increasing costs of labor – what Hicks observed in the 1930's, profit-seeking firms tend to introduce inventions that carry relatively higher marginal product/cost ratio. 'Labor-saving' technologies increase the marginal product of capital relative to labor and discriminates a subgroup of labor out of production. Not surprisingly, the group of less-skilled labor becomes the primitive victims of such a continuous process. Increasing scale of factor-cost-induced technological progress eventually results in increasing productivity gap between more-and less-skilled workers.

The technology-skill complementarity hypothesis has been preponderantly discussed in literature. For example, by formulating labor demand as basic constant elasticity of substitution function of more- and less-skilled workers, Violante (2008) shows that biased technical change increases the productivity of more-skilled labor, which further increases the demand for such workers. The process turns cyclical. His model well fits into the observed data. Similar concepts underlie in Acemoglu (2002) and Galor and Moav (2000).

Implication of technology-skill complementarity hypothesis to the impact of technology transfers on agricultural productivity gap in developing countries evolves threefold. First, since the production in non-agriculture is of more skill-intensive nature, available technologies embody skilled workers. Available stock of skills allows the adoption of new, usually men-power-saving technologies. Second, there is discrimination of labor with various skill levels in each sector. Decisions on how many of the skilled and unskilled labor to employ are made by rational, profit maximizing producers. Finally, due to the availability of relatively more skilled labor in non-agriculture, technology transfers tend to be biased in favor of that sector. The vicious cycle kicks in, where better technologies allocate more of skilled labor into non-agriculture and this further intensifies the bias in the relative technical progress. In each stage of the vicious cycle there is equilibrium where agricultural productivity gap is determined by the inter-sectoral division of, heterogenous in skills, labor as well as existing skill premium. These propositions are formalized in a simple model in the following section.

2.3. The Model

Consumers

Economy produces two goods: agricultural (Y_A) and non-agricultural (Y_N). There are M individuals with homothetic and quasi-concave preferences. Individual utilities (u_i) are represented by following constant elasticity of substitution (CES) function:

$$u_i(A,N) = \left(\alpha Y_N^{\gamma} + (1-\alpha)Y_A^{\gamma}\right)^{1/\gamma} \quad (1)$$

Where, α is the share of non-agricultural good, $\gamma = (\chi - 1)/\chi$ and χ is elasticity of substitution between Y_A and Y_N. If $\chi = 0$ goods are perfect complements; if $\chi = \infty$ consumers perceive the products as perfect substitutes, and with $\chi = 1$ utility function simplifies to the popular Cobb-Douglas form. Hereof, χ is assumed to be less than 1 implying that agricultural and non-agricultural goods are 'gross complements[38]' for consumers. Despite there is no empirical estimation of χ within this specific context, consumers purchase food (agricultural) and non-food (non-agricultural) goods in conjunction, hence, these goods rather complement each other. This assumption plays an important role in later sections.

[38] Term 'gross complements', as in Acemoglu (2002), implies to the case when elasticity of substitution between factors of production is less than unitary. Similarly, 'gross substitutes' refer to elasticity of substitution being higher than 1.

Markets are perfectly competitive and prices (p_N, p_A) are exogenously determined. Equilibrium levels of Y_A an Y_N maximize:

$$\int_1^M u(A,N)(i)di \qquad (2)$$

First order conditions imply:

$$\left[\frac{Y_N}{Y_A}\right]^* = \left[\frac{p_A}{p_N}\frac{\alpha}{1-\alpha}\right]^\chi \qquad (3)$$

It can simply be shown that $\partial(Y_N / Y_A)/\partial(p_N / p_A) = -\chi$, i.e. relative increase in the prices of any good decreases its aggregate relative demand.

Producers

There are two sectors in economy: agriculture and non-agriculture. Producers in each sector employ any combination of skilled (S) and unskilled (U) labor. We stick to 'the conventional wisdom' that production in non-agriculture is assumed to be more skill-intensive than that in agriculture[39].

Production functions are in generalized CES forms:

$$Y_A = A\left(a(A_A S_A)^\rho + (1-a)U_A^\rho\right)^{1/\rho} \text{ and } Y_N = A\left(n(A_N S_N)^\rho + (1-n)U_N^\rho\right)^{1/\rho} \qquad (4)$$

[39] See, for example, Caselli (2005).

Where A sums the pervasive technologies available universally across sectors; a and n are shares of skilled labor in production; A_A and A_N are technologies that are sector specific and augment the skilled labor only. S_A (U_A) and S_N (U_N) are number of skilled (unskilled) workers in agriculture and non-agriculture, respectively. $\rho = (\sigma - 1)/\sigma$, where σ is the elasticity of substation between skilled and unskilled labor in production, assumed to be same in both sectors for simplicity. It is further assumed that $\sigma > 1$, which implies producers treat skilled and unskilled labor as gross substitutes. This assumption is not only intuitionally plausible but also in compliance with available empirical estimations on elasticity of demand between educated and uneducated workers[40].

Marginal products in each sector are positive ($\partial Y / \partial S >> 0$ and $\partial Y / \partial U >> 0$) and there are diminishing returns to factors of productions ($\partial^2 Y / \partial S^2 << 0$ and $\partial^2 Y / \partial U^2 << 0$). Pervasive technological improvements increase the marginal product of both skilled and unskilled workers, whereas sector-specific skill-biased technical change improves the productivity of the skilled in each sector.

There are two rather complementing assumptions. First, there is free mobility of labor in and across sectors. Second, in equilibrium wage rate for the skilled is identical in both agriculture and non-agriculture. Same is true for the unskilled. Intuition behind this assumption is straightforward: if a skilled worker in agriculture is paid higher wage than

[40] See, for example, Richard Freeman (1986). Elasticity of substitution between skilled and less skilled workers is estimated to be in the interval of 1 and 2.

his counterpart in non-agriculture there will be flow of skilled workers into agriculture from non-agriculture until differences in wages are dispersed off.

Labor supply is assumed to be fixed, so is the total number of the skilled and the unskilled workers. Total number of the skilled and the unskilled is divided between the two sectors and there is full employment:

$$\begin{aligned} w_S &= w_{S_A} = w_{S_N} \\ w_U &= w_{U_A} = w_{U_N} \\ \overline{S} &= S_A + S_N \\ \overline{U} &= U_A + U_N \\ \overline{L} &= \overline{S} + \overline{U} \end{aligned} \qquad (5)$$

Without the loss of generality, number of producers in each sector is normalized to unity. Given above assumptions, producers face following optimization problem to produce Y_A and Y_N demanded by consumers:

$$\max\,[pY - (w_S S + w_U U)]$$

First order conditions provide relative demand for S and U in each sector.

$$\left(\frac{S}{U}\right)_A^* = A_A^{\sigma-1}\left[\frac{w_U}{w_S}\frac{a}{1-a}\right]^{\sigma} \qquad (6)$$

$$\left(\frac{S}{U}\right)_N^* = A_N^{\sigma-1}\left[\frac{w_U}{w_S}\frac{n}{1-n}\right]^{\sigma}$$

There are three implications of the derived relative demand equations. First, increasing cost of unskilled labor increases the relative demand of skilled labor. Second, skill-biased sector-specific technological change increases the demand for skilled workers in both sectors since $\sigma > 1$ (relative demand for skilled labor is elastic with respect to relative wages). Third, denoting *I=S/U* as a measure of skill-intensity in the sectors, relative wages for skilled and unskilled workers are irrelevant for relative skill intensities (I_A/I_N), which on the other hand is in positive relationship with relative sector-specific skill-biased technology levels (A_A/A_N):

$$\frac{I_A}{I_N} = \left(\frac{A_A}{A_N}\right)^{\sigma-1}\left[\frac{a}{n}\right]^{\sigma}\left[\frac{1-n}{1-a}\right]^{\sigma}$$

With constant returns to scale in production, applying Euler's law of zero profits and equal equilibrium wage conditions in (5), intersectoral division of labor can be formulated in terms of relative prices and sector-specific technologies as:

$$\left(\frac{S_N}{S_A}\right)^* = \left(\frac{P_N}{P_A}\right)^{\sigma-\chi}\left(\frac{A_N}{A_A}\right)^{\sigma-1}\left(\frac{\alpha}{1-\alpha}\right)^{\chi}\left(\frac{n}{a}\right)^{\sigma} \qquad (7)$$

$$\left(\frac{U_N}{U_A}\right)^* = \left(\frac{P_N}{P_A}\right)^{\sigma-\chi}\left(\frac{\alpha}{1-\alpha}\right)^{\chi}\left(\frac{1-n}{1-a}\right)^{\sigma}$$

Equations in (7) define the optimal equilibrium allocation of skilled and unskilled labor in the economy between agriculture and non-agriculture. Two points are worth emphasizing. Relative increase in the skill-biased sector-specific technologies in favor of non-agricultural production allocates relatively more skilled labor to non-agriculture. Increasing relative price of Y_N attracts more of the skilled workers into production of Y_N if and only if elasticity of factor demands by producers surpasses the elasticity of demand for goods by consumers. In other words, as long as employing more skilled workers does not bring about any marginal losses to producers.

Equilibrium APG

APG is measured as the ratio of average per-worker value added in non-agriculture (AP_N) to that in agriculture (AP_A). Defining the skill premium by $\hat{w} = w_S / w_U$ and using the zero profit conditions in each sector and APG can be redefined as:

$$APG == AP_N / AP_A = \frac{\hat{w}S_N + U_N}{\hat{w}S_A + U_A} \times \frac{S_A + U_A}{S_N + U_N} \qquad (8)$$

Further, from equations (7), conditionally denoting the right-hand side terms as k and m:

$$S_N^* = kS_A^* \text{ and } U_N^* = mU_A^* \qquad (9)$$

With little algebra, using equilibrium labor supply conditions in (5), model can be closed and APG can be represented as a function of prices, wages, technologies, consumers' and producers' constant elasticity terms:

$$APG = \frac{\hat{w}k\bar{S}(1+m) + m\bar{U}(1+k)}{k\bar{S}(1+m) + m\bar{U}(1+k)} \div \frac{\hat{w}\bar{S}(1+m) + \bar{U}(1+k)}{\bar{S}(1+m) + \bar{U}(1+k)} \qquad (10)$$

First and second terms in (10) correspond to average worker productivity in non-agriculture and agriculture, respectively.

Technical change and APG

Implicitly, productivity gap between agriculture and non-agriculture is related to technical change through skill premium and relative skill intensities:

$$APG = f\left[\hat{w}(A_N / A_A), I(A_N / A_A)\right] \quad (11)$$

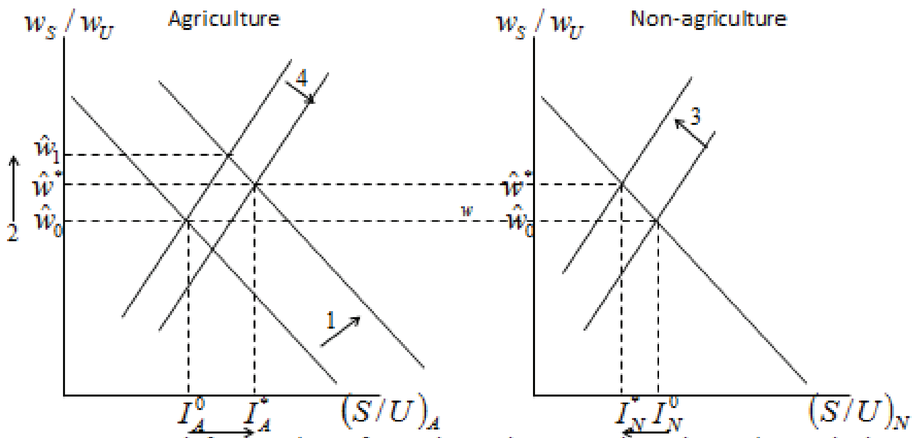
Therefore, to demonstrate that any increase in A_N/A_A will increase APG, proving following two conditions will be sufficient:

$$\text{(i)} \ \frac{\partial \ln APG}{\partial \hat{w}} > 0$$

$$\text{(ii)} \ \frac{\partial \ln AP_N}{\partial (A_N / A_A)} > 0 \ \ and \ \frac{\partial \ln AP_A}{\partial (A_N / A_A)} < 0$$

With some tedious calculus, it can be shown that partial derivative of APG with respect to skill premium is positive if and only if $k>m$ i.e. proportionately more skilled workers settle in non-agriculture than agriculture[41]. From factor demand equations (6) any increase in A_A, A_N, or both results in higher skill premium in economy. Figure 2 summarizes an example of a new equilibrium in inter-sectoral factor demand market resulting from technical change in agriculture.

Figure 10. Skill premium and labor allocation with technical change in agriculture



Increase in A_A shifts the relative factor demand curve to the right resulting in higher skill premium in agriculture (w1). Due to free mobility of labor some of skilled labor from non-agriculture moves into agriculture. In new equilibrium w*>w0, skill intensity is higher in agriculture and lower in non-agriculture.

Initially, economy is in equilibrium with skill intensities I_A^0 in agriculture and I_N^0 in non-agriculture, and equilibrium skill premium of W_0 . Relatively intense technical change shifts the demand for the skilled labor in agriculture. Without barriers to the mobility of workers and fixed number of the skilled in economy, a portion of the skilled labor moves

---

41 $$\frac{\partial \ln APG}{\partial \hat{w}} = (k-m)\frac{\bar{S}\bar{U}(1+k)(1+m)}{\left(\hat{w}k\bar{S}(1+m)+m\bar{U}(1+k)\right)\left(\hat{w}\bar{S}(1+m)+\bar{U}(1+k)\right)} >> 0 \ if \ k>m$$

out from non-agriculture into agriculture. A portion of the unskilled in agriculture is released into non-agriculture due to new technologies. The economy satiates at new equilibrium characterized with higher skill premium W_0^* and relatively higher skill intensity in agriculture. The opposite holds in case of a more intense technical change in non-agricultural sectors.

Second condition (*ii*) states that in equilibrium relative improvement in A_N/A_A increases the per-worker value added in non-agriculture and decreases that in agriculture. Corresponding partial derivatives show that propositions hold provided $\hat{w}>1$, k>m, and $\sigma>1$[42]. Skill premium being higher than unity is a conventional axiom – that, the skilled labor is paid more than the unskilled. The proposed impact of technology transfers on productivity gaps in developing countries is quantified in the following section.

---

42 $$\frac{\partial \ln AP_A}{\partial (A_N/A_A)} = (1-\hat{w})(\sigma-1)\frac{\overline{U}\overline{S}(1+m)}{\left(\hat{w}\overline{S}(1+m)+\overline{U}(1+k)\right)\left(\overline{S}(m+1)+\overline{U}(1+k)\right)}\left(\frac{P_N}{P_A}\right)^{\sigma-\chi}\left(\frac{A_N}{A_A}\right)^{\sigma-2}\left(\frac{\alpha}{1-\alpha}\right)^{\chi}\left(\frac{n}{a}\right)^{\sigma}$$

$$\frac{\partial \ln AP_N}{\partial (A_N/A_A)} = (\hat{w}-1)(k-m)(\sigma-1)\left[\frac{m\overline{S}\overline{U}(1+m)}{\left(\hat{w}k\overline{S}(1+m)+m\overline{U}(1+k)\right)\left(k\overline{S}(1+m)+m\overline{U}(1+k)\right)}\right]\left(\frac{P_N}{P_A}\right)^{\sigma-\chi}\left(\frac{A_N}{A_A}\right)^{\sigma-2}\left(\frac{\alpha}{1-\alpha}\right)^{\chi}\left(\frac{n}{a}\right)^{\sigma}$$

Chapter III. Estimations, Results, and Inferences

Formal framework presented in the previous chapter implies that relatively rapid technical change in a sector increases the skill premium in the economy and, more importantly, the skill-intensity of production in that sector relative to others. Technical change in developing countries takes place, mostly, due to technology transfers from more advanced economies, which are observed to be strongly biased in favor of non-agricultural production according to empirical data. Our theoretical propositions, therefore, attribute the changes in the puzzlingly large and increasing portion of APG in developing countries to the technology transfers.

In this chapter we quantify our postulations using two sets of estimations. In the first specification, the impact of technology imports on productivity gaps is estimated on longitudinal data from 1995 to 2014. Technology imports are instrumented using predicted values based on geographical and proximity factors as well as the innovative intensity of technology producers. In the alternative specification, we estimate the impact of technology imports into non-agriculture relative to agriculture by controlling for dynamic persistence of APG over time. Results from both specifications provide strong support for our theory.

3.1. Estimation Specification

In a naive form, the structural equation that represents the linear relationship between technology transfers and productivity gaps takes the following form:

$$APG_{i,t} = \beta_0 + \beta_1 X_{i,t} + \sum_{k=2}^{n} \beta_k \Phi + u_{i,t} \qquad (3.1)$$

Where, $APG_{i,t}$ is agricultural productivity gap in country i in year t; $X_{i,t}$ is technology transfers into country i in year t; $u_{i,t}=e_i+v_{i,t}$ error term composed of fixed country effects (e_i) and time-variant idiosyncratic error term ($v_{i,t}$); and Φ is a vector of other related covariates.

Simple OLS is likely to be biased for two reasons. Firstly, it is impossible to control for all relevant covariates, thus, omitted variables might be correlated with the technologies imported. Consider, for example, outward migration of skilled workers from developing countries. In theory, since more of the skilled work in non-agriculture than in agriculture, outward skill migration should have negative impact on APG. Similarly, skill migration may induce more technology transfers if the skilled discover profitable technologies abroad and send them home. On the other hand, skill migration may drain the domestic pool of the skilled and deteriorate the demand for foreign technologies at home. Omitting the outward skill migration from the structural equation may result in upward (downward) bias in the estimated coefficient of technology imports if the relationship between technology transfers and outward skill migration is positive (negative). Secondly, there is also a potential problem of reverse causality. By theory developed in this work, APG might be induced by technology transfers, but simultaneously, countries with low aggregate productivity may have less capacity to engage into international exchange of goods and services and, consequently, enjoy less technology spillovers from world markets. In technical terms, the β_1 in (3.1) will be inconsistent if following condition does not hold:

$$Cov(x_{i,t}; u_{i,t})=0 \qquad (3.2)$$

Removing country fixed effects (e_i) is not a sufficient solution since it is highly likely that unobserved time-variant errors ($v_{i,t}$) may contain covariates correlated with the technology transfers. To overcome this endogeneity problem, in the subsequent sections, we construct an instrument for technology transfers to isolate its impact on APG from other possibly omitted factors. Before going into the details of the instrument, some light should be shed on the issues related to measuring the technology transfers.

3.2. Measuring Technology Transfers

Despite common recognition of the importance of technology transfers for development, measuring them has remained a difficult task. Prominent channels through which knowledge cross borders include trade, migration, foreign direct investments, and direct transfers through licensing and patenting (Hoekman, Maskus, and Sagii, 2004). Early works such as Coe and Helpman (1995) approximate the amount of technology transfers as trading partners' R&D capital stock weighted by observed bilateral import shares. They measure the R&D capital stock using the well-known investment perpetuity method. However, results they obtain are sensitive to depreciation rates applied. Later Coe, Helpman, and Hoffmaister (1998) use the share of bilateral machinery and equipment imports as weights for trading partners' R&D capital stock. Applying equal weights to the foreign R&D stock, on the other hand, provide surprisingly similar conclusions as shown by Keller (1998). According to Mayer (2000) the reason why different weights yield similar results is the public good nature of knowledge. He argues that bilateral trade intensity should play no role, but it is the volume of technology imports that matter for the host economies. Coe and Helpman (1995) and Coe, Helpman, and Hoffmaister (1998) additionally employ a simple sum of the R&D capital of trading partners in quantifying the impact of cross-country technology diffusions on home countries' productivity levels. Measuring technology transfers seems sensitive to underlying assumptions, especially, those in quantifying the R&D capital stock of trading partners.

Moreover, there are two major caveats in measuring the technology transfers as weighted foreign technological capital. To understand why, consider a hypothetical case where technologies are transferred into a less-developed country *A* from countries *B* and *C*. Assume that *C* is more technologically advanced than *B*. Assume further that 90% of *A*'s total imports are composed of grain from country *B,* and 10% of A's total imports are composed of actual technologies from country *C*. In this case, measuring technology transfers into A as import-share-weighted R&D capital in countries B and C would be strongly biased. Because imports from B into A does not carry any technologies, whether embodied or disembodied, yet B's technological capital stock receives most of the weight applied. Weighting the foreign R&D capital stock, by applying bilateral shares in whether trade or direct investments, is as if the weights are predetermined. However, we cannot override the possibility that the corresponding shares might be determined by the technological capital stock of advanced countries, and not the other way around.

Another approach to measuring technology diffusions is to utilize the data on patenting. For instance, Eaton and Kortum (1999) use the patenting data to fit their technology diffusion model to the sample of five leading research countries: the US, Germany, UK, France, and Japan. However, this approach cannot be easily applied to the case of technology transfers into developing countries because of the unavailability of international patenting data.

A more direct approach is taken in this work. Technology transfers is measured as the imports of machinery and equipment – classified as Section 7 of Standard International Trade Classification (SITC) of United Nations Statistics Division as of Rev.3 in 2016. On average, machinery and equipment imports constitute roughly one third of total merchandise imports by developing countries, and three fourths of them originate from developed countries. The subsection 72 of SITC 7 represents the volume of technology imports that are specialized for distinct industries. As discussed above, there is a strong bias in the technology transfers when imports of machinery and equipment are considered. On average, 93% of the specialized technology imports are for non-agricultural use, whereas only 7% is for agriculture production. The key characteristics of technology imports by developing countries for the period of 1995-2004 are summarized in Table A2 in appendices.

3.3. Construction of Instrument

We construct an instrument for technology imports, X_{it}, in a modified framework of Jeffrey Frankel and David Romer (1999). Frankel and Romer use the cumulative sum of bilateral trade determined by geographical and proximity factors as an instrument for trade. A similar approach can be utilized in this work since technologies imported by each country *i* in year *t* is cumulative sum of bilateral technology imports between the country *i* and the rest of the world. For example, total technology imports by Uzbekistan for any given year is the sum of technologies the country imports bilaterally from the US, Russia, Korea, China, and the remaining other partners.

The gravity model, the details of which are too popular to be discussed here, implies that bilateral trade between two countries is positively correlated with their sizes and negatively related to the distance between them. Each set of bilateral technology imports can also be estimated as a function of geographical and proximity factors. The sum of bilateral technology imports predicted based on the exogenous factors should serve as an instrument for actual technology imports. However, direct application of Frankel and Romer's approach does not work in our case. Because, geographical factors and size variables alone cannot explain why one country is importing different scale of technologies from two different countries that are of same sizes and are *equally* far from (or close to) the importer. In other words, the equation (3.1) cannot be identified using the geographical and proximity factors alone. For identification there must be some other factor determining the technology transfers, and not affecting the dependent variable.

Assume country A is on equal distance from countries B and C with equal sizes, both economically and geographically. If country A is importing more technologies from B comparing to C, then B must have a competitive advantage in producing technologies than C (putting politics aside). Countries producing more, and better technologies are the ones that invest more into research and development. But do countries producing new technologies want to sell them directly? Maybe ‘yes’, maybe ‘no.’ After all, it is not relevant. Schumpeter’s ‘creative destruction’ induces technology creators export more technologies given they create new ones more intensively. Because we do not distinguish the types of technologies imported, whether new or old, R&D intensity of exporting countries should be an important determinant of technology flows into the developing countries. At the same time, R&D intensity of one country is unlikely to be a determinant of agricultural productivity gap in another country. Therefore, measuring and including the innovative intensity of exporting countries into the gravity model of bilateral trade of technologies should enable us to identify and estimate the equation of interest.

The innovative intensity of a country can, roughly, be measured by the share of aggregate R&D spending in its GDP. By incorporating related geographical and size factors, following equation can be estimated on bilateral technology imports to construct an instrument for actual technology imports:

$$\begin{aligned} \ln(x_{i,j,t}) = \alpha_0 + \alpha_1 (RD/GDP)_{j,t} + \alpha_1 \ln Dist_{i,j} + \alpha_3 \ln Dist_{i,j} * (RD/GDP)_{j,t} + \\ + \alpha_4 \ln Pop_{i,t} + \alpha_5 \ln Pop_{j,t} + \alpha_6 \ln Area_i + \alpha_7 \ln Area_j + \alpha_8 L_i + \alpha_9 L_j \end{aligned} \tag{3.3}$$

Where, $x_{i,j}$ is the imports of technologies by country i from country j in year t; 'i' refers to the importing country and 'j' denotes the exporting country; $Dist_{i,t}$ is the distance between most populated cities of countries i and j; *Pop* is the population in year t; *Area* is the area of the countries measured in *sq.km*; $(RD/GDP)_{j,t}$ is the R&D expenditure as percentage of GDP in country j in year t; L is a dummy equal to unity if country is landlocked.

The underlying intuition behind (3.3) is straightforward. Bilateral technology transfers between two countries are positively correlated with their sizes, which is approximated by population, and negatively correlated to the distance between them. People in countries with larger geographic areas tend to trade relatively more inside the country and relatively less with other countries. So, α_6 and α_6 are expected to be negative. Bilateral technology imports should be comparatively less if one or both countries are landlocked, since the landlocked countries face higher transportation costs. Technology exports should be higher in the countries with higher R&D intensity. The coefficient of the interactive term, $Dist_{i,j}*(RD/GDP)_j$, should be negative since 'attractiveness' of the technological intensive exporters to the importing country tend to fade out over the longer distances, or equally, higher transportation costs.

The data on bilateral imports of machinery and equipment is available from the United Nations Conference on Trade and Development (UNCTAD), geographical and proximity variables are provided in CEPII database, and the missing geographical data are compiled from other sources without any threats to the credibility of the quality of data.

A challenging step in estimating the equation (3.3) is that the R&D data is not universally available. We collect the R&D/GDP ratio from different sources including World Development Indicators, OECD datasets, and the UN statistical units. For the case of some low-income countries for which the pertinent data are not available, R&D/GDP ratio is assumed to be zero. This should have negligible impact on the results since technologies are mostly imported from the advanced economies. The summary statistics of the variables included in the equation (3.3.) are provided in the appendices.

Table 8.	**Estimation of Instrument: Bilateral technology imports**		
$(RD/GDP)_j$	3.65***	$\log(Distance_{ij})$	-1.09***
	(0.06)		(0.01)
$\log(Population_i)$	0.67***	$Landlocked_i$	-0.80***
	(0.00)		(0.01)
$\log(Population_j)$	0.85***	$Landlocked_j$	-1.29***
	(0.00)		(0.01)
$\log(Area_i)$	-0.05***	$\log(Distance_{i,j})*(RD/GDP)_j$	-0.18***
	(0.00)		(0.01)
$\log(Area_e)$	-0.31***	Constant	0.64***
	(0.00)		(0.08)
Observations	431,825		
R-squared	0.48		
Root MSE	3.02		

Notes: Dependent variable is the log imports of technologies from country *j* into country *i*. Sample covers the period of 1995-2015. Subscripts *i* and *j* refer to importing and exporting country, respectively. *RD/GDP* is the ratio of research and development expenditure to GDP; $Distance_{i,j}$ is the simple distance between most populated cities of countries *i* and *j*; Landlocked is a dummy variable and is equal to 1 if country is landlocked. Area is the geographical territory measured in sq.km. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Results from estimating equation (3.3) are summarized in Table 8. In general, they are consistent with the theory. The impact of exporter's research intensity is, indeed, overwhelmingly large. Specifically, 1% increase in the share of R&D spending in GDP of the technology exporting countries is associated with average 3.7% increase in the bilateral flows of machinery and equipment into the importing country. Larger countries, in terms of population, tend to exchange technologies more. Nations with larger geographical areas are less inclined to import technologies as larger territories induce more internal, than external, trading. Being landlocked significantly reduces the technology transfers for both technology exporting and importing countries. Contrasting the estimated coefficients for landlocked dummies and area variables provide interesting inferences. In both cases, the magnitude of estimated negative impact is smaller for the importer. This is because demand for technologies are originating from the importers, they seem to be less sensitive to the geographical obstacles such as being landlocked and having large territories comparing to the exporting countries.

In the next step of instrument construction, bilateral technology imports from the estimations in Table 8 are predicted linearly. Since predicted values are in log forms, they are raised to exponentials and cumulated for each country in each year over all trading partners as:

$$\widehat{X}_{i,t} = \sum_{i \neq j} e^{\alpha' \mathrm{H}}$$

Where, H is the vector of variables in equation (3.3).

The cumulative sums ($\widehat{X}_{i,t}$) represent part of the technology imports by country *i* in year *t* that is solely explained by geographical and proximity factors, as well as the innovative intensity of the exporters. The key assumption for the validity of the constructed instrument is that the APG observed in a country is not affected by the R&D intensity of other countries except through technologies imported. We will return to this issue in the robustness section.

3.4. Testing the Quality of the Instrument

Despite conditional independence given by (3.2) may now be satisfied, how ‘strong’ might the constructed instrument be? Weak relationship between the constructed IV and the actual technology imports seriously undermine the credibility of the estimations. To check for the quality of the instrument, a simple ‘first-stage-like’ exercise can be performed. To do so, we run a panel GLS on the actual technology transfers and the predicted ones[43]. The results are summarized in Table 9.

As shown in the first column of Table 9, in general, the relationship between actual and predicted technology imports is positive and statistically significant. Just the constructed instrument itself and the constant term capture 54 percent of variations in actual technologies imported. Inclusion of the variables representing the economic and geographic sizes reduces the estimated coefficient by almost one third, from 0.57 to 0.44. Both population and area are important determinants of technology imports, the impact of

[43] This is the first step in IV estimations.

the former being larger. Comparing columns (3) and (4) reveals the approximate contribution of the constructed instrument in explaining the actual imports of technology and equipment. Not surprisingly, it is around 15 percent. Because the instrument is estimated over 1995-2014, and the geographical variables are constant over years, one should not expect large variations in instrument. In fact, except population, the only time-variant factor in the (3.3) is the R&D expenditure of the technology exporters.

Table 9. Actual and predicted technology transfers

VARIABLES	(1)	(2)	(3)	(4)
log(Predicted Technology Transfers)	0.57***	0.47***	0.44***	
	(0.03)	(0.03)	(0.04)	
log(Population)		0.71***	1.07***	2.55***
		(0.08)	(0.16)	(0.16)
log(Area)			-0.43***	-1.25***
			(0.11)	(0.14)
Constant	2.44***	-6.45***	-6.38***	-10.93***
	(0.57)	(0.94)	(0.95)	(1.32)
Observations	4,240	4,240	4,240	4240
R-squared	0.54	0.57	0.54	0.39
Number of countries	206	206	206	206

Notes: Dependent variable is log of actual technology transfers. Simple RE GLS estimations. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Overall, geographical factors, size variables, and innovative intensities of partner economies do explain significant portion of technology imports both across countries and over time. This allows to proceed with the estimation of the structural equation (3.1) using the constructed instrument.

3.5. Technology Transfers and APG: Estimation Results

Simple panel OLS estimations are presented in the Table 10. The dependent variable is APG – the ratio of labor productivity in industry and services to that in agricultural sector. Columns (1) to (4) summarize the 'random effects' specification with different geographical factors included for the sample of 150 developing countries. The panel is unbalanced, with some countries having number of observations as small as one for the entire sample period of 1995-2014.

In the first column, the estimated coefficient of interest is statistically significant. The second specification controls for latitude and the dummy, which is equal to 1 if the country is landlocked. There is a solid rationale for the inclusion of latitude and landlocked dummy into the structural equation. The dependent variable is the ratio with the denominator being agricultural productivity. Agricultural productivity is strongly correlated with the climate that can be represented by the latitude to a certain extent. The estimated coefficient for latitude is negative and statistically significant implying that the countries on higher latitudes seem to have climate more suitable for agriculture. On the other hand, the landlocked countries may have lower land quality, thus, higher APG's. The results imply APG's is higher by 1.6 units in landlocked countries comparing to non-landlocked countries. Column (3) also controls for continent dummies. The dummy is 1 if the country is located on the representative continent. The benchmark, or the omitted, continent is the America and the Pacific. Results imply that the productivity gap is higher in African countries by over 3 units. The European developing countries, on the contrary, have APG's lower than the benchmark group by, average, 1.5 units. The Asian economies seem not to differ from the America and the Pacific in terms of the APG's implied by data. Inclusion of the continent dummies does not change the estimated coefficient of interest.

All geographic and continent dummies are estimated jointly in the column (4). Due to multicollinearity, coefficients on latitude and Africa dummy decreases slightly, yet they remain statistically significant. The Europe and landlocked dummies become insignificant. This is natural as there is strong correlation of the continent dummies with the latitude and the landlocked dummies. It is important to point out that the coefficients on all dummies and the latitude are lower comparing to cross-section estimations. These factors do not change over time, whereas the dependent variable is time-variant.

The column (5) is estimated by removing the country fixed effects. Surprisingly, the time-invariant country specific variables included in column (4) seem to capture the most of impact from the aggregate fixed effects since coefficient on the technology imports increases merely moving to column (5). Comparing column (1) and column (5), although there is 0.03 points increase in the coefficient of interest, the change is statistically significant since the relative change in the variance matrix is even smaller. In fact, the estimated p-value on the Hausman Chi-square is 0.008.

The specification in column (5) removes all the unobserved time-invariant variables. However, as discussed earlier, omitted time-variant factors still pose a doubt on the estimated impact of the technology imports on APG. The column (6) controls for two-way error components. The universal effects of time across countries are controlled for by including year dummies. The estimated coefficient increases substantially to 0.47. The null on the joint insignificance of the year dummies is rejected at 1% confidence level. Since the inclusion of year dummies does not control for omitted country specific time-variant factors, the results in column (6) can, by no means, treated as final. By contrast, year dummies may absorb the partial effect of technology imports that is universal over time across countries.

The columns (7) and (8) summarize the results for the developed countries and the full sample by removing the country-fixed-effects. Despite being positive, the impact of technology imports is both economically and statistically insignificant for the 'developed' sample. This, indeed, complies with the thorough discussion in previous chapters. In the case of full sample, including both developing and developed countries, 1 percent increase in the technology imports is associated with average 0.4 units increase in APG. It is lower comparing to that in column (6) due to the inclusion of the developed countries.

Table 10. Basic panel OLS results

Sample	Developing countries						Developed	Full sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	RE	RE	RE	RE	FE	FE	FE	FE
log(Technology Imports)	0.26**	0.27**	0.27**	0.28**	0.29**	0.47***	0.08	0.41***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.13)	(0.17)	(0.17)	(0.16)
Africa dummy			3.32***	3.13***				
			(0.85)	(0.86)				
Europe dummy			-1.49***	0.36				
			(0.57)	(0.89)				
Asia dummy			0.30	1.21				
			(0.73)	(0.85)				
Latitute		-0.06***		-0.05***				
		(0.01)		(0.02)				
Landlocked		1.59**		1.03				
		(0.79)		(0.79)				
Year dummies	no	no	No	no	No	yes***	No	yes***
Constant	0.49	0.85	-0.58	-0.57	-0.02	-2.42	0.78	-2.15
	(1.58)	(1.68)	(1.53)	(1.57)	(1.79)	(2.20)	(3.04)	(2.14)
Observations	2,644	2,644	2,644	2,644	2,644	2,644	439	3,083
R-squared					0.02	0.03	0.00	0.03
Number of countries	150	150	150	150	150	150	23	173

Dependent variable is APG. Sample covers the period 1995-2014. RE=Random effects, FE=Fixed effects. Continent dummies equal to 1 and 0 otherwise. Landlocked=1 if country is landlocked, 0 otherwise. Columns (1) to (6) summarize the results for developing countries. Column (7) and (8) are for developed countries and full sample, respectively. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Joint significant indicated on year dummies.

The constructed instrument can now be used to isolate the impact of technology transfers from that of omitted time-variant factors affecting APG. The size variables are used to obtain the predicted technology imports, so they are controlled for in the IV estimations presented in Table 11 below.

The first column in Table 11 is an analogous version of column (5) in Table 10 with the size variables added. Controlling for the size, the estimated coefficient of interest increases from 0.29 to 0.36. Countries with more population tend to exhibit lower APG, on average.

This might seem controversial. If population variable increases the technology transfers, which have positive impact on APG, by theory, why the relationship between the population and APG might be negative? The reason is that the direct impact of population seems to override its positive impact through technology imports.

Table 11. IV-estimation results			
Specification	FE	FE-IV	FE-IV
	(1)	(2)	(3)
VARIABLES	Developing	Developing	Low and middle income
log(Technology Imports)	0.36***	0.55***	0.56***
	(0.12)	(0.13)	(0.14)
log(Population)	-0.66	-1.31*	-1.20*
	(1.06)	(0.69)	(0.68)
Constant	9.37		
	(16.03)		
Observations	2,644	2,644	2,171
R-squared	0.02	0.01	0.01
Number of countries	150	150	119
Endogeneity		0.08	0.09
Underidentification		0.00	0.00
Weak Identification Kleibergen-Paap Wald F		283.5	132.0

Notes: Dependent variable is APG. All estimations control for country fixed effects. Sample period is 1995-2014. Import of technologies is instrumented using constructed technology transfers. Chi-sq(1) P-values reported for underidentification and endogeneity tests. Stock and Yogo (2005) critical values apply to weak-identification F-stat. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The second column in Table 11 summarizes the IV estimation results controlling for country fixed effects. Estimated impact of technology transfers increased to 0.55 from 0.36

in column (1). The null of it is being equal to zero is rejected at 1% critical level. Accordingly, 1% increase in imports of technologies increases the APG by 0.55 units. Change in the estimated coefficient is negligible when the sample of developing countries is restricted to low- and middle-income countries as classified by the World Bank.

The implied endogenity tests reject the null of technology imports being exogenous. The underidentification and weak identification tests also reject the underlying null hypotheses. Kleibergen-Paap F-stat well exceeds the Stock and Yogo's (2005) critical value of 16.4.

3.6. Robustness Checks

The key assumption in the construction of the instrument was that the research and development expenditure of technology exporters has no direct impact on APG in the importing countries except through technology imports. However, it is common that economies with intensive innovative activities also engage into foreign investments in developing countries. If so, the exclusion restriction on the RD/GDP will not be valid. To check whether the results in the IV estimations are robust to the critical exclusion assumption made, estimations in Table 12 control for the inflows of foreign direct investments (FDI).

The data on FDI is available from WDI for 147 developing countries. The first column of Table 12 is the baseline the fixed effects-IV estimation. The FDI inflows are included in the second column. The impact of the direct investments is positive, but it is significant neither economically nor statistically. The coefficient on technology imports slightly reduces from 0.52 to 0.51. In the first column, small but positive impact of FDI seems to be partially captured by technology transfers.

Conclusions from the Table 12 are still not adequate for the validity of the exclusion restriction used in the construction of the instrument. This is because, besides FDI and technology imports, there are other channels through which R&D intensity of the trading partners may affect the sectoral productivities in developing countries. However, due to the paucity of data representing the alternative impact-channels of R&D intensity of the technology exporters, the inferences from the IV estimations in Tables 11 and 12 should be made with caution.

Table 12. Alternative channels of technology transfers

VARIABLES	(1) FE-IV	(2) FE-IV
log(Technology Imports)	0.52***	0.51**
	(0.14)	(0.20)
log(Population)	-1.14	-1.14
	(0.75)	(0.75)
log(FDI inflows)		0.01
		(0.06)
Observations	2,493	2,493
R-squared	0.01	0.01
Number of countries	147	147

The dependent variable is APG. Sample includes developing countries for 1995-2014. Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Inclusion of the other variables relevant to APG is the subsequent part of the robustness checks as summarized in Table 13. In general, due to weak of multicollinearity, inclusion of additional variables results in slight changes in the estimated coefficient of interest. The main conclusion, however, remains robust.

Results in Table 13 allow us to derive important inferences regarding several theoretical propositions, namely, capital intensity, barriers for using intermediate inputs in agriculture, barriers for labor mobility between agriculture and non-agriculture, as well as the 'food problem' commonly used to explain the APG's observed in the developing countries.

In the previous chapters, we emphasized the importance of differences in capital intensity across non-agriculture and agriculture. Marginal product of labor is low in a sector with relatively less capital. Therefore, relatively higher capital intensity in non-agriculture than that in agricultural might be one factor resulting in high APG's. The column (1) is the baseline fixed-effects IV estimation. The column (2) controls for the ratio of monetary values of capital in non-agriculture and agriculture. The estimated coefficient for capital ratio is statistically different from zero. Both the coefficient of interest and its standard error slightly increased. Same is true for the population's coefficient. Findings support the hypothesis that capital plays important role in explaining the productivity gaps among the developing countries as in Caselli (2005) and Vollrath (2009).

Alternative stream of theories has pointed out the barriers for using inputs in agricultural production *e.g.* Restuccia et al (2008). We control for the fertilizer usage per arable land (column 3) as well as per agricultural land (column 4). Different countries use different types of fertilizers. To make them comparable, we measure the fertilizers as a cumulative sum of three most common chemicals *i.e.* nitrogen, phosphate, and potash in metric tons of plant nutrients. Both land and fertilizer data are available from FAO. The estimated coefficient is negative as expected. However, the null of impact from fertilizer per arable land being zero can be rejected at a lower confidence level. The impact is statistically significant at 10% critical level when fertilizer per agricultural land is considered. 1% increase in fertilizer use per unit of land is associated with APG being lower, on average, by 0.14 units. The impact from fertilizer use might be conditional on various factors such as land quality. Due to measurement issues, however, we lack reliable data on land quality to control for. The estimated marginal impact from the technology imports increases from 0.55 in baseline to 0.58 in column (4). Controlling for fertilizer use seems to leave out a portion of APG that is more correlated with the technology transfers. However, the change is statistically insignificant as the standard error of the coefficient doubles to 0.27.

In columns (5) and (6), we include the variables that approximately represent the barriers for labor mobility from rural to urban areas. Agriculture is a rural production, in general. Barriers for labor mobility tend to keep the labor in rural areas, hence, in agricultural production. More labor directly and negatively correlated with the implied labor productivity. The coefficients for share of rural population and the growth of rural population are positive, as expected. For instance, 1 percentage point increase in rural population growth increases the APG by, average, 0.2 units. The coefficients are statistically different from zero corroborating the theories emphasizing the importance of labor market frictions.

Table 13. Inclusion of related covariates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	FE-IV	FE-IV	FE-IV	FE-IV	FE-IV	FE-IV	FE-IV
log(Machinery Imports)	0.55***	0.57***	0.57**	0.58**	0.58***	0.51***	0.54***
	(0.13)	(0.14)	(0.27)	(0.27)	(0.12)	(0.12)	(0.16)
log(Population)	-1.31*	-1.56**	-3.77*	-3.74*	-0.74	-0.98	-1.18*
	(0.69)	(0.76)	(1.97)	(1.97)	(0.68)	(0.63)	(0.63)
log(Capital ratio, N/A)		0.22***					
		(0.08)					
log(Fertilizer per hectares of arable land)			-0.12				
			(0.08)				
log(Fertilizer per sq.km of agricultural land)				-0.14*			
				(0.08)			
Share of rural population					0.04**		
					(0.02)		
Growth of rural population						0.18**	
						(0.07)	
log(Food deficit)							0.44***
							(0.11)
Observations	2,644	2,409	1,397	1,397	2,644	2,608	2,053
R-squared	0.01	0.02	0.02	0.02	0.02	0.02	0.03
Number of countries	150	133	127	127	150	147	109

Sample includes developing countries and number of observations varies depending on availability of data. Capital ratio is the ratio of total capital (monetary values) in non-agriculture to that in agriculture. To make the fertilizer usage internationally comparable, we use three most common chemicals: Nitrogen, Phosphate, and Potash measured in metric tons of plant nutrients. Share of rural population is the % of total population living in areas classified as rural. Growth of rural population is the annual % growth of the rural inhabitants. Food deficit is measured as the depth of food deficit in daily kilocalories per person. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the last column (7) of the Table 13, estimations control for an arbitrary factor representing the prevalence of food shortage in the countries, measured as the depth of food deficit in daily kilocalories per person. This helps to examine, from the empirical point of view, whether the 'food problem' of Schultz (1953) applies to the sectoral productivity gaps observed in the developing countries. Results imply that 1% increase in daily food dietary deficiency per person is translated into 0.44 unit increase in the implied APG, on average. The effect is statistically and economically significant. The coefficient on technology imports, on the other hand, decreases to 0.54 comparing to the baseline in column (1). The change is statistically insignificant considering the differences in estimated standard errors.

Tests conducted so far show that the estimated coefficient of interest is robust to inclusion of alternative channel of technology transfers and does not significantly change when relevant covariates are controlled for. In the subsequent section, we present a discussion on whether 'technology transfers-APG' hypothesis still holds when alternative estimation specifications are considered.

3.7. Dynamic Panel Instrumental Variable Estimations

Due to the weak cross-country explanatory power of the instrument constructed and possibly dynamic prevalence of APG over time, findings from the previous section may well be subject to skepticism. Therefore, we provide further empirical evidence, using dynamic panel specifications, in support of the 'technology-transfers induced APG' hypothesis. In doing so, we can take advantage of the availability of data on sectoral decomposition of subsection 72 in SITC. Subsection 72 includes *'machinery specialized for particular industries'*, which is further broken down to details groups[44]. Hereafter, we consider subsections 721 (Agricultural machinery) and 722 (Tractors) as '*agricultural specialized technology imports*.' Subsections 723 to 728 are classified into '*non-agriculture specialized technology imports*.' To directly control for the observed sectoral bias in technology imports, we include the ratio of *'agricultural specialized technology imports*' to '*non-agriculture specialized technology imports*' into the dynamic estimations.

In table 14, estimation results for the full sample of 125 developing countries over 1995-2015 under dynamic specifications are summarized. We start with simple random-effects generalized least squares estimation summarized in the first column. The estimated coefficient for the ratio of non-agricultural to agricultural technology imports is positive and statistically highly significant. To account for common trends as well as country-fixed effects, year and country dummies are included in column (2). The coefficient of interest slightly increases to 0.31 and remains statistically significant. Potential limitations of the specification in column (2) are threefold. First, the ratio of sector-specific technologies maybe correlated with time-variant unobservable variables. Second, time dummies may

---

[44] SITC Section 72 is divided into following groups: 721 - Agricultural machinery (excluding tractors) and parts thereof, 722 - Tractors, 723 - Civil engineering and contractors' plant and equipment; parts thereof, 724 - Textile and leather machinery and parts thereof, n.e.s., 725 - Paper mill and pulp mill machinery, paper-cutting machines and other machinery for the manufacture of paper articles; parts thereof, 726 - Printing and bookbinding machinery and parts thereof, 727 - Food-processing machines (excluding domestic); parts thereof, 728 - Other machinery and equipment specialized for particular industries; parts thereof, n.e.s.

capture a portion of the actual impact of relative technology transfers on productivity gaps, resulting in underestimation of the true coefficient of interest. Finally, ordinary estimations incorporate neither the dynamic persistence of APG nor the lagged effects of technology imports on APG. These limitations are tackled in the subsequent modifications.

In column (3), we include three lags of both APG and the ratio of sector-specific technology imports without country and year dummies. The results show that dynamic impact of APG stretches to two years prior to the given year, but that none of the lagged relative technology imports is significant in explaining APG's. The magnitude of the impact of the contemporary relative technology imports decreases to a third, while remaining statistically significant. This estimation still suffers from possible contemporaneous correlation between the relative technology imports and omitted variables. We drop the statistically insignificant lags of both dependent and independent variables and control for country-specific and common trends in column (4). The coefficient of interest slightly increases to 0.12, and its statistical significance improves due to the exclusion of correlated lags of the independent variable. The results from column (4) are still subject to potential estimation bias due to unobserved time-varying variables not captured by common time trends.

Table 14. Dynamic panel IV-estimation results

VARIABLES	(1) REGLS	(2) REGLS	(3) Dynamic OLS	(4) Dynamic OLS	(5) AB-'difference' dynamic panel	(6) AB-'system" dynamic panel one-step	(7) AB-'system" dynamic panel two-step
L.apg			0.81***	0.64***	0.55***	0.84***	0.82***
			(0.07)	(0.05)	(0.06)	(0.06)	(0.07)
L2.apg			0.21***	0.19***	0.18***	0.16*	0.16*
			(0.07)	(0.05)	(0.07)	(0.09)	(0.08)
L3.apg			-0.06		0.00	-0.04	-0.04
			(0.07)		(0.05)	(0.07)	(0.08)
log(mach_N_A)	0.26***	0.31***	0.10*	0.12**	0.17*	0.17**	0.18***
	(0.10)	(0.11)	(0.05)	(0.05)	(0.09)	(0.08)	(0.06)
L.log(mach_N_A)			-0.03				
			(0.07)				
L2.log(mach_N_A)			-0.04				
			(0.06)				
L3.log(mach_N_A)			0.01				
			(0.05)				
Constant	2.85***	2.27***	0.03	0.22		-0.29	0.00
	(0.31)	(0.35)	(0.05)	(0.20)		(0.20)	(0.00)
Observations	1,248	1,248	813	911	731	819	819
Number of countries	125	125	74	77	71	74	74
Country fixed effects	no	yes	no	Yes	-	-	-
Year fixed effects	no	yes	no	Yes	No	yes	yes
R-squared		0.06		0.68			
Number of instruments					374	93	93
Arellano-Bond test for AR(2) in first differences (p-value)						0.11	0.47
Hansen Test (p-value)						0.94	0.94

The dependent variable is APG. Sample covers the developing countries from 1995 to 2015. AB=Arellano-Bond. L# is the #th lag of corresponding variables. Mach_N_A is the ratio of non-agriculture specific technology imports to those specialized for agricultural production. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The conclusive estimation outcomes are presented in the last three columns. In column (5), all right-hand side variables are instrumented by their all available lagged differences in compliance with Arellano and Bond’s (1991) GMM specification of Anderson and Hsaio (1981) methodology in order to treat for the possibly contemporaneous endogeneity of the variable of interest. In column (6), the estimation model is specified as a ‘system’ where, in addition to controlling for year-fixed effects, variables-in-levels are instrumented by lagged differences and variables-in-differences are instrumented by lagged variables in levels (Arellano and Bover, 1995; Arellano and Bond, 1998). The number of instruments is reduced from 374 to 93 in minimally arbitrary way by selecting the most relevant instruments in terms of correlations and estimated eigenvalues (See, for example, Mehrhoff, 2009 and Bai and Ng, 2010). Column (7) is a simple two-step speciation of column (6), where the estimated standard errors are corrected for possible downward biases as suggested by Windmeijer (2005). The estimated coefficients for the relative technology imports do not change significantly among columns (6), (7), and (8).

The results from dynamic modifications suggest that 1% increase in the ratio of non-agricultural-to-agricultural technology imports tends to increase the productivity gap between the sectors by 0.18. The estimated Hansen-statistics do not reject the validity of the instruments used.

Overall, the results from both panel FE-IV and dynamic panel IV estimations provide strong and robust empirical evidence for the hypothesis that technology transfers deteriorate the sectoral productivity disparities in developing countries.

Summary and Conclusions

Using the national accounts data, we found that labor productivity gap between non-agriculture and agriculture in 153 developing countries constitute the factor of 4, on average, for the period of 1995-2014. The gap is negatively associated with the level of income and signifies large potentials for improvements, especially, in the poor countries, where majority of labor are engaged in agricultural activities.

Roughly, the half of the magnitude of the gap can be attributed to the differences in human capital and barriers for free intersectoral mobility of labor. However, the remaining half has remained unexplained. Moderately increasing trend of the gap over time further amplifies the puzzle in literature. In this work, we presented a thorough examination of the productivity gaps in developing countries and presented a theory that leaves nothing ambiguous.

To begin with, we explored whether the productivity gaps are illusionary consequences of mismeasurement of value added and labor in national accounts data (Parente *et al,* 2000; Gollin *et al,* 2004). Using more consistent, corrected for self- and family-employment and output measures, data from household and firm-level surveys in KLEMS and GGDC sources, we showed that there are no significant differences in the APG's calculated for the developing countries common in the comparing samples. Our findings vindicate similar conclusions for a smaller sample of 10 developing economies in Gollin *et al* (2014). In the sample of developed countries, the productivity gaps are found to be slightly overestimated in the national accounts data as in the case of the US in Herrendorf and Schoellman (2012).

Labor productivities are calculated as the ratio of value added to number of workers in each sector. To check whether productivity gaps differ when measured using labor hours instead of headcounts, we collected data on weekly working hours 'actually worked' from the ILO labor force surveys for 47 countries. When averaged, not surprisingly, working hours in non-agriculture and agriculture came up to be almost identical in the case of 31 developing countries. For the remaining 16 developed countries, we found a nontrivial difference in the actual weekly working hours between the sectors. In general, our data-checking exercises showed that productivity gaps in the developing countries are real and cannot simply be attributed to miscalculations or the quality of national accounts data.

Further, we discussed the wage gaps between non-agriculture and agriculture to account for the human capital differences (Caselli and Coleman, 2001; Lagakos and Waugh, 2013; Young, 2013; Gollin *et al*, 2014; Herrendorf and Schoellman, 2012) and labor market frictions preventing free labor mobility (Henderson, 2006; Munshi and Rosenzweig, 2016). Our computations using monthly wage rates from labor force surveys showed that the wage gaps constitute the factor of 2.1 for a sample of 79 developing countries, where the average corresponding productivity gap stood at 3.9. Relying on the ratio of human capital levels between 1.3 and 1.4 from Gollin *et al* (2014), our inferences imply that from 1.5 to 1.7 factors of productivity gaps can be attributed to labor market frictions. In other words, relatively larger portion of productivity disparities result rather from barriers to labor mobility than human capital differences in developing countries.

The pattern of wage gaps exhibited relatively constant trend. Based on this observation, we presented that not only a significant portion of productivity gaps remains unexplained even after adjusting for wage-gaps but also the puzzling portion tends to increase over time. Raw implications of neither trade theories nor the ‘food problem’ hypothesis of Schultz (1953) seemed to provide any further plausible explanations. We concluded that the residual between productivity gaps and wage gaps cannot be explained except through labor shares of income.

Despite majority of empirical estimations assign equal or lower labor shares to agriculture comparing to non-agricultural sectors, there are significant variations in the estimated parameters depending on the underlying assumptions imposed. Labor shares are claimed to be roughly equal in Gollin *et al* (2014), whereas relatively lower in agriculture in Herrendorf and Schoellman (2012). On the contrary, we argued that the problems in measuring the labor shares of income evolve due to the presence of self-employed in the sectors and the resulting complications in imputing the worker compensations. Using more quality data on labor compensation and value added for a small sample of 11 developing countries, we showed that nothing much remains unexplained in the APG’s observed when correct labor shares are applied. Our results were found especially convincing for the countries where the self-employed make up small portion of labor in both agriculture and non-agriculture.

By conducting a basic accounting exercise, we demonstrated that changes in the ratio of labor shares of income can primarily be ascribed to changes in relative technologies in non-agricultural and agricultural productions. The relationship between relative technical change and productivity gap was formalized in a two-sector, two-good model with heterogenous skill levels in labor. In our formal framework, technical change that is more intense in one sector would encourage the accumulation of skilled labor, which would further induce more technical change in that sector relative to the other. Division of skilled and unskilled labor in economy is determined by demand of profit maximizing firms in contrast to the supply side decisions in Lagakos and Waugh (2013) and Young (2013), where workers self-select into non-agriculture and agriculture based on observable and unobservable skills. Evidencing on the bias in technology imports, we proposed that the technology transfers from abroad is an important determinant of changes in APG levels in developing countries.

We empirically substantiated our theory using two sets of panel instrumental variable estimations and obtained solid supporting evidence. In the initial estimations, results implied that 1% increase in the imports of machinery and equipment would induce 0.55 units increase in the productivity gap levels in developing countries. By controlling for dynamic persistence of APG, in the second set of estimations, we found that 1% increase in the ratio of non-agriculture specialized technology imports to those specialized for agriculture production would increase the productivity gaps by, on average, 0.18 units. Estimated impacts of technology transfers on APG's are found to be robust to inclusion of related covariates such as relative capital intensities, fertilizer use in agriculture, share of rural population and its growth, and the depth of food deficit.

Overall, our findings imply that significant productivity disparities are not a typical manifestation of industrialization and development. In that sense, the theoretical propositions presented in this work challenge the appropriateness of technologies transferred into, especially, poor countries. New technologies created in advanced countries are typically best fitted for the level of development and local market conditions, which tend to match with those in less developed states to a limited extent.

Our empirical findings corroborate longstanding views that without technical change traditional agricultural production technologies deliver decreasing returns at increasing rate (Theodore Schultz, 1953, 1964; Arthur Mosher 1966; Yujiro Hayami and Vernon Ruttan, 1985; Peter Timmer, 1988). High and increasing labor productivity gaps in developing countries suggest that the central importance of agriculture in development, at least in terms of the existence of large pools of less productive workers in the sector, seems yet to be tackled properly. Surplus resources appear to be predominantly directed to non-agricultural sectors at the cost of delaying agricultural, perhaps overall, development. Intense adoption of sector-biased technologies seems to encourage unbalanced development path in the developing economies.

Particularly, our analysis and results suggest that, in the short run, development policies ought to emphasize on the elimination of barriers to free labor mobility between agriculture and non-agriculture, or equally, rural and urban areas. In the long-run, governments should pay greater attention to technical change in the agricultural productions, whether through domestic development or adoption of appropriate technologies from more advanced countries. Accumulation of human capital in the economy, overall, would make more skilled labor available for both traditional and modern sectors to embrace technical changes more easily and consistently. Our suggestions require more rigorous welfare and policy analysis for implementation, which we leave for future work.

Bibliography

Acemoglu, D. (2002). "Directed Technical Change," The Review of Economic Studies, Vol.69 No.4, pp.781-809

Acemoglu, D. (1998). "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," Quarterly Journal of Economics 113, 1055-1090.

Adam Smith, (1776). "Wealth of Nations," London

Adamopoulos, T., and D. Restuccia. (2014). "The Size Distribution of Farms and International Productivity Differences." American Economic Review, 104(6): 1667-97.

Anderson, T. W., and C. Hsiao. (1981). "Estimation of dynamic models with error components." Journal of the American Statistical Association 76: 598-606.

Arellano, M. and O. Bover. (1995). "Another look at the instrumental variable estimation of error-components models." Journal of Econometrics 68: 29-51.

Arellano, M. and S. Bond. (1991). "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." The Review of Economic Studies 58: 277-97.

Arellano, M. and S. Bond. (1998). "Dynamic Panel data estimation using DPD98 for Gauss: A guide for users." [Online] Available from: ftp://ftp.cemfi.es/pdf/papers/ma/dpd98.pdf

Arifovic, J., Bullard, J. and Duffy, J. (1997). "The Transition from Stagnation to Growth: An Adaptive Learning Approach." Journal of Economic Growth, 2(2), pp. 185–209.

Atkinson, A. and J. Stiglitz. (1969). "A New View of Technological Change." Economic Journal, 1969, vol. 79, No. 315, pp.573-78

Au, Ch. and J. V. Henderson (2006). "Are Chinese Cities Too Small?" Review of Economic Studies, Vol. 73, No. 3, pp. 549-576

Bai, Ch., and Z. Qian. (2010). "The Factor Income Distribution in China: 1978-2007." China Economic Review 21, pp.650-670.

Bai, J., and S. Ng. (2010). "Instrumental Variables Estimation in a Data Rich Environment." Econometric Theory 26(6): 1577-1606.

Bardhan, P. (1984). "Land, Labour and Rural Poverty." Oxford University Press, New Delhi.

Basu, S. and D. Weil. (1998). "Appropriate Technology and Growth." The Quarterly Journal of Economics, Vol. 113, N.4, pp.1025-1054

Cai, W. and M. Pandey. (2015). “The Agricultural Productivity Gap in Europe”. Economic Inquiry 53(4), 1807–1817.

Cai, W. and M. Pandey. 2015. “The Agricultural Productivity Gap in Europe”. Economic Inquiry 53(4), 1807–1817.

Caselli, F. (2005). “Accounting for Cross-Country Income Differences.” Handbook of Economic Growth, Vol. 1, pp. 679–741

Caselli, F., and Coleman II, J.W. (2001). “The US structural transformation and regional convergence: a reinterpretation,” Journal of Political Economy 109 (3), 584–616.

Caselli, F., and Coleman, W.J., (2001). "Cross-Country Technology Diffusion: The Case of Computers." American Economic Review, 91(2): 328-335.

Chanda, A. and Dalgaard, C.J. (2008). “Dual Economies and International Total Factor Productivity Differences: Channeling the Impact from Institutions, Trade, and Geography.” Economica, Vol.75, No.300, pp.629-661.

Chao, K. (1986). “Man and land in Chinese history: An economic analysis,” Stanford, CA: Stanford University Press

Chow, G. (1993). “Capital formation and economic growth in China.” Quarterly Journal of Economics 108 (3), pp.809–842.

Clark, C. (1957). “The Conditions of Economic Progress,” Macmillan, London

Coe David and Helpman, E. (1995). “International R&D Spillovers,” European Economic Review, 39, pp. 859–887.

Coe, D., E. Helpman, and A. W. Hoffmaister. (1998). “International R&D Spillovers and Institutions.” IMF Working Paper 08/104.

Crafts, N.F.R., (1985). ‘Income Elasticities of Demand and the release of labor by agriculture during British industrial revolution: A further appraisal. In: Mokyr, J. (Ed.), The Economics of Industrial Revolution. Rowman & Allanheld, Totowa, NJ.

Dekle, R. and G. Vandenbroucke. (2012). “A quantitative analysis of China’s structural transformation.” Journal of Economic Dynamics and Control, 36, pp.119-135.

Dercon, S. (2002). “Income Risks, Coping Strategies, and Safety Nets.” World Bank Research Observer, 17 (2), pp. 141-66.

Donovan, K. (2011). “Agricultural risk, intermediate inputs, and cross-country productivity differences.” University of Notre Dame Working Paper

Dwight, P.H. (1969). “Agricultural Development in China 1368–1968,” Edinburgh: Edinburgh University Press.

Eaton, J. and S. Kortum. (1999). “International Technology Diffusion: Theory and Measurement.” International Economic Review, Vol. 40, No. 3, pp. 537-570

Eberhardt and Vollrath, (2016). “The Effect of Agricultural Technology on the Speed of Development.” World Development, April 8, 2016.

Feenstra, R., R. Inklaar, and M. Timmer. (2015). “The Next Generation of the Penn World Table.” American Economic Review, Vol.105, No. 10, (pp. 3150-82)

Frankel A.J., and Romer D., (1999). “Does Trade Cause Growth?” The Journal of American Economic Review, Vol.89, No.3. pp.379-399

Freeman B.R. (1986). “Demand for Education,” Handbook of Labor Economics, Vol.1, pp.357-386

Fuglie, K. (2010). “The Shifting Patterns of Agricultural Production and Productivity Worldwide.” Ch. 4. Iowa State University.

Galor, O. and Moav, O. (2000). “Ability Biased Technological Transition, Wage Inequality Within and Across Groups, and Economic Growth.” Quarterly Journal of Economics 115, 469-97.

Galor, O., and Moav, O. (2001). “Evolution and Growth”, European Economic Review 45: 718-729

Galor, O., and Weil, D.N. (2000). “Population, Technology, and Growth: From Malthusian Stagnation to the Demographic Transition and beyond,” The American Economic Review, Vol. 90, No. 4, pp. 806-828

Gollin, D. (2002). Getting income shares right. Journal of Political Economy, 110, 458–74.

Gollin, D., Lagakos, D., & Waugh, M. E. (2014). “The Agricultural Productivity Gap,” The Quarterly Journal of Economics, pp.939-993

Gollin, D., Lagakos, D., and Waugh, M.E. (2014). "Agricultural Productivity Differences across Countries." American Economic Review, 104(5): 165-70.

Gollin, D., Parente, S., and Rogerson, R., (2002) “The Role of Agriculture in Development” American Economic Review Papers and Proceedings XCII, 160-164

Gollin, D., Parente, S., and Rogerson, R., (2004): “Farm Work, Home Work and International Productivity Differences,” Review of Economic Dynamics, 7

Gottlieb, Charles, and Jan Grobovˇsek. 2015. “Communal Land and Agricultural Productivity.” University of Edinburgh Working Paper

Grossman, G.M. and Helpman, E. (1994). “Endogenous Innovation in the Theory of Growth,” Journal of Economic Perpectives, Vol. 8, No. 1.

Hansen, G.D., and Prescott, E.C., (2002) “Malthus to Solow,” American Economic Review, 92(4), 1205-1217.

Harris, J. R. and M. P. Todaro. (1970). "Migration, Unemployment and Development: A Two-Sector Analysis." American Economic Review, 60 (1): 126–142

Hayami, Y. (1969). “Sources of Agricultural Productivity Gap Among Selected Countries”, American Journal of Agricultural Economics, 51, 564-575.

Hayami, Y. and V. W. Ruttan. (1985). “Agricultural Development: An International Perspective.” Johns-Hopkins University Press, Maryland.

Hayami, Y. and V. W. Ruttan. (1970). “Agricultural Productivity Differences among Countries.” The American Economic Review, Vol. 60, No. 5, pp. 895-911

Hayami, Y. and V. W. Ruttan. (1985). “Agricultural Development: An International Perspective.” Johns-Hopkins University Press, Maryland.

Herrendorf, B. and Schoellman, T. (2015). “Why is measured productivity so low in agriculture?” Review of Economic Dynamics. Vol. 18 (4): 1003–1022

Herrendorf, B., and T. Schoellman (2017). “Wages, Human Capital, and Structural Transformation” CESIFO Working Paper No. 6426

Herrendorf, B., and Teixeira, A. (2011). “Barriers to Entry and Development,” International Economic Review, 52(2), 573–602.

Hicks, S. (1932), “The Theory of Wages,” 1st ed., London, Macmillan&Co.

Hoekman, B. M., Maskus, K. E., & Saggi, K. (2005). “Transfer of technology to developing countries: Unilateral and multilateral options.” World Development, 33 (10): 1587–1602.

Huffman, W.E. and R.E. Evenson. (1993). “Science for Agriculture: A Long-Term Perspective.” Ames, IA: Iowa State University Press.

International Monetary Fund. “World Economic Outlook 2017.” Washington, DC.

Jacoby, H., and G. Mansuri. (2009). “Incentives, supervision, and sharecropper productivity.” Journal of Development Economics, Vol.88, No.2, pp. 232-241

Jäger, K. (2016) “EU KLEMS Growth and Productivity Accounts 2016 release - Description of Methodology and General Notes.” EU KLEMS Consortium

Jones, Ch. I. (1999). “Was the Industrial Revolution Inevitable? Economic Growth Over the Very Long Run.” Stanford University (Manuscript)

Juraev, S. Sirojiddin and You, Jong-il (2017). “Agricultural Productivity Gap and Technology Transfers in Developing Countries”. KDI School of Public Policy and Management, Working Paper.

Keller, W. (1998). “Are International R&D Spillovers Trade-Related? Analyzing Spillovers Among Randomly Matched Trade Partners.” European Economic Review, Vol.42, pp.1483-1491.

Kirsten, J. (2016). “EU KLEMS Growth and Productivity Accounts 2016 release - Description of Methodology and General Notes.” European Consortium

Kogel, T. and Prskawetz, A. (2001). “Agricultural productivity growth and escape from the Malthusian trap,” Journal of Economic Growth, Vol. 6, No. 4, pp. 337-357

Kuznets, S. (1971): Economic Growth of Nations: Total Output and Production Structure. Harvard University Press.

Kuznets, S. (1973). “Modern Economic Growth: Findings and Reflections,” The American Economic Review, Vol. 63, No.3, 247-258.

Lagakos, D. and M. E. Waugh. (2013) “Selection, Agriculture, and Cross-Country Productivity Differences.” American Economic Review, 103(2): 948-980.

Lewis, A. (1955). The Theory of Economic Growth, Homewood, IL, Richard D. Irwin

Lewis, W. A., (1954). “Economic Development with Unlimited Supplies of Labor,”

Malthus, T. (1789). “An Essay on the Principle of Population”, London

Marx, K., (1867). “Capital: A Critique of Political Economy,” Chicago: Charles H. Kerr and Co. (Published data: 1906)

Mayer, J. (2000). “Globalization, technology transfer and skill accumulation in low-income countries.” UNCTAD, WIDER Paper No.150.

McMillan, M. and D. Rodrik. (2011). “Globalization, Structural Change and Productivity Growth,” NBER Working Paper No. 17143.

Mehrhoff, J. 2009. “A solution to the problem of too many instruments in dynamic panel data GMM.” Discussion Paper Series 1. No 31/2009.

Morten, M. (2016). “Temporary Migration and Endogenous Risk Sharing in Village India.” NBER Working Paper No. 22159

Mosher, A. T. (1966). “Getting agriculture moving; essentials for development and modernization.” New York.

Munshi, K., and Rosenzweig, M. (2016). "Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap." American Economic Review, 106(1): 46-98.

O’Mahony, M., and M. Timmer (2009), “Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database”, Economic Journal, 119(538), pp. F374-F403.

Otsuka, K., Chuma, H. and Hayami, Y. (1992). “Land and Labor Contracts in Agrarian Economies: Theories and Facts.” Journal of Economic Literature, Vol. 30, No. 4, pp. 1965-2018

Parente S.L., Rogerson, R. and Wright, R. (2000) “Homework in Development Economics: Household Production and the Wealth of Nations,” Journal of Political Economy, Vol. 108, No. 4, pp. 680-687

Peter, P. Ch. (1988). “The Agricultural Transformation.” Handbook of Development Economics, Ch.8, Vol.1, pp 275-331

Restuccia, D., Yang, D.T., and Zhu, X. (2008). “Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis”, Journal of Monetary Economics 55 (2):234–250.

Ricardo, D. (1817). “On the Principles of Political Economy and Taxation (1 ed.),” London: John Murray

Richard B. Freeman and Remco H. Oostendorp. (2001). “The Occupational Wages around the World data file.” International Labor Review, Vol. 140. No.4.

Romer, P. (1990). (1993). “Idea gaps and object gaps in economic development.” Journal of Monetary Economics. Vol.32(3): 543–573

Romer, P. (1990). “Endogenous Technological Change,” Journal of Political Economy, 98, pp. S71–S102.

Romer, P. (1993) “Idea gaps and object gaps in economic development.” Journal of Monetary Economics. Vol.32(3): 543–573

Schultz T.W. (1953). “The Economic Organization of Agriculture”. New York, Mc Graw Hill Book Company.

Schultz, T. W. (1964). “Transforming traditional agriculture.” Chicago: University of Chicago Press

Solow, Robert (1956). “A Contribution to the Theory of Economic Growth,” Quarterly Journal of Economics, 70, 65-94.

Swan, T. (1956). “Economic Growth and Capital Accumulation,” Economic Record 32.63: 334-361

Timmer, M., G. deVries, and K. deVries. (2015). “Patterns of Structural Change in Developing Countries.” In J. Weiss, & M. Tribe (Eds.), Routledge Handbook of Industry and Development. (pp. 65-83). Routledge.

Timmer, M., Moergastel, T., Stuivenwold, E., Ypma, G., O’Mahony, M., and Kangasniemi, M. (2007). “EU KLEMS Growth and Productivity Accounts,” EU KLEMS Consortium

Tombe, T. (2011). “The Missing Food Problem: How Low Agricultural Imports Contribute to International Income and Productivity Differences,” Unpublished Manuscript, University of Toronto

Violante, G. L. (2008). “Skill-Biased Technical Change,” in ‘The New Palgrave Dictionary of Economics’, S. N. Durlauf and L. E. Blume (eds.), Basingstoke, England: Palgrave Macmillan

Vollrath, D. (2009). “How Important are Dual Economy Effects for Aggregate Productivity?” Journal of Development Economics, 88(2), 325–334.

Wallis, P., Colson, J., and Chilosi, D. (2016). “Puncturing the Malthus Delusion: Structural change in the British economy before the industrial revolution, 1500-1800”, London School of Economics, Economic History Working Papers No: 240/2016

Windmeijer, F. (2005). “A finite sample correction for the variance of linear efficient two-step GMM estimators.” Journal of Econometrics 126: 25-51.

Wu, H. and K. Ito. (2015). “Reconstructing China’s Supply-Use and Input-Output Tables in Time Series.” RIETI Discussion Paper Series 15-E-004

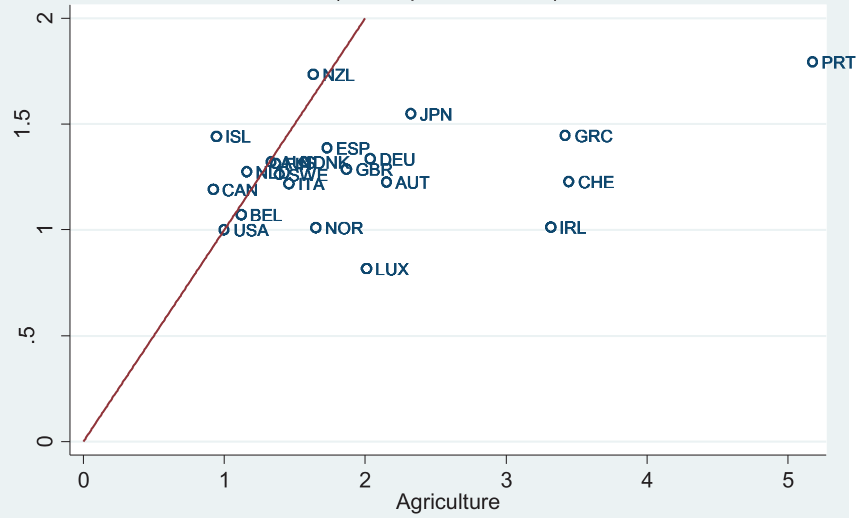
You, Jong-il and Juraev, S. Sirojiddin (2017). “Agricultural Productivity Gap: A New Look at the Measurement Problem”. KDI School of Public Policy and Management, Working Paper.

Young, A. (2013). “Inequality, the Urban-Rural Gap, and Migration,” Quarterly Journal of Economics 128 (4): 1727–1785.

Table A1. Summary statistics of variables used to compute APG

Variables	N	Mean	Median	Max	Min
Share of agricultural value added in GDP (%)	176	14.03	9.7	54	0.07
Share of non-agricultural value added in GDP (%)	176	85.97	90.3	99.9	46
Share of employment in agriculture (%)	176	28.3	19.1	88.5	0.12
Share of employment in non-agriculture (%)	176	71.7	80.9	99.8	11.5
APG	176	3.92	2.6	22.5	0.4
Note: *Country averages over 1995-2014 are reported.*					

Figure A1. Labor productivity relative to US: agriculture vs. non-agriculture
(developed countries)



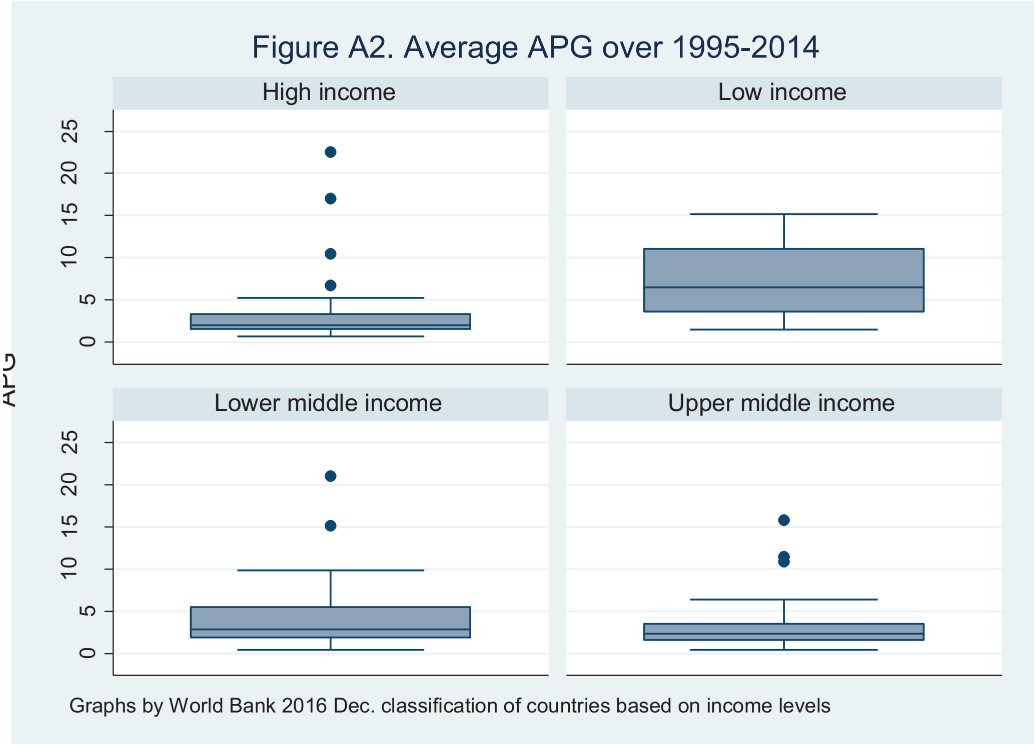


Table A2. Summary Statistics of Key Variables

Variables	Obs	Mean	Std. Dev.	Min	Max
log(Machinery Imports)	175	14,51	2,38	9,63	20,23
ln(Population)	175	15,60	2,03	9,88	20,98
ln(FDI inflows)	174	20,12	2,32	13,70	25,98
ln(Area)	175	11,50	2,49	3,97	16,65
ln(Capital ratio, N/A)	159	4,09	1,02	1,51	7,61
ln(kg of Fertilizer per hectare of arable land)	154	4,06	1,80	-1,13	8,84
ln(kg of Fertilizer per sq.km. of agricultural land)	154	7,42	2,10	1,31	13,36
Share of rural population %	176	44,79	23,26	0	90,33
Growth of rural population %	173	0,54	1,54	-5,75	4,81
Depth of food deficit (daily kilocalories per person)	111	125,30	94,62	4	392,19
Share of technology imports in total imports (%)	168	24,62	7,65	11,46	49,63
Share of agricultural technologies in total imports of sectoral technologies (%)	175	8,11	5,94	0,46	35,04
Share of agricultural technologies in total technology imports (%)	175	0,92	0,86	0,007	4,53
Ratio of non-agriculture specialized technology to agriculture specialized technology	175	31,17	37,96	2,08	227,11

Notes: *Country averages over 1995-2014 are reported.*

Table A4. Accounting Identity Breakdown using Alternative Labor Shares from KLEMS

No.	Countries	Sample period	*LS*	*LS*a	*LS*n	LSG	APG	AWG	APG*	APG**
1	Australia	1995-2007	0.61	0.53	0.62	0.86	1.42	1.52	0.93	1.08
2	Austria	1995-2014	0.67	1.76	0.65	2.78	3.92	2.12	1.85	0.67
3	Belgium	1995-2014	0.63	0.69	0.63	1.11	1.96	1.7	1.15	1.04
4	Canada	1995-2010	0.58	0.42	0.58	0.73	1.23	1.28	0.96	1.32
5	China	1995-2012	0.5	0.89	0.41	2.17	5.36	2.26	2.37	1.09
7	Cyprus	1995-2007	0.59	0.52	0.59	0.88	1.82	1.98	0.92	1.05
8	Czech Republic	1995-2007	0.59	0.63	0.59	1.08	1.68	1.36	1.24	1.16
10	Denmark	1995-2007	0.68	0.7	0.68	1.03	1.93	1.62	1.19	1.16
12	Estonia	1995-2007	0.57	0.55	0.57	0.97	1.74	1.54	1.13	1.16
13	Finland	1995-2014	0.66	0.92	0.65	1.43	2.12	1.54	1.38	0.97
14	France	1995-2014	0.67	0.99	0.66	1.52	2.1	1.74	1.21	0.8
9	Germany	1995-2014	0.67	0.99	0.67	1.47	2.75	1.89	1.45	0.98
15	Great Britain	1995-2014	0.63	0.71	0.63	1.08	1.94	1.77	1.09	1.01
16	Greece	1995-2007	0.56	0.81	0.55	1.47	3.51	2.34	1.5	1.01
17	Hungary	1995-2007	0.6	0.55	0.61	0.94	1.31	1.61	0.81	0.86
6	India	1995-2012	0.49	0.54	0.48	1.12	5.49	5.4	1.02	0.91
18	Ireland	1995-2007	0.56	0.93	0.55	1.69	4.02	1.67	2.41	1.42
19	Italy	1995-2014	0.64	0.84	0.64	1.32	2.11	1.94	1.09	0.83
20	Japan	1995-2009	0.61	0.49	0.61	0.81	3.63	3.28	1.11	1.37
21	Korea	1995-2007	0.52	0.64	0.51	1.23	2.93	1.38	2.12	1.72
24	Latvia	1995-2007	0.53	0.88	0.52	1.69	3.51	2.03	1.73	1.02
22	Lithuania	1995-2007	0.53	0.73	0.51	1.45	3.57	1.81	1.97	1.37
23	Luxembourg	1995-2007	0.56	1.03	0.55	1.85	3.87	1.74	2.14	1.15
25	Malta	1995-2007	0.57	0.41	0.58	0.71	1.07	1.56	0.69	0.97
26	Netherlands	1995-2014	0.69	0.71	0.69	1.02	1.49	1.42	1.05	1.03
27	Portugal	1995-2006	0.66	1.2	0.64	1.85	4.58	1.99	2.3	1.24
28	Russia	1995-2009	0.55	0.8	0.53	1.61	2.46	1.43	1.72	1.07
29	Slovakia	1995-2007	0.5	0.46	0.5	0.91	1.4	1.38	1.01	1.11
30	Slovenia	1995-2006	0.75	2.83	0.68	4.17	3.96	1.23	3.22	0.78
11	Spain	1995-2014	0.65	0.38	0.66	0.58	1.9	2.38	0.8	1.38
31	Sweden	1995-2014	0.56	0.69	0.55	1.27	1.65	1.16	1.42	1.13
32	USA	1997-2009	0.62	0.75	0.62	1.20	1.61	1.79	0.89	0.74

Notes: LS= labor share in GDP; LS_a = labor share in agriculture; LS_n = labor share in non-agriculture; LSG = LSa/LSn; APG* = APG/AWG; APG** = APG*/LSG. Labor shares are calculated from EU-KLEMS; APG from WDI; AWG from ILO. Country averages over the respective sample periods are reported.