LABOUR REALLOCATION OUT OF AGRICULTURE. EVIDENCE FROM DEVELOPING COUNTRIES

by

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To my lovely daughter Tanzim, and wonderful son Mazin

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Abstract

This dissertation studies the process of reallocation of labour out of agriculture in developing countries. I develop a two-sector general equilibrium model where land is a quasi-fixed factor, and population growth constrains the reallocation of labour from agriculture. Productivity growth in agriculture can alleviate this constraint. The quantitative analysis shows that during the 1970-2010 period, population growth accounted for most of the changes in employment in agriculture in developing countries, while the attenuating contribution of productivity growth was negligible. In the absence of population growth, compared to data, agricultural employment would have declined 1.5% more, while agricultural labour productivity would have increased 0.5% more per year.

I, then, study the effect of Green Revolution in agriculture on the speed of labour reallocation out of agriculture. Green Revolution is a form of land-augmenting technical change which increases labour-intensity and hence, slows down the reallocation of labor out of agriculture. I present a model with land-augmenting technical change. Using cross-national data on the adoption of high yielding varieties technology, I find that the Green Revolution can explain 28 percent of the increase in agricultural employment in the adopting countries over the period 1965 to 2000. Finally, I study the relation between agricultural land productivity and share tenancy. Using district-level data from rural Bangladesh, this study finds no evidence of a negative relation between farm output per unit of land and share tenancy. The reason is that while, in Bangladesh, share tenancy is highly prevalent, the land is scarce, about ten percent of the farm households are landless, contracts are short term, and non-farm jobs are limited.

List of Abbreviations Used

APO	Asian Productivity Organization
AEZ	Agro-Ecological Zones
BBS	Bangladesh Bureau of Statistics
CES	Constant Elasticity of Substitution
CIMMYT	International Centre for Wheat and Maize Improvement in Mexico
COV	Covariance
CRS	Constant Return to Scale
CV	Coefficient of Variation
DiD	Difference in Difference
FAO	Food Agriculture Organization
FAOSTAT	Food Agriculture Organization Statistics
GAEZ	Global Agro-Ecological Zone
GDP	Gross Domestic Product
GGDC	Groningen Growth and Development Centre
GR	Green Revolution
HYV	High Yielding Variety
IRRI	International Rice Resource Institute

IV	Instrumental Variable
KG	Kilogram
MPL	Marginal Product of Labour
PWT	Penn World Table
OLS	Ordinary Least Square
RMSE	Root Mean Square Error
TFP	Total Factor Productivity
USAID	United States Agency for International Development
WWII	World War II
2SLS	Two Stage Least Square

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My final words are for my mother and deceased father, who always want to see me tall among all. I really miss my father as he is not there to join my success. But, I know in a world of limited resources your love and blessings are unlimited.

Chapter 1

Introduction

This dissertation studies the process of reallocation of labour from agriculture to non-agricultural sector in developing countries. In economic development literature, this process is widely known as structural change, defined as a secular decline of the share of agriculture in output and employment. Along the long-run development path, all currently industrialized countries have undergone a process of reallocation of resources, mainly significant reallocation of labour from agriculture to non-agricultural sectors.[1] Kuznets (1971) thus included this structural change as one of his six stylized facts of economic development. This suggests that the forces that give rise to this change is key to our understanding of the development process.

Dating back to the nineteenth century, economists have attempted to understand the underlying forces of structural change. Its main drivers are: 1) improvements in agricultural productivity combined with Engels law release resources from agriculture ("demand forces"); and 2) Baumol's effect, higher productivity growth in agriculture relatively to non-agriculture pushes farm workers to produce complementary non-farm goods ("supply forces").

While insightful, existing models on structural change ignore population growth (explicitly) and those models mainly focus on current

[1]For example, agricultural employment share in the United States fell from about 74% in 1800 to about 2% in 2000 (Dennis and İşcan, 2009).

industrialized countries, with no or less focus on developing countries. These models assume a constant return to scale (CRS) production function without a fixed factor like land. Under CRS technology, population growth affects the level of income, but not the pace of labour reallocation across sectors and increases in population can be absorbed in the long run through factors that can be accumulated. But, if land is a fixed factor that produces subsistence good and included in the production function, then population growth affects the pace of structural change.

I consider population growth as a determinant of structural change and provide a decomposition of the changes in agricultural employment due to both population and per worker productivity growth. Chapter 2 studies the impact of population growth on the pace of labour reallocation from agriculture to non-agricultural sectors. I develop a two-sector general equilibrium model where land is a quasi-fixed factor, and population growth constrains the reallocation of labour from agriculture. Productivity growth in agriculture can alleviate this constraint. The quantitative analysis shows that during the 1970-2010 period, population growth accounted for most of the changes in employment in agriculture in developing countries, while the attenuating contribution of productivity growth was negligible. In the absence of population growth, compared to data, agricultural employment would have declined 1.5% more, while agricultural labour productivity would have increased 0.5% more per year.

The classical models on structural change show how productivity growth in agriculture can release labour from this sector.[2] However, there is less empirical evidence on the differential effect of land versus labour bias technological change in agriculture on the labour reallocation from agriculture. Land-biased technical change like mechanization of agriculture, reduces the demand for labour without a change in output per unit of land. By contrast, labour-biased technical change like biological technology (e.g. fertilizers or pesticides) increases effective land, and other things being equal, increases the demand for labour. For example, Hayami and Ruttan (1970) show that starting from 1880s till 1930s, Japan experienced higher yield per hectare than the United States as during that period Japan adopted biological techniques, while the United States adopted mechanical technology and as a result had higher output per worker than Japan. During this period Japan also experienced high employment in agriculture. Since the 1930s, Japan started to adopt mechanical technology like the United States followed by declining yield as well as employment in agriculture.

In Chapter 3, I provide empirical evidence on the effects of technical change in agriculture on the agricultural labour reallocation by studying the widespread adoption of a common agricultural technology- 'Green revolution' by several developing countries in the late 1960s. Green Revolution is a form of land-augmenting technical change which increases labour-intensity and hence, slows down the reallocation of

[2]For exapmle, Üngör (2013), where he shows that growth of output per worker in agriculture combined with subsistence requirement in agriculture is able to explain most of the secular declines in the agricultural employment share in several countries around the world.

labour out of agriculture. I present a model with land-augmenting technical change. Using cross-national data on the adoption of high yielding varieties technology, I find that the Green Revolution can explain 28 percent of the increase in agricultural employment in the adopting countries over the period from 1965 to 2000, and that in the absence of the Green Revolution on average the share of employment in agriculture would have declined by 6 percentage points more in the adopting countries.

It is well documented that High Yielding Varieties (HYVs) seeds cultivation requires more labour than local crops (Ahmed, 1977; Regmi, Oladipo, and Bergtold, 2016). This, couples with the existence of a large pool of landless farmers, would increase the value of land through competition between landless farmers for scarce land, and would thus increase land productivity, but at the expense of labour productivity. In Bangladesh, for an example, the mean deviation between output per worker and yield per acre in rice production was 1.53 metric ton in 2008 (Bangladesh agricultural census, 2008). Now, if the purpose of development is to improve standard of living, then it essentially implies increase of the productivity of labour and the reduction of labour employed per unit of output or land. I study Bangladesh as a case-study because this country is one of the pioneers of the HYV seeds adopting countries and it employs approximately 50% of its labour force in agriculture.

In Chapter 4, I examine the relation between agricultural land productivity and share tenancy. Share tenancy is inefficient if tenants supply suboptimal effort due to the fact that they are not the full claimant of the residual income. However, the economic significance of this inefficiency depends on whether tenants have non-farm job options. Using district-level data from rural Bangladesh, this chapter finds no evidence of negative relation between farm output per unit of land and share tenancy. The reason is that while, in Bangladesh share tenancy is highly prevalent, land is scarce, about ten percent of the rural households are landless, contracts are short term, and non-farm jobs are limited.

The rest of the dissertation is organized as follows. Chapter 2 provides a general equilibrium model to distinguish the population effect and productivity effect on the pace of structural change for several developing countries during the period 1970 to 2010. Chapter 3 describes an empirical model on the relation between a common labour-biased technological change and the agricultural labour reallocation in 33 HYV seeds adopting countries over the period 1965-2000. Chapter 4 examines the effects of share tenancy on the agricultural land productivity in Bangladesh. Chapter 5 concludes the dissertation. The appendix provides additional details on each chapter separately.

Chapter 2

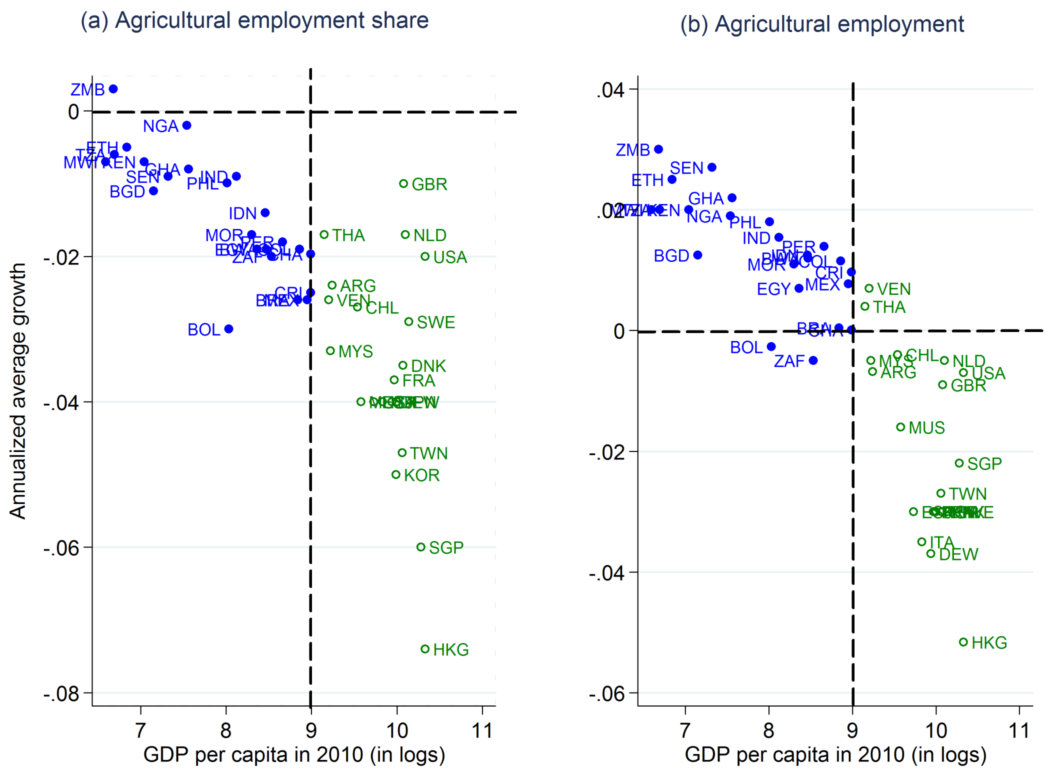
Demographics, Productivity Growth and Structural Change: Evidence from Developing Countries

2.1 Introduction

Development of an economy typically goes hand-in-hand with a declining share of agriculture in output and employment (Kuznets, 1957). This process of sectoral transformation is known as structural change in the literature on economic development. Along the long-run development path, all currently industrialized countries have undergone a process of reallocation of resources, but mainly significant reallocation of labour from agriculture to non-agricultural sectors. Kuznets (1971) thus included structural change as one of his six stylized facts of economic development (see also Bah, 2009; Herrendorf, Rogerson, and Valentinyi, 2013a). What is interesting about this development process in developed countries, however, is that not only the share of employment, but also total employment in agriculture has declined over time.

By contrast, over the last four decades in most developing countries, although the share of employment in agriculture has declined, employment in agriculture has also increased. Figure 2.1 documents this fact across 44 countries with different stages of economic development. Panel (a) shows the annual growth rate of agricultural employment share and panel (b) shows the same for the actual employment

Figure 2.1: Agricultural employment and employment share across countries; 1970 - 2010



Note. In the above graph, annualized growth rates of employment and employment share in agriculture are plotted against log of GDP per capita in 2010. There are 44 countries in the sample. The vertical dashed line shows the income cut off for higher middle income countries in the World Bank definition for 2010.
Source: Employment data are from GGDC 10 sector database and Asian Productivity Organization(APO) database. GDP per capita is in 1990 international Geary-Khamis (GK) dollars and are from Maddision project database.

in agriculture. The vertical dashed line in the figure shows the income cut off for higher-middle income countries according to the 2010 World Bank definition. For those countries above the higher-middle income cut off, both employment and the share of employment in agriculture has declined over the period 1970-2010 (negative growth rates in both cases). However, for those below this cut off, while the share of employment in agriculture has declined over this period (negative growth rate), employment in agriculture actually increased on average (positive growth rates). In this chapter, I shed light on the consequences of this divergence between developed and developing countries for structural change. I argue that increased employment in agriculture has led to a decreasing land-labour ratio through putting pressure on the quasi-fixed factor land, a declining average labour productivity in agriculture and thus to an overall low aggregate productivity.

What are the factors that might explain this divergence between the developed and developing countries? I consider population growth as a determinant of structural change and provide a decomposition of the changes in agricultural employment due to both population and per worker productivity growth. I show that stronger population growth relative to agricultural labour productivity growth in developing countries mostly account for this fact. A country can provide food for the extra mouth either by increasing agricultural output per worker, or by increasing proportion of employment in agriculture or by both. While the developed countries with relatively low population growth have managed to increase food production by enhancing their agricultural output per worker, the developing countries with high population growth ended up employing additional labour in agriculture, which in turn reduced land-labour ratio and leading to slower output per worker in agriculture growth, thus overall aggregate productivity growth.[1] This happens when the growth rate of population is high and land being a quasi-fixed factor produces subsistence food.

While this observation is important and was central to earlier work on structural change (e.g. Johnston and Kilby, 1975), the more recent structural change literature has overlooked the contribution of population growth to the process of structural change.[2] There is a large literature on the long-term drivers of structural change and this literature has identified two major drivers: preference-driven and technology-driven structural change. The first explanation, consistent with Engel's law, argues that when per capita income of a country rises, consumption demand shifts away from agriculture, due to low income elasticity of demand and non-homothetic preferences; see, among others, Echevarria (1997); Kongsamut, Rebelo, and Xie (2001); and Foellmi and Zweimüller (2008). The second explanation works through technological differences across sectors and three alternative mechanisms have been proposed; i) the first mechanism works through differential sectoral productivity growth (see e.g. Ngai and Pissarides, 2007); ii) the second mechanism works through sectoral differences in the elasticity

[1] Even in a purely accounting sense, land-labour ratio has an impact on agricultural productivity. Output per worker in agriculture ($\frac{Y_a}{L_a}$) can be written as a product of yield per hectare ($\frac{Y_a}{T}$) and land-labour ratio ($\frac{T}{L_a}$): $\frac{Y_a}{L_a} = \frac{Y_a}{T} \times \frac{T}{L_a}$. If land-labour ratio decreases even when yield per hectare increases, output per worker grows at a slower rate because of the inverse effect of land-labour ratio. However, both Y_a and L_a are endogenous variables.

[2] Johnston and Kilby (1975) agrue that population growth determines the rate and direction of structural change. They stated that in Ceylon, Egypt and Indonesia high population growth rate equalled or surpassed non-farm employment growth rate so that structural change ceased or reversed. With a simple equation, which they termed rate of structural transformation (RST), they showed the rate of structural chnage from agriculture to non-agrculture: RST $= \frac{L_n}{L_t}\left(\dot{L}_n - \dot{L}_t\right)$, where L_n is non-farm amployment, L_t is total labour force and $\dot{L}_n$ and $\dot{L}_t$ are their respective rates of chnage (for detail, see page 83-84 of Johnston and Kilby, 1975).

of output with respect to capital across sectors (see e.g. Acemoglu and Guerrieri, 2008), and iii) the last one is termed as factor rebalancing effect proposed by Alvarez-Cuadrado, Long, and Poschke (2016) that works through the sectoral differences in the degree of capital-labor substitutability. There is a third line of research that combines the interplay between both of the drivers (see e.g., Dennis and İşcan, 2009; Alvarez-Cuadrado and Poschke, 2011).[3]

While insightful, the existing structural change literature focuses largely on the share of employment in agriculture, defined as agricultural employment as a percentage of total employment, with less attention on actual employment in agriculture. Consistant with this focus, the modern literature on structural change mostly uses constant returns to scale (CRS) production functions without any fixed factor of production. From a theoritical standpoint, under a CRS technology there is virtually no difference between using the share of employment in agriculture or actual employment. This is because in the long-run population growth affects the level of income, but not the pace of reallocation of labour across sectors. See, for instance, Kongsamut et al. (2001), Ngai and Pissarides (2007); and Dennis and İşcan (2009). By contrast, when land is a fixed factor and produces a subsistence good, population growth matters for the scale of production and affects the

[3]In the literature, preference and technology driven channels are also termed as 'Engel's law effect' and 'Baumol's effect', respectively; e.g., Dennis and İşcan (2009). In Alvarez-Cuadrado and Poschke (2011), they term preference driven channel as 'labour push hypothesis', while technology driven forces as 'labour pull hypothesis'. However, in this paper, I combine both the absolute productivity growth in agriculture and relative productivity growth in agriculture and non-agriculture under 'productivity-effect' and compare its contribution to structural change relative to 'population-effect'.

pace of structural change.

Of course, while land is a fixed factor, it can be "augmented" through technological progress. To study the separate impacts of population growth and productivity growth, I construct a two sector general equilibrium model. A key characteristic of the framework studied here is that land is a quasi-fixed factor and as such the production technology in agriculture exhibits decreasing returns to scale. Unlike the constant returns to scale technology, where increases in population can be absorbed in the long run through factors that can be accumulated, under decreasing returns to scale population growth constrains the reallocation of labour from agriculture. While a fixed supply of land imposes limits on agricultural production, changes in productivity in this sector can alleviate this constraint. I show that under a quasi fixed factor such as land that is essential for the production of a subsistence good both the preferences-driven effects and the technology-driven effects are still relevant but are modified. Moreover, the decreasing returns to scale allows to quantify the independent contributions of population growth and productivity growth on structural change.

To conduct the quantitative analysis, I compile data across a sample of countries from 1970 to 2010, estimate sector-specific productivity growth rates, and calibrate the model parameters. I then combine the calibrated parameters with country-specific time-varying sectoral productivity growth and population growth rates to obtain model-based time paths for agricultural employment. Overall the model matches the empirical counterparts of both agricultural employment and the share of employment in agriculture and both for developing and developed countries. To assess the separate effects of population growth and productivity growth, I fix one of the variables (either population or productivity) in the initial year of the sample period, 1970 and allow the remaining variables to change over time. For developing countries, I find that most of the increase in agricultural employment implied by the model during the period is due to population growth, while the attenuating contribution of productivity growth is negligible. A counterfactual experiment with no population growth suggests that agricultural labour productivity would have increased on average by 0.5% more per year relative to the data during 1970-2010 period. This would have also led to a reduction of agricultural employment by 1.5% more per year. By contrast, in developed countries, I find that observed agricultural employment pattern is driven mainly by productivity growth, while the effect of population growth is weaker.

The rest of the chapter is organised as follows. Section 2 reviews the relevant literature on structural change. Section 3 documents the stylized facts. Section 4 introduces the model and the analytical framework. Section 5 presents the quantitative results and conducts a sensitivity analysis. An extension of the model with capital is offered in section 6. Section 7 concludes.

2.2 Related literature

Reallocation of resources, mainly labour, across sectors is at the heart of structural change, which is studied in development economics as part of the process of long-run economic growth; Johnston (1970);

Matsuyama (2008); Barrett, Carter, and Timmer (2010). In fact, empirical evidence suggests a close association between economic growth and structural change (Gollin, Parente, and Rogerson, 2002; Temple and Wößmann, 2006; Block, 2010; McMillan, Rodrik, and Verduzco-Gallo, 2014). In economic development, this process is studied as one of the Kuznet (1971) facts consisting of un-balanced growth, by contrast to much studied and researched 'neoclassical' balanced growth (Kongsamut et al., 2001). Along a balanced-growth path, the growth rate of output, the capital-output ratio, consumption-income ratio, the real interest rate, and the factor share of income remain broadly constant over time (Kaldor, 1961). Kongsamut et al. (2001), however, argue that even when aggregate variables follow a balanced growth path, at the sectoral level there can be unequal growth and inter-sectoral resource reallocation.

The most well-established empirical incidence of this resouce reallocation is the secular decline in the agricultural labour force; Fisher (1939) and Clark (1967), Ojala (1952), and Latil (1956) (quoted in Johnston, 1970) provide empirical evidence based on long-term changes in the United States, Sweden, and the UK. Kuznets (1957) provides the first comprehensive examination of the changing industrial structure of the labour force and national product associated with economic growth; ses also Clark (1967), and Chenery (1960). In this literature, as the economy becomes rich, structural change emerges through either preference related and technology related forces.

The mechanism of structural change led by preference-based or demand forces is consistent with the Engel's law, one of the most robust empirical regularities in economics (Boppart, 2014). In this case, since the income elasticity of food is inelastic, the share of income spent on food changes in the opposite direction as changes in income. By contrast, the income elasticity of demand for service and manufacturing good is elastic, thus when per capita income of a country rises, consumption demand shifts away from agriculture (Dennis and İşcan, 2009). This enhanced demand combined with productivity growth in agricultural pulls labour out of agriculture in favour of the sector where additional demand shifts to (Nurkse et al., 1966; Gollin et al., 2002; Üngör, 2013). This preference-driven channel of structural change is also termed as 'Engel effect' (Dennis and İşcan, 2009) or 'labour push' hypothesis (Alvarez-Cuadrado and Poschke, 2011).

Kongsamut et al. (2001) propose a general equilibrium model in which structural change is driven by non-homothetic preferences with subsistence requirement in agriculture. They also show that under certain conditions, structural change is consistent with a constant real interest rate, which they label as a generalized balanced growth path (GBGP). However, Herrendorf et al. (2013a); Ngai and Pissaarides (2007) argue that the condition which underpins the GBGP in Kongsamut et al. (2001) relates the parameters of preferences and technology to each other, and is therefore a "fragile" condition. Other papers that focus on income effects and non-homothetic preferences include Nurkse et al. (1966), Echevarria (1997), Laitner (2000), Caselli and Coleman II (2001), Gollin et al. (2002), Foellmi and Zweimüller (2008), Restuccia, Yang, and Zhu (2008), and Buera and Kaboski (2009).

Technology or the supply driven forces, stem from two supply-side effects, one due to differential sectoral productivity growth rates, which is also termed as 'Baumol effect' (Dennis and İşcan, 2009) or as 'labour pull hypothesis' Alvarez-Cuadrado and Poschke (2011); and the other to differential capital deepening (Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008), Dennis and İşcan (2009)). This mechanism places an emphasis on sectoral differences in factor proportions due to differences in the elasticity of output with respect to capital across sectors. Initial work on supply driven forces, dates back to Baumol (1967) and is known as Baumol's "cost disease".[4] In this case, differences in productivity growth rates between agriculture and non-agriculture change their relative price and, depending on the elasticity of substitution across goods, the sector with a higher productivity growth rate either sheds or gains labour.

In a recent study, Alvarez-Cuadrado et al. (2016) propose a complementary channel under the supply-side forces, which they term as the 'factor rebalancing effect'. They show that if the degree of capital-labour substitutability across sectors differs, then the more flexible sector use the abundant input intensively. As a result, sectoral capital-labour ratios grow at different rates, and the fractions of aggregate capital and labour allocated to a sector change. Using a general equilibrium model and drawing data on the postwar USA, they argue that this channel was an important contributor to structural change out of agriculture in the United States.

[4]Baumol divided the economy into two sectors, a progressive sector that registers increasing productivity due to innovation and grows at a constant rate and a stagnant sector that uses mostly labour as the input and suffers from less productivity growth. If the demand for goods/services produced by stagnant sector is either income elastic or price inelastic than because of factor mobility, the production costs and prices of the stagnant sector should rise. This is known as Baumol's cost disease.

There is a third line of research that combines the interplay of both Engel's effect and Baumol's effect. Dennis and İşcan (2009) in a unified model decompose the forces behind the structural change in the United States' economy and show that before the WWII Engel's law mostly explained the structural change, while it is the Baumol effect that explains the change in the aftermath of WWII. They combined both non homothetic preference and differential sectoral productivity. Following their lead, Alvarez-Cuadrado and Poschke (2011) study 12 industrialized countries and argue that productivity improvements in the non-agricultural sector were the main driver of structural change before 1960, while after that productivity changes in agriculture acted as a driver of changes.

Thus, two "traditional" explanations for structural change are non-homothetic preferences and sector-biased technological progress (Buera and Kaboski, 2009). Alongside the productivity factor, some studies also incorporate international trade to understand the process of structural change. For example, Betts, Giri, and Verma (2013), Sposi (2012), Teignier (2009) and Uy, Yi, and Zhang (2013) have studied structural change in South Korea during its "growth miracle" during the period 1970 to 2005. They show that international trade accelerated the transition out of agriculture into industry and services. Üngör (2011), using data from Latin America and East Asia, shows that differences in sectoral productivity growth rates account well for the different sectoral reallocations in the two regions. Thus, while the impact of sectoral productivity gains and the growth of trade have been investigated, the literature has paid less attention on the role of population growth in the process of structural change. The exception is Leukhina and Turnovsky (2015), where they show that population growth played a major role in structural development in England, with especially notable contributions to post-1750 rise in the manufacturing employment share. By contrast, this paper studies 12 developing countries and shows that faster population growth relative to productivity growth (mixture of both agricultural productivity and unbalanced productivity growth across agriculture and non-agriculture) mostly account for the slower pace of labour reallocation from agriculture over the 1970 - 2010 period.

Developing countries have also received less attention in the structural change literature. While the determinants of structural change in the case of developed countries are well documented, little is known about the drivers in developing countries. Bah (2009) and Herrendorf et al. (2013a) point out that developing countries follow distinct structural transformation paths that deviate from that followed by developed countries. For exmple, Gollin et al. (2002) suggest that structural change could be integral in the development process for developing countries if it improves aggregate productivity through labour reallocation.

Studies that deal with developing countries include Dekle and Vandenbroucke (2012) on China during the 1978-2003 period and Verma (2012) on India during the 1980-2005 period. Dekle and Vandenbroucke (2012) using a two-sector model show that China's sectoral transformation was accelerated significantly by the gradual reduction in the size of government. Verma (2012) with a three-sector model and Indian data, show that faster TFP growth in services mainly drive the sectoral transformation of value-added share, although her model poorly matches the sectoral employment share in industrial sector. All these studies ignore population growth as a determinant of resource reallocation.

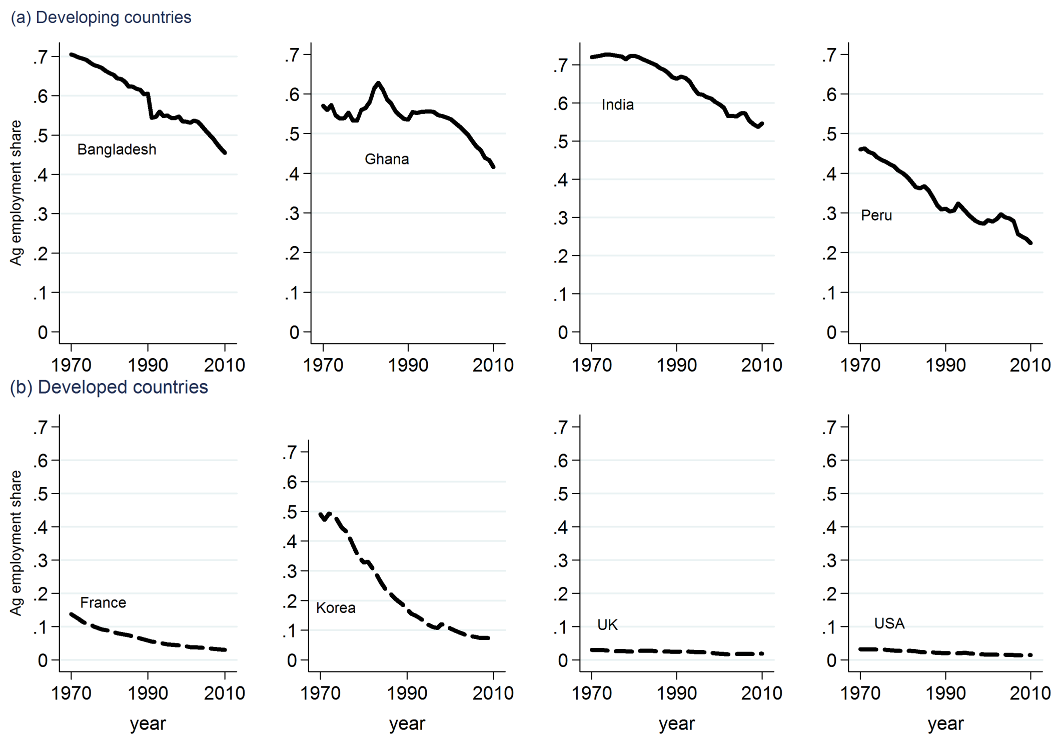
2.3 Stylized facts

The primary focus of this chapter is sectoral reallocation of labour from agriculture to non-agriculture. In this section, I document four empirical regularities for both developed and developing countries. The data are mainly from three sources: i) Groningen Growth and Development Centre (GGDC) 10-sector database, ii) The World Bank, World Development Indicators database, and iii) Penn World Table (PWT) 8.0.

Fact 1: Agricultural employment share declined over the period 1970-2010 both in developed and developing countries, while employment in agriculture in developing countries increased in contrast to developed countries.

Figures 2.2 and 1a show that agricultural employment as a share of total employment (i.e. $l_a = \frac{L_a}{L}$) has declined over time in all the countries considered here regardless of the state of development. For instances, in Bangladesh agricultural employment share was 70% in 1970, which slid down to 43% in 2010 and in France, too, share of employment in agriculture decreased from 2% in 1970 to 1.5% in 2010 (Figure 2.2). However, the trend of the actual employment in agricultural is quiet different for developed and developing countries. Figures 2.3 and 1b depict that actual employment increased in the case of

Figure 2.2: Share of agricultural employment in selected countries; 1970 - 2010

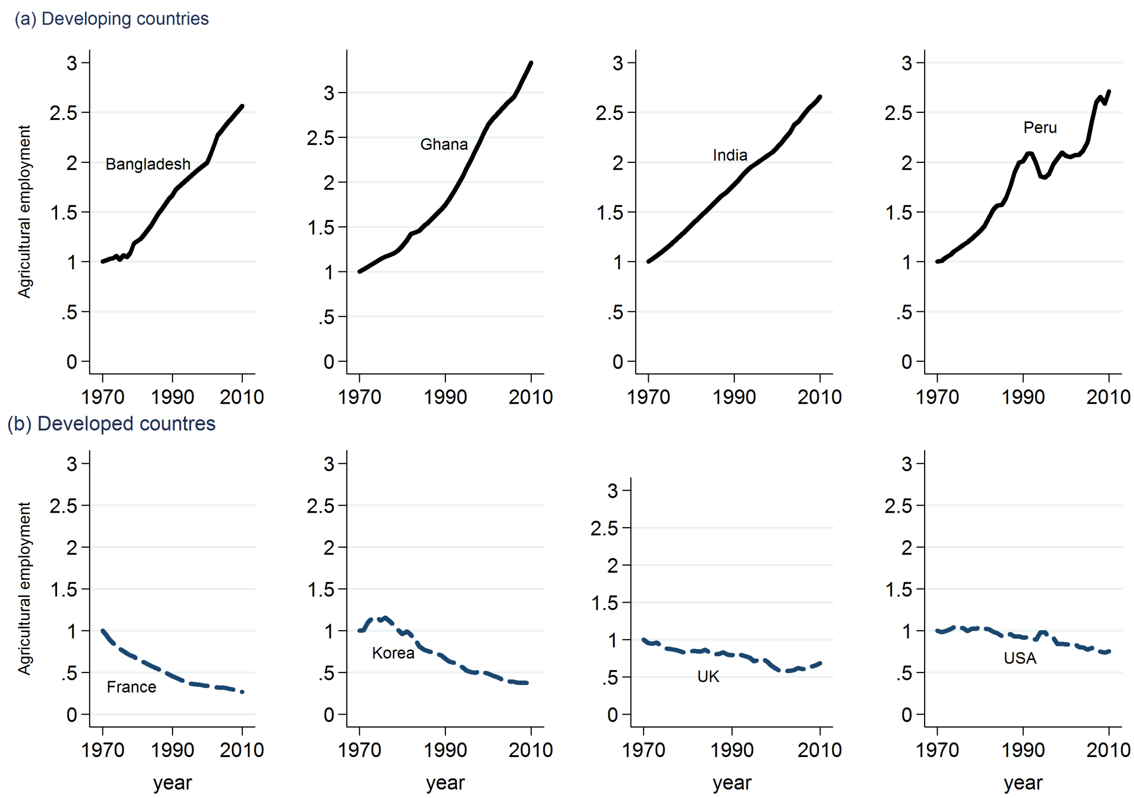


Source. GGDC 10-sector database, except for Bangladesh, which is from Asian Productivity Organization (APO) website database.

developing countries, while the opposite happened in the case of developed countries. For instance, in 2010 there were 2.5 times more people employed in agriculture in Bangladesh than it was in 1970. In France, by contrast, employment in agriculture was less than 50% in 2010 than it was in 1970 (Figure 2.3).

Fact 2: During the 1970-2010 period, both arable land and total employment increased in most of the developing countries, while in most of the developed countries arable land and employment either declined or increased at a modest rate.

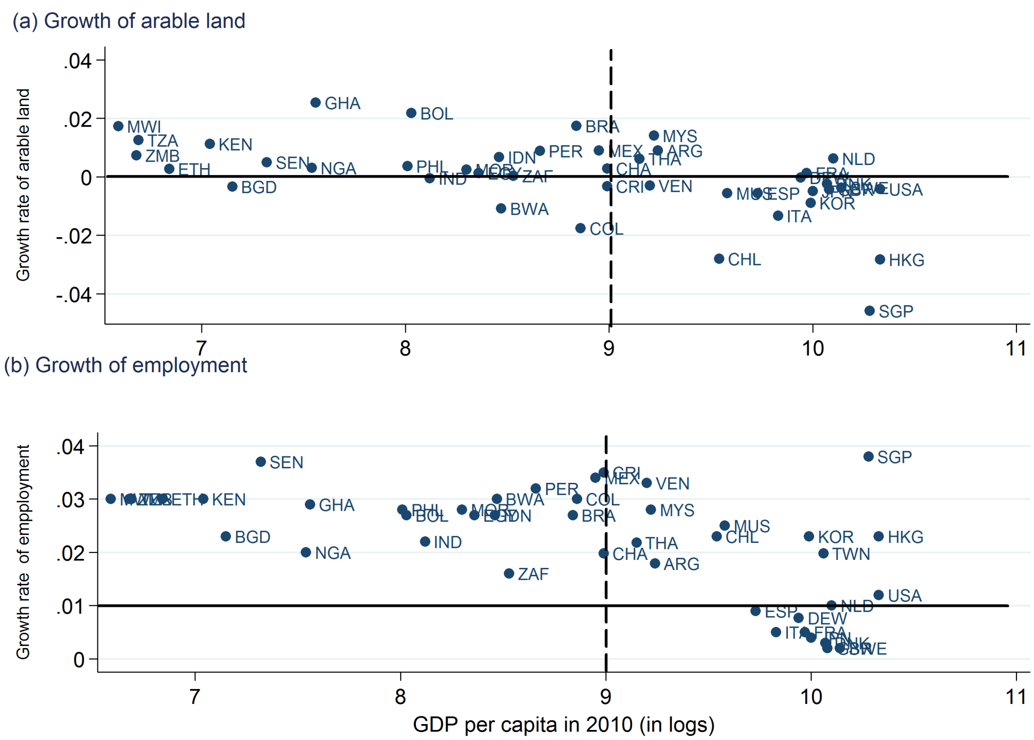
Figure 2.3: Agricultural employment, selected countries; 1970 - 2010



Note. Agricultural employment data are normalized to 1 in 1970. Data are from GGDC 10 sector database and APO database.

The upper panel of figure 2.4 plots the growth rate of arable land for 44 developed and developing countries, and the lower panel shows the growth rate of total employment for the same group of countries from 1970 to 2010. It shows that, except for Bangladesh, Botswana, and Colombia, arable land increased in developing countries, whereas in developed countries there was little or no change in arable land during the period. The data also suggests that in the case of developing countries, the average annualized growth rate of employment was within the range of 1.5% to 4%, whereas for the developed countries it was

Figure 2.4: Annualized average growth rates of arable land and total employment; 1970 - 2010



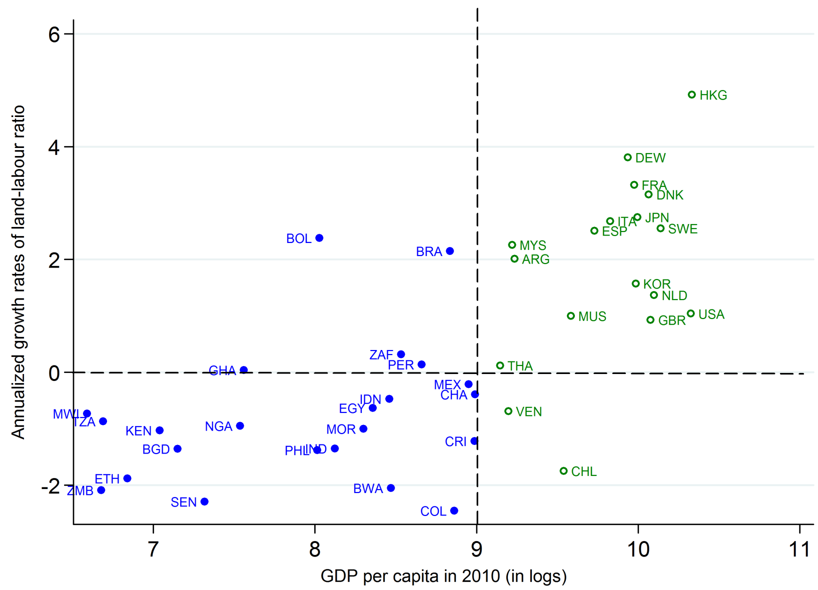
Note. The vertical dash line is the income cut off for the higher-middle income countries for the year 2010 according to the World Bank definition.
Source: Arable land data from World Development Indicator (WDI), the World Bank and the employment data are from Penn World Table (PWT), version 8. GDP per capita is in 1990 international Geary-Khamis (GK) dollars and are from Maddision project database

within the range of 0.5% to 1%. Hence, developing countries created employment over the period 1970-2010 but the bulk of this increase was in agriculture.

Fact 3: Land-labour ratio increased in developed countries, while it decreased in developing countries.

From 1970 to 2010, land available for each person employed in agriculture, represented by the land-labour ratio, declined in developing

Figure 2.5: Annualized growth rates of land-labour ratio; 1970 - 2010



Note. The vertical dash line is the income cut off for the higher-middle income countries for the year 2010 according to the World Bank definition. Total arable land of each country is divided by the number of persons employed in agriculture.
Source: Land data are from WDI, and the agricultural employment data are from GGDC 10 sector database. GDP per capita is in 1990 international Geary-Khamis (GK) dollars and the source is Maddison project database.

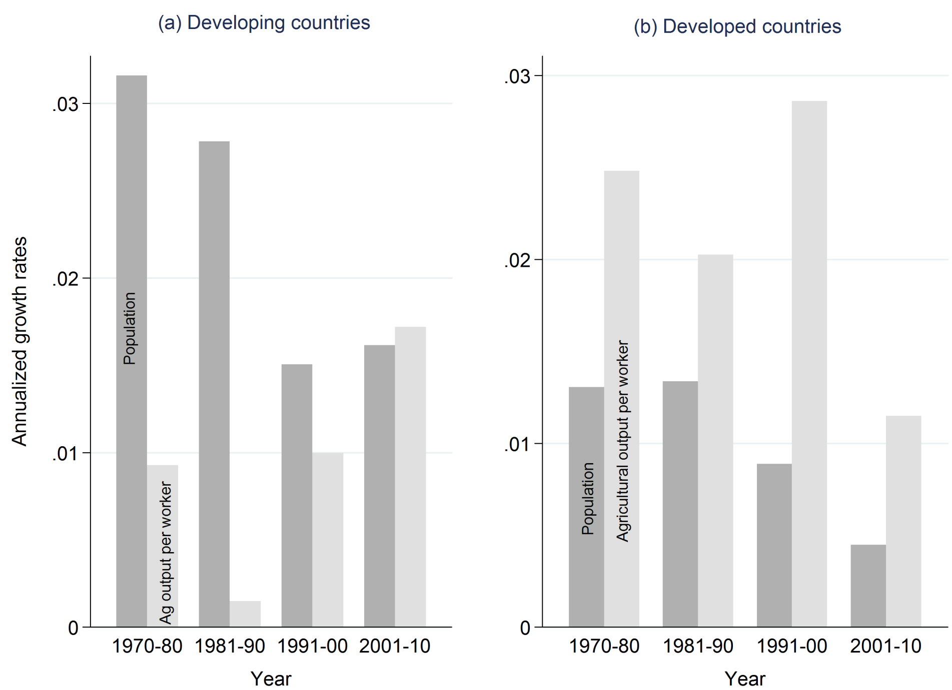
countries, while it increased in developed countries. Figure 2.5 documents this fact, where I plot the annualized growth rate of land-labour ratio against GDP per capita in 2010. A negative growth rate of land-labour ratio suggests a rising scarcity of land. Figure 2.5 shows that in all the developing countries in the sample, except Bolivia, Brazil, Peru, and South Africa, the land-labour ratio declined over time despite the fact that arable land increased in those countries during the same period (figure 2.4). By contrast, in developed countries there was an increase in the land-labour ratio. Hence, in terms of the land-labour ratio, developed and developing countries exhibit systematically different patterns.

Fact 4: During the 1970-2010 period, population grew faster than labour productivity in agriculture in developing countries. By contrast, in developed countries agricultural labour productivity grew faster than population.

In the last 40 years, population in this sample of developing countries increased at an annualized average rate of 2.3% as opposed to the agricultural labour productivity growth rate of 0.92% per year. By contrast, in developed countries agricultural labour productivity increased at an annual average rate of 2%, while in the same period population increased at an average annual rate of 0.96%. In figure 2.6, I document population and agricultural productivity growth rates for both developed and developing countries by decade. In each decade, productivity grew faster than the population growth in developed countries (panel b). In contrast, in each decade, population grew at a faster rate than productivity in developing countries (panel a).

To summarise, in developing countries, over the sample period the growth rate of agricultural productivity was less pronounced than their growth rates of population, and their land-labour ratio declined over time. By contrast, both productivity and land-labour ratio increased in the developed world. Moreover, this divergence is likely to be due to the increased agricultural employment in developing countries. Why was the pattern of actual employment in agriculture distinct between developed and developing countries? I argue that this issue can be examined within the context of a standard structural change model which includes both land as a factor of production and population growth, which is generally ignored in recent structural change model, and that

Figure 2.6: Growth rates of agricultural labour productivity and population; 1970 - 2010



Source. GGDC 10-sector database for all countries except Bangladesh. Since, GGDC 10-sectors database does not include Bangladesh, I obtain this data from Asian Productivity Organization (APO) database.

this model does a good job in accounting for structural change in developing countries.

2.4 Analytical framework

In this section, I develop a framework which is designed to study the reallocation of labour from agriculture in developing countries and features population growth. There are two sectors and structural change is driven by unbalanced sectoral productivity growth (Baumol effect); unbalanced sectoral demand growth due to non-homothetic preferences (Engel effect); and population growth. Models with the first and the second channels are widely used in the literature (see for example Kongsamut et al., 2001; Duarte and Restuccia, 2007; Dennis and İşcan, 2009; Alvarez-Cuadrado and Poschke, 2011), while models incorporating the third channel is novel here.

4.1 Economic environment

The economy is closed and the problem is stated as a static resource allocation problem. There is a large number of identical families, each composed of L_t identical individuals at time t. The evolution of population over time is exogenous.[5]

4.2 Production

The production of non-agricultural good uses labour (L_n). Agricultural output is a function of land (T) and labour (L_a). Land is a quasi-fixed factor and thus agricultural production function features decreasing returns to scale in labour. With an eye towards calibration, I consider the following production functions for the two sectors:

$$Y_{at} = A_{at} L_{at}^{\alpha} T_t^{1-\alpha}, \tag{2.1}$$

$$Y_{nt} = A_{nt} L_{nt}, \tag{2.2}$$

where, A_{at} and A_{nt} are the factor neutral technology terms for agriculture and non-agriculture, respectively; and $0 < \alpha < 1$ is the labour

[5]The model developed in this section abstracts from capital accumulation to fully concentrate on a production economy with land and labour as the productive inputs in the production process. For the maintained hypothesis of this chapter, I need to concentrate on a fixed factor like land, but that does not imply that capital is less important. In section 6, I extend the model to include capital accumulation channel and calibrate the model to several sample countries to show that the results are not sensitive.

share in agricultural output.

4.3 Preferences

Each representative family has a CES instantaneous utility function, defined over consumption goods produced by the two sectors, agriculture (c_{at}), and non-agriculture (c_{nt}):

$$u(c_{at}, c_{nt}) = \left[\eta_a(c_{at} - \overline{c}_a)^{\frac{\varepsilon-1}{\varepsilon}} + \eta_n(c_{nt})^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}. \tag{2.3}$$

In equation (2.3), ε is the elasticity of substitution across consumption goods, η_i is the relative weight of each good with $\sum_{i=a,n} \eta_i = 1$, c_{it} is the per capita consumption of the ith-sector good, where i is agriculture and non-agriculture, $\overline{c}_a$ is a subsistence food requirement. Incorporating a subsistence level requirement of food consumption delivers a non-homothetic utility function and an income elasticity of the demand for food that is less than unity.

Each individual is also endowed with one unit of productive time per period. Each representative family maximizes the utility function given in equation (2.3), subject to the budget constraint:

$$L_t(P_{at}c_{at} + P_{nt}c_{nt}) \leq w_t(L_{at} + L_{nt}), \tag{2.4}$$

where, P_{it} denotes the price of each sector's final output, w_t is the economy-wide wage rate.

Demand. The representative family maximises his utility given by equation (2.3) subject to the budget constraint as given in equation (2.4). Non-agriculture is treated as numerior and hence $P_{nt} = 1$. Optimal consumption allocations satisfy

$$P_{at}^{\varepsilon} = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} \left(\frac{C_{nt}}{C_{at} - \overline{C}_a}\right), \tag{2.5}$$

where, upper case letters to denote aggregate quantities: $C_{nt} = c_{nt}L_t$, $C_{at} = c_{at}L_t$, and $\overline{C}_a = L_t\bar{c}_a$. From the above equation, the optimal consumption is (see Appendix A):

$$C_{at} = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} P_{at}^{-\varepsilon}(C_{nt} + \overline{C}_a). \tag{2.6}$$

Now, I need an expression for P_{at}.

Supply. There is perfect factor mobility across sectors. This leads to a unique wage rate. Product markets are competitive, so the value of marginal product of labour (VMPL) is equalized across sectors:

$$\underbrace{P_{at}.MPL_a(t)}_{VMPL_a} = \underbrace{MPL_n(t)}_{VMPL_n}.$$

Solving for the MPL terms in the above equation gives,

$$P_{at} = \left(\frac{A_{nt}}{A_{at}}\right) \left(\frac{1}{\alpha(\frac{T}{L_{at}})^{1-\alpha}}\right). \tag{2.7}$$

4.4 Market clearing

In equilibrium, total labour absorbed in all sectors equals to L_t. The share of labour in each sector is:

$$l_i = \frac{L_{it}}{L_{at} + L_{nt}}.$$

Goods produced in all two sectors are consumed. Markets clearing conditions are given below:

$$\text{Goods market:} \qquad L_t c_{it} = Y_{it}, \qquad i = a, n, \tag{2.8}$$

$$\text{Labour market:} \qquad L_{at} + L_{nt} = L_t. \tag{2.9}$$

4.5 Equilibrium allocations

Competitive equilibrium. A competitive equilibrium consists of a sequence of relative prices, (P_{at}), consumption decisions by households, $\{C_{at}, C_{nt}\}$, and factor allocations, $\{L_{at}, L_{nt}\}$, such that given prices, the firms maximize profits, households maximize utility and all product and factor markets clear.

In this section, I describe the equilibrium allocations of consumption and employment in agriculture, and non-agriculture (Appendix A presents the derivations). To derive an expression for agricultural employment equation, use equations (2.8), (2.9), (2.6), and (2.7):

$$L_{at} = \alpha^{\varepsilon} \underbrace{\left[\left(\frac{\eta_a}{\eta_n} \right)^{\varepsilon} \left(\phi_t \frac{A_{nt}}{A_{at}} \right)^{1-\varepsilon} (L_t - L_{at}) \right]}_{\text{modified Baumol effect}} + \underbrace{\left[\phi_t \frac{L_t \bar{c}_a}{A_{at}} \right]}_{\text{modified Engel effect}} . \tag{2.10}$$

where, $\phi_t = \frac{1}{\left(\frac{T}{L_t - L_{nt}}\right)^{1-\alpha}} = \frac{1}{\left(\frac{T}{L_{at}}\right)^{(1-\alpha)}} = \left(\frac{L_{at}}{T}\right)^{1-\alpha}$ depends on the inverse of land-labour ratio.

In equation (2.10), agricultural employment is expressed in terms of sector specific productivities, employment in non-agricultural sector, subsistence requirement and a scale term ϕ_t . The quasi-fixed factor, T scales both Engel and Baumol effects, and as such modifies the traditional structural change model.

I now discuss the relevance of each of the terms in equation (2.10) for structural change:

1. **Demand-side effect:** In equation (2.10) the demand forces of structural change are shown as the 'modified Engel effect'. Three factors $\overline{c}_a; A_{at}$, and ϕ_t are important in determining employment in agriculture, L_{at}. As productivity in agriculture increases, the demand for the agricultural good increases. However, since Engel's law holds, the demand for agricultural goods increases proportionately less than the increase in aggregate income. Since in equilibrium $C_{at} = Y_{at}$, labour reallocates out of agriculture. The presence of subsistence consumption is ultimately responsible for the low elasticity of demand effect for agricultural goods (Engel Law). However, high value of ϕ_t or in other words, a low value of land-labour ratio slows down the reallocation of labour out of agriculture. This is because a decreasing land-labour ratio slows down the agricultural output per worker growth. If population growth is positive, a country can feed additional people either by increasing agricultural output per worker or by employing more people in agriculture. Therefore, a country with low productivity growth in agriculture ends up with a decreasing land-labour ratio and allocating more people to agriculture.

2. **Supply-side effect:** This force originates from differences in sectoral productivity growth rates (labelled as 'modified Baumol effect' in equation (2.10)). But elasticity of substitution between consumption of agricultural and non-agricultural goods ε is important here to determine whether the sector with higher productivity

growth sheds or gains labour. There are three possibilities:

- when $\varepsilon = 1$ this effect vanishes;
- when $\varepsilon < 1$ (gross complementarity); with faster productivity growth in agriculture labour moves out of agriculture. An increase in ϕ_t amplifies this effect.
- when $\varepsilon > 1$ (gross substitutability); with faster productivity growth in agriculture, labour moves into the farm sector. An increase in ϕ_t reduces this effect.

3. **Fixed factor effect:** In equation (2.10), ϕ_t is the fixed factor effect and either amplifies or dampens Engel and Baumol effects. Depending on the magnitude of the elasticity of substitution, both land-labour ratio, and the labour share of output, α, matter for this effect. For a given α,

   - when $\varepsilon = 1$, this effect vanishes;
   - when $\varepsilon < 1$, employment in agriculture increases, if land-labour ratio decreases;
   - when $\varepsilon > 1$, employment in agriculture decreases, if land-labour ratio decreases.

However, the role of land in structural change is captured well by the agricultural relative price P_{at}, i.e. by equation 2.7, restated here for convenience:

$$P_{at} = \left(\frac{A_{nt}}{A_{at}}\right)\left(\frac{1}{\alpha(\frac{T}{L_{at}})^{1-\alpha}}\right).$$

It is clear from the above equation that productivity increase in agriculture (i.e. increase in A_{at}) reduces the agricultural price, by contrast declines in land per worker increase the agricultural price. If population grows faster, the second term of the above equation will be stronger. Other things equal, it will shift resources into agriculture.[6]

When $\alpha = 1$, the model reduces to a pure Ricardian model. In this case, agricultural employment is given by:

$$L_{at} = \underbrace{\left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon}\left(\frac{A_{nt}}{A_{at}}\right)^{1-\varepsilon}}_{\text{Bamoul effect}} L_t - L_{nt} + \underbrace{\frac{L_t\overline{c_a}}{A_{at}}}_{\text{Engel effect}}, \tag{2.11}$$

which is familiar from the earlier literature (Dennis and İşcan, 2009).

2.5 Quantitative analysis

2.5.1 Data

I study 16 countries, 12 developing and 4 developed countries, from across the world and the data that I used in this study come from different sources. I use 4 decades of data to isolate the long-term trends. The employment and value added data come from GGDC 10 sector database. It includes annual data on employment and value added at constant 2005 national prices for Asia (China, India, *Japan*, *Korea*, Philippines), Africa (Kenya, Nigeria, Senegal, Tanzania), Latin America (Chile, Colombia, Mexico, Venezuela), Europe *(France)*, North America *(USA)* (see Vries, Timmer, and Vries (2014)).[7] Arable land data come from World Development Indicators, the World Bank and GDP per capita data are from Maddison Project database (see Bolt

[6]For example, Ricardo (1821) mentioned that population growth attracts capital towards the agricultural sector through the relative price effect and he put this in the following way: "...population increases, and the demand for corn raises its price relatively to other things — more capital is profitably employed on agriculture, and continues to flow towards it..".

[7]The countries in *italic* are developed countries according to the World Bank defination for 2010.

and Zanden (2014)). However, agricultural employment and value added data for Bangladesh come from Asian Productivity Organization (APO) database.

Table 2.1 reports the annualized growth rates of total employment,

Table 2.1: Average annualized growth rates of employment and sectoral labour productivity; 1970 - 2010

Countries	Annualized growth rates				
	Employment (total)	Employment (agriculture)	Labour productivity (agriculture)	Labour productivity (non-agriculture)	TFP (agriculture)
	Asia				
Bangladesh	2.40	1.26	0.99	0.21	1.51
China	2.00	0.01	3.90	5.40	3.79
India	2.20	1.54	1.10	2.70	1.65
Philippines	2.80	1.75	0.64	0.42	1.08
	Africa				
Kenya	3.40	2.13	0.06	−2.04	0.38
Nigeria	2.10	1.95	1.73	1.08	2.25
Senegal	3.70	2.78	−1.20	−2.00	−0.43
Tanzania	3.01	2.41	1.04	−1.08	1.40
	Latin America				
Chile	2.30	−0.45	3.90	0.94	4.67
Colombia	3.01	1.16	1.50	0.11	2.43
Mexico	3.40	0.78	1.20	−1.10	1.12
Venezuela	3.30	0.72	1.40	−2.3	1.76
	Developed countries				
France	0.50	−3.29	5.10	1.60	4.05
Japan	0.03	−3.33	4.50	2.20	3.58
Korea	2.30	−2.58	4.50	2.80	3.91
USA	1.30	−0.71	3.70	1.00	3.62

Notes: Labour productivity is defined as value added per worker. All numbers are in percent.
Source: Calculations are based on data from the GGDC 10-Sector database and Asian productivity Organization (APO) database.

labour productivity in both agriculture and non-agriculture. The table shows that labour productivity growth has been dismal in Africa; in most cases labour productivity growth rates were either very low or even negative. For example, in Senegal it was negative in both agriculture and non-agriculture. By contrast, employment growth was higher in Africa. Developed countries, by contrast, experienced higher labour productivity growth rates in both agricultural and non-agricultural sectors alongside moderate growth rates of employment, while the developing countries in my sample experienced both dramatic population growth and non-negligible reallocation of labour across sectors. For example, agricultural employment in 12 developing countries increased from 463 million in 1970 to 637 million in 2010 with an annualized growth rate of 0.8%.[8]

Table 2.1 also reports country-wise annualized growth rates of Total Factor Productivity (TFP) in agriculture, computed as a Slow residual using agricultural production function (equation (2.1)). For non-agriculture, I use labour productivity (column 5).

2.5.2 Calibration

The calibration strategy aims at selecting parameter values for the model so as to match the agricultural employment data as closely as possible. The parameters to be calibrated are: $\bar{c}_a, \eta_a, \eta_n, \varepsilon, \alpha$. There are two main sources for the calibration exercise: several parameters are directly calibrated to the data or taken from the literature, and others are set to achieve a target comparable to the data. This is done in two steps. First, the model parameter values, such as $\bar{c}_a, \varepsilon$ are calibrated to match initial (here 1970) employment given by the data. I also target $L_0 = L_{1970}$; $A_{a,0} = A_{a,1970}$ and $A_{n,0} = A_{n,1970}$ to match $L_{n,1970}$ and $L_{a,1970}$. Second, the calibrated parameters are combined

[8]However, if I weight agricultural employment by population, agricultural employment in those 12 countries increases from 201 million in 1970 to 225 million in 2010 with an annualized growth rate of 0.3%.

with time varying and sector-specific productivity growth in agriculture (A_{at}) and non-agriculture (A_{nt}), the actual historical time series of population, L_t to obtain the model-based time path for agricultural employment. Here, I generate the model-based employment for non-agriculture first, and agricultural employment is determined then from the resource constraints ($L_t = L_{at} + L_{nt}$). I then assess the empirical fit of the model in accounting for structural change in the sample countries.

Preference parameters. The baseline strategy calibrates country-specific parameters, $\bar{c}_{ai}, \eta_{ai}, \eta_{ni}$ and ϵ_i, where i denotes country in the sample. The consumption share parameters η_{ai}, and η_{ni} are calibrated to match the actual expenditure share for country i and this data are from the National Accounts dataset published by the United Nations . Given the country-specific consumption shares, I calibrate the model for country-specific elasticity of substitution, ϵ_i and subsistence requirements, $\bar{c}_{ai}$ by minimising the root mean square error (RMSE) of the model's prediction for sectoral employment.[9] Table 2.2 reports the parameter values for developing countries and Table 2.3 shows the same values for developed countries.

Production parameter. I calibrate the labour share of output in agriculture, α to .68. This is consistent with the empirical findings of Hayami and Ruttan (1985) and Mundlak (2001).

The benchmark case corresponds to a choice of consumption elasticity of substitution ε and the agricultural subsistence requirement $\bar{c}_a$

[9]RMSE is normalized root-mean square errors. Since, there is no consistent means of normalization in the literature, I used the range of the measured data defined as the maximum value minus the minimum value i.e. I used the following formula to find NRMSE: $\frac{\text{rmse}}{\text{y}_{\max} - \text{y}_{\min}}$, where, $\text{y}_{\max}$ is the maximum value of the model-based agricultural employment data, and $\text{y}_{\min}$ is the minimum value.

Table 2.2: Calibrated parameter values for developing countries

Country	$\overline{c_a}$	η_a	η_n	α	ϵ	$RMSE$
Bangladesh	.76	0.43	0.57	0.68	0.90	.05
Chile	.73	0.16	0.84	0.68	1.08	.29
China	.85	0.39	0.61	0.68	0.75	.32
Colombia	.65	0.23	0.77	0.68	0.95	.17
Kenya	.84	0.58	0.42	0.68	1.20	.08
India	.66	0.43	0.57	0.68	0.72	.08
Mexico	.86	0.24	0.76	0.68	1.20	.21
Nigeria	.30	0.60	0.40	0.68	0.80	.30
Philippines	.50	0.40	0.60	0.68	0.97	.09
Senegal	.81	0.58	0.42	0.68	1.30	.05
Tanzania	.46	0.58	0.42	0.68	0.40	.03
Venezuela	.92	0.32	0.68	0.68	1.70	.11

Note: The target consumption shares, η_a and η_n, are the actual expenditure shares obtained from the United Nations' National Accounts dataset. Consumption expenditure share data are not available for Bangladesh, Senegal and Tanzania. I use the data on Kenya to proxy for Senegal and Tanzania and on India to proxy for Bangladesh. RMSE is normalized root-mean square errors. The normalization uses the difference between the maximum and minimum values of the model-based agricultural employment data.

inferred by the minimum RMSE criteria. In Table 2.2 and 2.3, I report these parameters for both developed and developing countries together with associated RMSE. Column 6 of Table 2.2 and 2.3 suggests that elasticity of substitution term ε varies between 0.40 in Tanzania and 1.7 in Venezuela and I use this country-specific elasticity parameter to estimate model-based agricultural employment. Why have I used different parameter values for preference for each country? This methodology seems to be plausible for the following reasons: First, this country-specific parameter values are data-driven. This is a feature of tastes and in a sense, a country-specific calibration points to the assumption that tastes change across countries. Second, the parameter ε is crucial in explaining structural transformation through supply-side channels. However, in the empirical literature there is still no agreement on the

Table 2.3: Calibrated parameter values for developed countries

Country	$\overline{c_a}$	η_a	η_n	α	ϵ	$RMSE$
France	0.91	0.14	0.86	0.68	1.5	.09
Japan	0.93	0.17	0.83	0.68	1.6	.05
Korea	0.94	0.16	0.84	0.68	1.2	.19
USA	0.82	0.11	0.89	0.68	1.5	.32

Note: RMSE is normalized root-mean square errors. The normalization uses the difference between the maximum and minimum values of the model-based agricultural employment data.

estimate for the elasticity of substitution. For example, Buera and Kaboski (2009) and Herrendorf et al. (2013) suggest that Leontief utility ($\varepsilon \to 0$) may be a good approximation in the U.S. case. By contrast, Hansen and Prescott (2002), Doepke (2004) and Lagerlöf (2010) implicitly assumed perfect consumption substitutability between two sectoral goods ($\varepsilon \to \infty$). To study the structural change in the USA over the period 1800 to 2000, Dennis and İşcan (2009) use elasticity of substitution equal to 0.1, while Alvarez-Cuadrado and Poschke (2011) indicate to a ε which is greater than one. Verma (2008) in a study on India estimates ε equal to 4.3.

Thus the different parameter values for preference for each country are not inconsistent with the existing literature and confer economic intuition. However, as a robustness check I also estimate the model giving each country an identical preference parameter ε. Hence, I simply follow Buera and Kaboski (2009) and set $\varepsilon = 0.5$. Using identical preference parameter value ($\varepsilon = 0.5$), the fit of the model is worse based on RMSE as criterion. The RMSE for identical preference parameter are higher compared to the baseline specification and even greater than one in some cases.

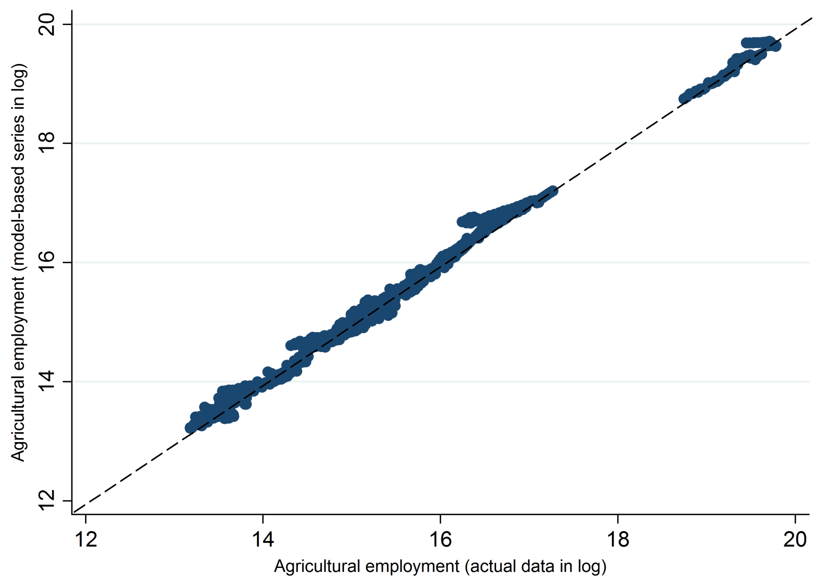
I combine calibrated parameters with a time varying sectoral labour productivity growth and population growth rate to obtain the time path for the agricultural employment. I then report the 'population effect' and 'productivity effect' by decomposing the model-based series. In order to assess the separate effects of population on the model-based agricultural employment, I keep the productivity constant at its 1970 level. The difference between the agricultural employment under model-based series and no-productivity growth counterfactual series constitutes the population effect. To assess the contribution of the productivity effect, I keep population constant at its 1970 level.

2.5.3 Results

For most countries, the model-based agricultural employment series are quite comparable to the actual labour observed in the data. Figure 2.7 reports the model-based agricultural employment series against the data for 12 developing and 4 developed countries over the period 1970-2010. All the data points of Figure 2.7 almost cluster around the 45^0 line suggesting an overall good fit of the model. For a country-wise performance of the model, in Figure 2.8, I report the percentage change in the agricultural employment between the first and the last periods in the data and in the model, it also suggests a good fit for all the developing countries in the sample.

In the data, there is significant heterogeneity among countries pertaining to the changes in the agricultural employment, growth rate of population and the growth rate of productivity. Therefore, I also use

Figure 2.7: Agricultural employment: data and model; 1970 - 2010

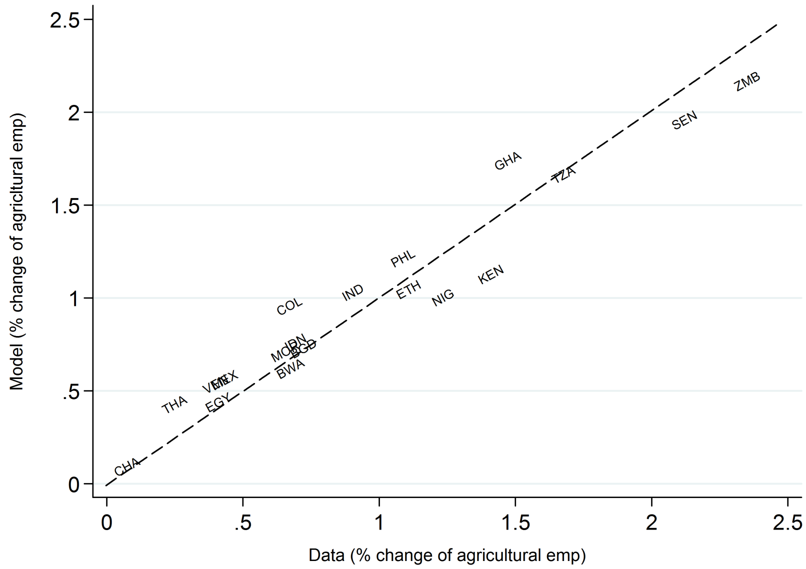


Note: The dotted line is a 45^0 line. Model-generated agricultural employment data are plotted against actual agricultural employment data. The data are from GGDC 10-sector database and APO database.

country-specific plots and compare the model-based agricultural employment series and the actual data at annual frequency. Figures B1 through B4 show the model-based agricultural employment and compare them with the actual data for each country in three regions: Asia, Africa and Latin America and also in developed countries for comparison. The solid lines of the left hand panel in each figure are the actual agricultural employment by country. The dashed lines are the model-based agricultural employment.

In the case of developing countries with the exception of Chile and China, model-based agricultural employment rises as much as its empirical counterpart (Figures B1 to B3). For instance, in Bangladesh, agricultural employment in the data increased from 13.6 million in 1970

Figure 2.8: Annualized growth rates of agricultural employment: data and model; 1970 - 2010



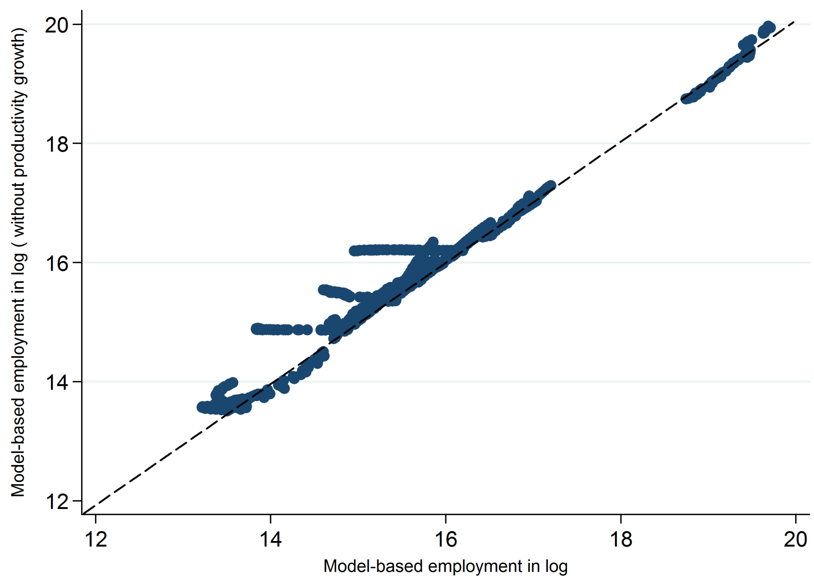
Note: The dotted line is a 45^0 line. The data are from GGDC 10-sector database and APO database.

to 22.5 million in 2010 with an increase of 1.6% per year, while model-based agricultural employment increased to 23.0 million with an annual increase of 1.7%. Figure B4 reveals that in the case of developed countries, the agricultural employment series generated by the model falls as much as its empirical counterpart. For example, in Japan agricultural employment decreased from 10.8 million in 1970 to 2.8 million in 2010 at a per year decrease of 3.3%, while the model-based agricultural employment series decreased to 3.1 million at an annual rate of -3.1%.

Population effect

To assess the independent effect of population growth on agricultural employment, I compare the employment series from the baseline model

Figure 2.9: Model-based agricultural employment: model and model without productivity growth; 1970 - 2010



Note: The dotted line is a 45^0 line. Agricultural employment only with population growth are plotted against baseline model generated agricultural employment series. The data are from GGDC 10-sector database and APO database.

with those model-based series that keep the sector-specific productivities fixed at their 1970 level. Figure 2.9 reports the results for all the sample countries. I report country-specific results in the right hand panel of Figures B1 through B4. Overall, the results show that the model only with population growth can generate agricultural employment that is close to those from the baseline model, except for the developed countries.

Developing countries. In the case of developing countries, the right panels of Figures B1 through B3 ('Model decomposition') show that population growth was unambiguously a major factor behind the observed agricultural employment over the period 1970-2010. A closer look into the model decomposition results suggests that the 'population effect' moves hand-in-hand with the upward trend in actual agricultural employment, and these two series almost coincide during the period from 1970 to 1990. For example, in India, while the model-based agricultural employment increased by 1.7% per year over the period 1970-2010, the population effect alone suggests an increase of 1.8% per year over the same period as against 1.5% in actual data. In 1990, in India, the population effect alone suggests agricultural employment of 215 million, which is 96% of 225 million agricultural employment observed in the data. Thus, the upward trend in agricultural employment in developing countries is mainly accounted for by population growth.

Developed countries. As shown in Figure B4, in the case of developed countries both total population and total employment have also been increasing over time. Yet, agricultural employment has been decreasing. If, as in the case of developing countries, the population effect would have determined the long-run trend of agricultural employment in developed countries, one would see also an upward trend in actual agricultural employment. Yet actual agricultural employment moves opposite to the 'population effect'. For example, in Japan, while the model-based agricultural employment decreased by 3.3% per year over the period 1970-2010, the population effect alone suggests an decrease of 0.01% per year over the same period as against -2.8% in the actual data. Hence, in the case of developed countries population growth does not appear to be an important determinant of the agricultural employment.

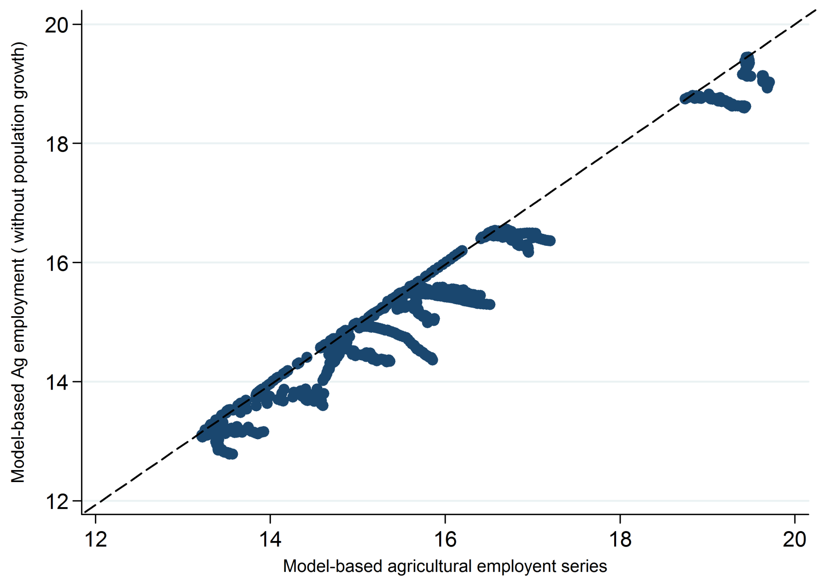
Productivity effect

I now turn to the 'productivity effect' which combines both the unbalanced productivity growth across sectors (the supply-side effect), and higher productivity growth in agriculture together with non-homothetic preferences (the demand-side effect). I show how these two channels combined have determined labour reallocation out of agriculture. I thus turn off the population effect by fixing population in 1970.

Specifically, to assess the contribution of productivity growth to changes in agricultural employment, I fix population in each country at its 1970 level and only allow the sector-specific productivity to change. First, I report the results for all countries in Figure 2.10, where the results show that most of the calibrated values are away from the 45^0 line and hence, model with productivity effects alone deviate from the overall model-based employment series. Thus the model with only productivity can not account for agricultural employment in developing countries; see also Figures B1 to B3.

Figures B1 through B4 show that if productivity effect alone were to dictate the agricultural employment, then we would have observed a decreasing trend of agricultural employment both in developing and developed countries. Yet such trend is only observed in developed countries (and partly in China after 2000). Figure B4 also shows that the agricultural employment dynamics in developed countries is mostly accounted for by the productivity growth, specially in the case of France and Japan, with population growth playing no role. In contrast, in developing countries, productivity growth is not strong enough to outweigh the population growth effects. Over this period, productivity

Figure 2.10: Model-based agricultural employment: model and model without population growth; 1970 - 2010



Note: The dotted line is a 45^0 line. Agricultural employment only with productivity growth are plotted against baseline model generated agricultural employment series. The data are from GGDC 10-sector database and APO database.

growth channel was essentially too weak to outweigh strong population growth and thus had a negligible effect on the long run trend in agricultural employment.

For example, in developing countries, actual agricultural employment increased from 463 million in 1970 to 637 million in 2010, at an annualized rate of 0.8%, while with 'productivity effect' alone agricultural employment decreased to 325 million in 2010, at an annualized rate of −0.88%.[10] By contrast, in Japan actual agricultural employment decreased from 10.8 million in 1970 to 2.8 million in 2010 with an annualized growth rate of −3.3%, while under 'productivity effect'

[10]Weighting by population, however, in developing countries, agricultural employment increased from 201 million in 1970 to 225 million in 2010, at an annualized rate of 0.33%, while with 'productivity effect' alone agricultural employment decreased to 122 million in 2010, at an annualized rate of −1.23%.

alone agricultural employment decreased to 3.0 million in 2010 with an annualized rate of −3.1%. Therefore, in developing countries, stronger population growth relative to productivity growth explains the observed increase in employment in agriculture, while the opposite is true for developed countries.

2.5.4 Agricultural productivity: counterfactuals

The analysis in the preceding section shows that in the case of developing countries, population growth has been a key driver of the observed pattern of labour reallocation from agriculture. By contrast, in developed countries productivity growth has been the main driver of the observed decline in agricultural employment. Using the calibrated model and several counterfactual scenarios, I discuss the impact of population growth on agricultural labour productivity growth and through that, on structural change.

First, I conduct an analysis with no population growth: I fix the population at the initial year and simulate the model holding everything else as in the benchmark model. This exercise provides a new series of agricultural employment. Then, with this model-based employment series and the production function in agriculture, I back out the agricultural labour productivity level for each country separately.[11]

In Figure 2.11, I plot the dynamics of model generated agricultural employment and labour productivity alongside the data weighting by population for the sample of developing countries as a whole. During

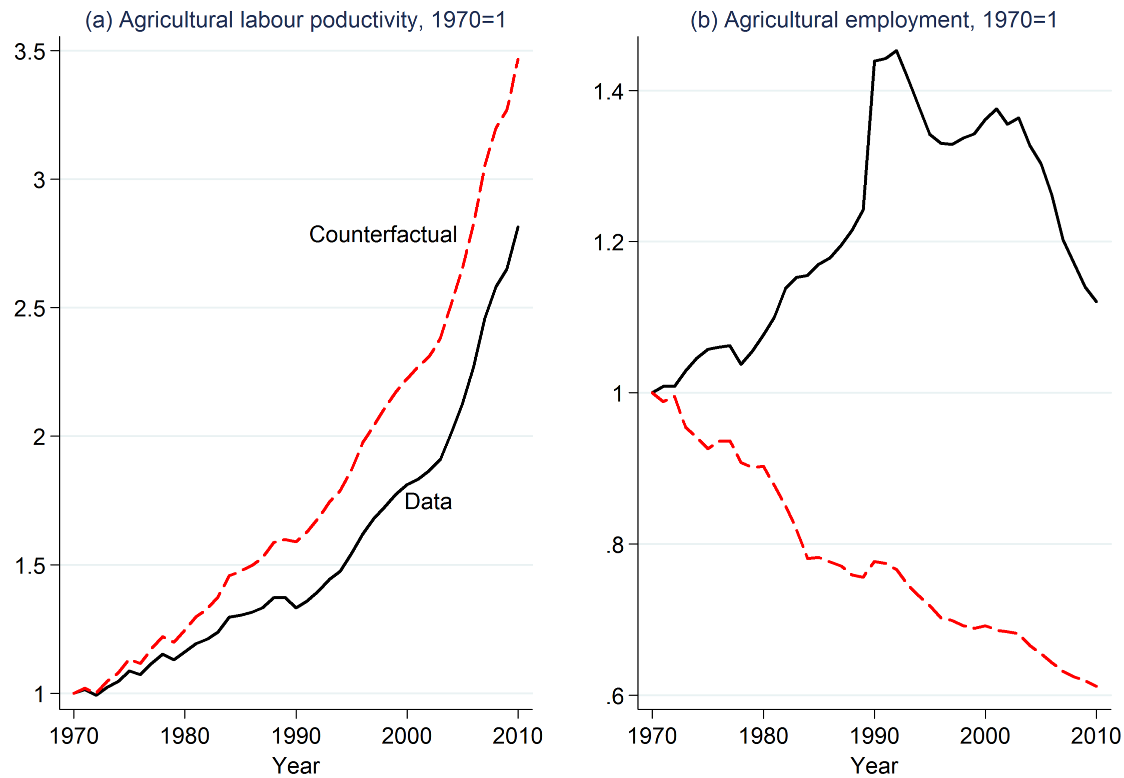
[11]To, estimate the model-based agricultural labour productivity, I calculate agricultural value added, $\hat{Y}_a$, by imputing the model-generated agricultural employment series, $\hat{L}_a$ into the production function: $\hat{Y}_a = A_a \hat{L}_a^{\alpha} T^{1-\alpha}$. Then, I divide this model-based value added by $\hat{L_a}$ to get model-based agricultural labour productivity with no-population growth.

the period 1970 to 2010, agricultural employment in the data grew at an annual rate of 0.3% per year, while with no-population growth counterfactual suggests a negative annual growth rate (−1.2%). During the same period, agricultural labour productivity grew at a rate of 2.5% per annum, while the model-based productivity grew at an annual rate of 3.11%. Thus, with no population growth, relative to data agricultural employment for the sample developing countries together would have declined 1.5% more per year, while agricultural labour productivity would have increased on average 0.5% more per year over the last 40 years.

Moreover, in the case of the share of agricultural employment, the model-based aggregate series substantially differs from the data. Agricultural employment share for 12 developing countries, on average, declined by 37 percentage points over the period 1970 to 2010, from 79% in 1970 to 42% in 2010. By contrast, with no population growth, agricultural employment share would have declined 56 percentage points to 23% during the same period (see Figure B6 for a region-wise comparison of agricultural employment share between data and no-population counterfactual).

A closer look into Figure 2.11 indicates a dismal performance of the agricultural sector in terms of labour productivity in developing countries, which is more pronounced in the initial two decades, 1970 to 1990. The vertical distance in the above figure shows the productivity gain in the absence of population growth; until 1990, the data and counterfactual productivity almost moves hand-in-hand, and only after that there

Figure 2.11: Agricultural employment and labour productivity with no population growth: aggregate for sample countries



Note: Panel (a) and (b) of the above figure show the population-weighted actual and counterfactual agricultural labour productivity and employment with no-population growth, respectively. The graph shows the aggregate statistics for 12 sample developing countries. The dashed line is the counterfactual and the solid line is actual data.
Source: The data are from GGDC 10-sector database except Bangladesh which are from APO database.

is a negligible jump in productivity. For instance, Figure B8 shows the actual and counterfactual agricultural productivity for Nigeria, where agricultural productivity growth in Nigeria (solid line) was almost flat until the early 2000s and rose sharply afterwards. The agricultural productivity generated under the conterfactual experiment shown by the dashed line, also follows a similar pattern but increases sharply after the 1990s. This is a common phenomenon for almost all the sample developing countries.

Region-wise counterfactual experiments. In the above exercise, agricultural productivity and employment of both model-based and data are weighted by population. Since, in terms of population China is a relatively larger country, it might be that the counterfactual results were driven mainly by China. For example, in Figure 2.11 the aggregate agricultural employment appears to be declining after mid-1990s, which is largely due to the influence of China. To address this concern, I conduct a similar analysis by region by fixing populations in their 1970 levels and allowing every thing else to change. After weighting by respective regional populations, I report the results of this exercise in Figure B5.

Figure B5 shows that under the no-population growth counterfactual, agricultural labour productivity gains for all regions are more pronounced in the last decade (2000-2010), while these gains are almost nil for Africa in the initial two-decades (1970-1990) and also negligible in other two regions. For example, in Africa, productivity grew at an annual rate of 1.3% in the data, in contrast the counterfactual shows an annualized growth of 2.1%. The same statistics for Asia are 2.8% in data and 3.3% in the counterfactual, and for Latin America, agricultural productivity grew at an annual rate of 1.4% in the data as opposed to 2.4% in the counterfactual. As for, agricultural employment, the data for all regions show positive annualized growth rates (ranging from .35% in Asia to 1.7% in Africa). By contrast, the counterfactual series show that agricultural employment share would have declined at an annual average rate of -0.7% in Africa, -1.16% in Asia and -0.9% in Latin America.

I also conduct a counterfactual experiment, where population grows at a common rate: Korean population growth rate of 1.06% per annum over the period 1970 to 2010.[12] I first generate a new population series for each country using Korean population growth rate,($\text{pop}_{1970} \times (1+0.0106)^t$) and compute a new ratio of the employment to population ($\frac{\text{L}}{\text{Pop}}$). Finally, using the empirical agricultural employment share, I find a new series of agricultural employment. I then estimate the counterfactual agricultural labour productivity for each country and compare this new series with the actual agricultural labour productivity series. I still find that the growth rate of population outweighs the agricultural labour productivity growth in each country. I report these new agricultural productivity gains in Figure B7. The figure shows the annualized growth rates of the model generated agricultural productivity against the annualized growth rates of the data for both experiments.

Finally, the analysis of this section so far hints at two things: First, population growth has slowed down the agricultural labour productivity in many developing countries over the last four decades, which is even more pronounced during the 1990 to 2010 period. Second, the extent of the agricultural productivity to be gained under no or moderate population growth depends on the performance of the agricultural sector itself, and this has been dismal as well. Relating these with structural change, the following conclusions emerge: i) population growth constrained the reallocation of labour from agriculture in developing countries; and ii) moderate agricultural labour productivity growth could not fully offset

[12] I picked Korean population growth rate for following reasons: in 1970, Korea was almost an agrarian economy that employed approximately 49% of its labour force in agriculture, population growth rate was higher too, e.g., during the period 1970 to 1980, population grew at an annualized rate of 3.5%.

the adverse effects of the population growth, leading to the expansion of non-negligible subsistence agriculture in many developing countries.

2.6 Extensions

In this section, I explore the robustness of the predictions of my model to the inclusion of capital in production. The environment is similar as the baseline model, but production technologies are modified. At time t production takes place according to the following Cobb-Douglas technologies:

$$Y_{at} = A_a T_{at}^{\alpha} K_{at}^{\beta} L_{at}^{1-\alpha-\beta},$$
$$Y_{nt} = A_n K_{nt}^{\psi} L_{nt}^{1-\psi}.$$

where, Y_i is the output for each sector $i = a, n$, $K_i \geq 0$ is the capital stock, $L_i \geq 0$ is labour input, T is land, A_i is an efficiency parameter, $0 < \beta < 1$ and $0 < \psi < 1$ are the elasticities of output with respect to capital in agriculture and non-agriculture respectively. And, $0 < \alpha < 1$ is the elasticity of output with respect to land. All resources are fully used:

$$K_{at} + K_{nt} = K_t \text{ and } L_{at} + L_{nt} = L_t.$$

While agricultural production can be used only for consumption purposes, the production of the non-agricultural sector could be either consumed or costlessly transformed into capital. Thus, market clearing in product markets implies:

$$C_{at} = A_a T_{at}^{\alpha} K_{at}^{\beta} L_{at}^{1-\alpha-\beta},$$

$$I_t = A_n K_{nt}^{\psi} L_{nt}^{1-\psi} - C_{nt}. \tag{2.12}$$

Equation-(2.12) is the law of motion of capital stock. Preferences are as in the baseline model.

Factors are freely mobile and product markets are competitive. Productive efficiency requires the marginal rates of transformation to be, at all times, equal across sectors. Since there is factor mobility, there is a unique wage rate and rental rate of capital. Normalizing the price of the n-good to 1, and denoting P_a as the relative price of the a-good, I solve for the relative price of the a-good using the productive efficiency condition (marginal rates of transformations across sectors are equal) and the equilibrium condition that the marginal value product of labour is identical across sectors:

$$(1-\alpha-\beta)A_a\left(\frac{T}{L_a}\right)^{\alpha}\left(\frac{K_a}{L_a}\right)^{\beta}.P_a = (1-\psi)A_n\left(\frac{K_n}{L_n}\right)^{\psi}.1,$$

$$P_a^* = \left(\frac{1-\psi}{1-\alpha-\beta}\right)\left(\frac{A_n}{A_a}.\frac{(\frac{K_n}{L_n})^{\psi}}{(\frac{T}{L_a})^{\alpha}(\frac{K_a}{L_a})^{\beta}}\right). \tag{2.13}$$

Finally, the equality of the marginal rates of substitution between a- and n-good gives the optimal consumption for a-good in terms of n-good as in the baseline model:

$$C_a^* = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} P_a^{-\varepsilon} C_n + \overline{C}_a. \tag{2.14}$$

I derive the sectoral allocation of labour when both product and factor market clear and using both productive efficiency and consumption efficiency conditions. Since, $Y_a = C_a$, I write equation (2.14) as following:

$$Y_a = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} P_a^{-\varepsilon}(Y_n - I_t) + \overline{C}_a.$$

where, $C_n = Y_n - I_t$. After some algebra, I obtain an expression for the employment in agriculture:

$$L_{at} = \underbrace{\left(\frac{1-\alpha-\beta}{1-\psi}\right)^{\varepsilon}\left(\frac{(\frac{K_n}{L_n})^{\psi}}{(\frac{K_a}{L_a})^{\beta}}\right)^{1-\varepsilon}}_{\textbf{Capital deepening}} \underbrace{\left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon}\left(\phi_t\frac{A_n}{A_a}\right)^{1-\varepsilon}}_{\textbf{modified Baumot effect}}$$

$$\underbrace{\left(1-\frac{I_t}{Y_n}\right)}_{\textbf{capital accumulation}} (L_t - L_{at}) + \underbrace{\phi_t\frac{L_t\overline{c}_a}{A_a(\frac{K_a}{L_a})^{\beta}}}_{\textbf{Engel's effect}} \tag{2.15}$$

where, ϕ_t is a fixed factor as in the baseline model.

Next, I discuss the implication of each of the terms in equation (2.15) for structural change:

- Baumol's effect: As in the baseline model without capital.
- Engel's effect: There is an extra term from the baseline model, $(\frac{K_a}{L_a})^{\beta}$, which is the capital-labour ratio in agriculture. Given values for $\phi, A_a, \overline{C}_a$, when capital-labour ratio in agriculture increases, agriculture sheds labour.
- Capital accumulation: when capital-output ratio in non-agricultural sector increases, then agriculture sheds labour through this channel.
- Capital deepening: Differential capital deepening effect originates

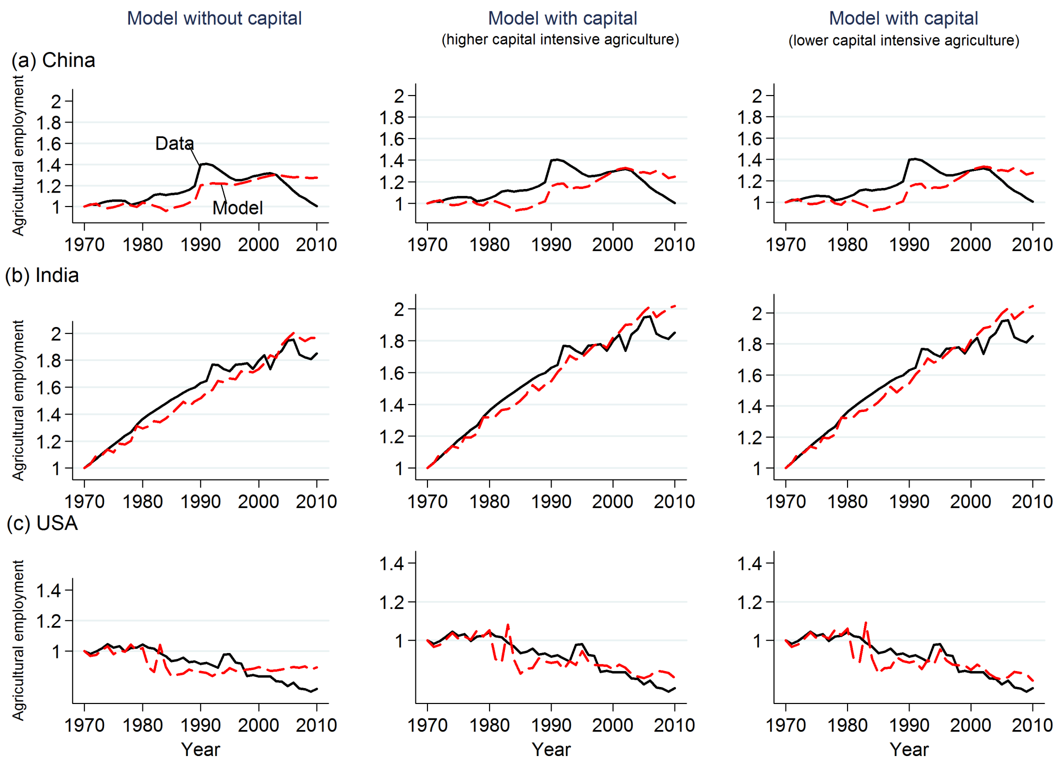
from differential capital intensities ($\psi \neq \beta$). However, this effect depends on the elasticity of substitution between agriculture and non-agricultural goods, ε. This effect vanishes when $\varepsilon = 1$. When $\varepsilon < 1$, more capital intensive sector would grow faster, and in equilibrium, the faster growing sector would face decline in the relative price and this will cause some of the labour and capital to reallocate away from the faster growing sector.

In the baseline specification, the model ignores capital so as to work as closely as possible on a production economy with labour and land. Capital is excluded not because it is not an important factor, but because most of the developing countries in the sample are highly agrarian economies producing mainly for subsistence consumption and their production technologies are labour intensive. Moreover, capital is poorly measured in many developing countries compared to labour. Finally, abstracting from capital shuts down one of the channels ("capital deepening") of the structural change process, which has relatively weak impact on the process. Working with the pre-war USA data, Dennis and İşcan (2009) documented a very insignificant contribution of the 'capital deepening' channel on the process of structural change (see Table 2, page-199). Alvarez-Cuadrado and Poschke (2011) show that the response of labour allocation and the relative price to changes in the productivity parameters with capital are consistent with the ones without capital accumulation.

However, as a robustness check, in this section I calibrate the model with capital and report the results in Figure 2.12 for three countries from my sample. In doing that I encounter several challenges. First, I need data on the sectoral capital stock per worker, $k_a; k_n$. Unfortunately, data on sector-wise capital stock are not available. I estimate K_a, and K_n following the methodology suggested by Herrendorf and Valentinyi (2012). Secondly, there is no agreement on the parameter estimates of the sectoral capital intensities, β and ψ. I resort to prior studies and exhaust two possible alternatives of capital deepening: i) $\beta > \psi$, meaning a higher capital share in agriculture; and ii) $\psi > \beta$, meaning a lower capital share in agriculture. Following Jorgenson, Gollop, and Fraumeni (1987), I set $\beta = .30$ and $\psi = .40$ and following Herrendorf and Valentinyi (2008), I set $\beta = .36$ and $\psi = .33$. In both alternatives, I set $\alpha = .18$ according to Herrendorf and Valentinyi (2008).

Figure 2.12 shows the differential capital deepening effect and capital accumulation effect. Differential capital deepening effect, however, is only present when $\beta \neq \psi$. Left Panel of the figure shows the case without capital, and the reaming two panels show the case with capital, where the middle panel shows higher elasticity of output with respect to capital in agriculture, and right panel shows the opposite. A careful examination of the figure suggests consistent results between the model with capital and without capital, except for the USA after 2000, when the model with capital provides a better fit of the data. Thus, the conclusion of Figure 2.12 coincides with Alvarez-Cuadrado and Poschke (2011) and Dennis and İşcan (2009) regarding the impact of capital on the process of structural change.

Figure 2.12: Model generated agricultural employment: with and without capital



Note: In the above figure, the solid line shows the data and the dashed line represents the model generated agricultural employment. The left panel shows the model without capital (baseline results); middle panel and the right panel are the calibration results with capital.
parameter values: high capital intensive agriculture: $\alpha = 0.18; \beta = 0.36; \psi = 0.33.$; and low capital intensive agriculture: $\alpha = 0.18; \beta = 0.36; \psi = 0.40$. See the text for detail.

2.7 Conclusion

In this paper, I have examined separately the effects of both productivity and population growth on the structural change for 12 developing and 4 developed countries. I build a two-sector general equilibrium model to undertake a quantitative study. The quantitative results show that population growth explained most of the observed increasing employment in agriculture in developing countries between 1970 and 2010. The counterfactual with no population growth indicates to a dismal performance of the agricultural sector during the same period; even without population growth, agricultural labour productivity would have grown at a very moderate rate. However, without population growth, agricultural employment would have decreased at a faster rate. By contrast, in developed countries productivity growth is the main driver of the observed declining employment in agriculture over the same period.

A key characteristic of my framework is that land is a quasi-fixed factor and as such production technology in agriculture exhibits decreasing returns to scale in labour. Unlike the constant returns to scale technology, where population increases can be absorbed in the long run through factors that can be accumulated, under a model with fixed factor like land, population growth constraints the reallocation of labour from agriculture when agriculture produces subsistence good. While a fixed supply of land imposes limits on agricultural production, changes in productivity in this sector can alleviate this constraint. Thus, the model allows to decompose the separate contribution of the productivity growth and population growth on the observed change in the agricultural employment.

Chapter 3

Agricultural Productivity and Labour Reallocation: Lessons from the Green Revolution

3.1 Introduction

The reallocation of labour from agriculture to other sectors is one of the most important stylized facts of economic growth and development (Kuznets, 1957; Foster and Rosenzweig, 2008; Herrendorf, Herrington, and Valentinyi, 2015), and it is important to understand the forces that give rise to this reallocation. Productivity growth in agriculture is one such force.[1] While classical models of structural transformation show how productivity growth in agriculture can release labour from this sector, there is relatively less empirical evidence on the differential effect of land-versus labour-biased technological change in agriculture on the reallocation of labour from agriculture. Land-biased technical change (e.g., mechanization of agriculture or raising human capital of farmers) reduces the demand for labour without a change in output per unit of land. By contrast, labour-biased technical change (e.g., biological technology like fertilizers or pesticides) increases effective land, and other things being equal increases the demand for labour.[2] In this chapter I provide empirical evidence on the effects of technical change

[1] For example, Dennis and İşcan (2009) in a general equilibrium setup show that mainly agricultural productivity growth explains the structural change in the USA in the pre WW II period. See also Üngör (2013), where he shows that growth of output per worker in agriculture combined with subsistence requirement in agriculture is able to explain most of the secular declines in the agricultural employment share in several countries around the world.

[2] While, technical change is factor-augmenting technical change is explicit in the production function, however factor-bias depends on the interaction of the factor-augmentation and the elasticity of

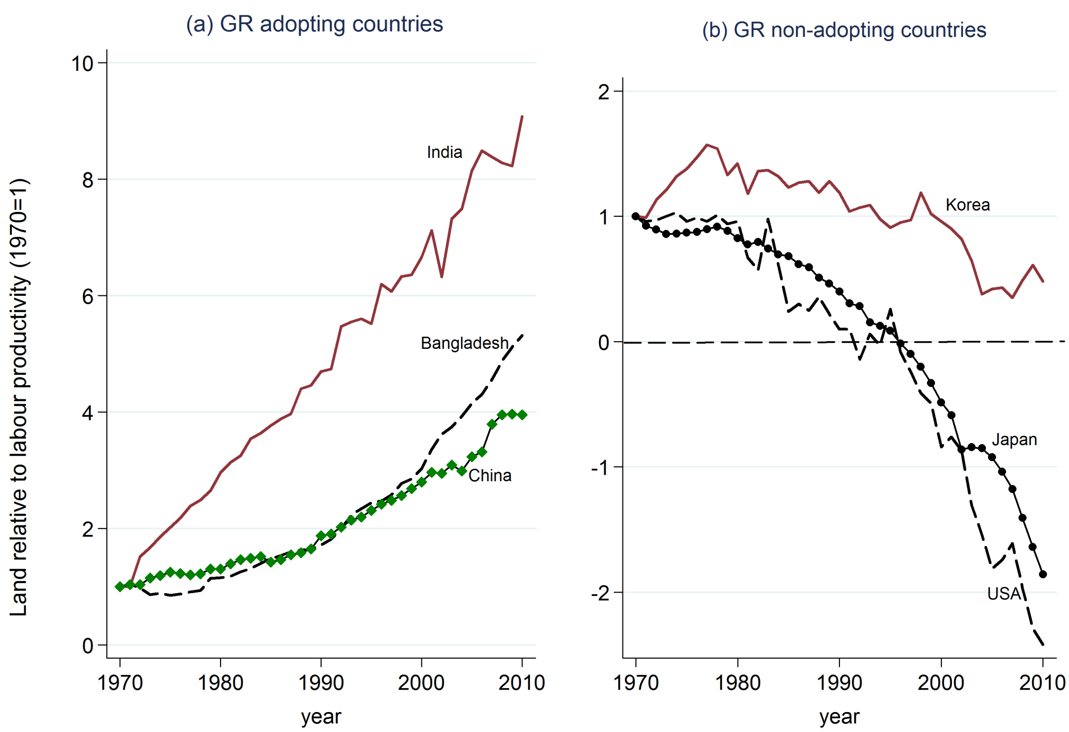
in agriculture on the agricultural labour reallocation by studying the widespread adoption of a common agricultural technology-'Green revolution' by several developing countries in the late 1960s.

In the early phases of their structural change, for example, USA, Japan, and South Korea all adopted land-biased technological change and experienced faster growth in labour productivity (output per worker) than land productivity (output per acre of land) and they had been successful in reallocating resources towards non-agriculture. For example, Hayami and Ruttan (1970) argue that until 1930s Japan adopted labour-biased technology in agriculture, while United States adopted mechanical technology (land-biased) and Japan experienced slower structural change up until 1930s (see also Johnston and Kilby, 1975). It appears, however, that the opposite has happened in at least several developing countries. Figure 3.1, for instances, shows the difference between land and labour productivity for three countries that adopted Green Revolution technology (a labour-biased technological change) and three countries that did not adopt it.[3] In adopting countries land productivity exceeded the labour productivity, whereas, in non-adopting countries labour productivity exceeded land productivity over the period 1970-2010. In this chapter, I argue that understanding the cross-national differences in labour and land productivity growth rates is important in appraising the pace of labour reallocation out of

substitution between the factors. Thus, if land and labour are complements in production, labour-augmenting technical change is land-biased. Similarly, land-augmenting technical change is labour-biased when land and labour are complements in production (for a comprehensive explanation on this issue, see Bustos, Caprettini, and Ponticelli, 2016).

[3] These six countries together accounted for 61% of the world population in 2000.

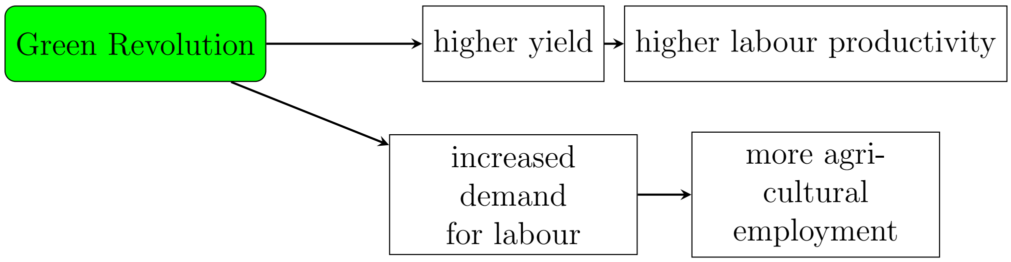
Figure 3.1: Relative change in yield and value added per labour in agriculture; 1970 - 2010



Note. The above graph shows the difference between land and labour productivity in agriculture. Labour productivity is defined as output per worker, while land productivity is output per acre of land. All data are normalized to 1970.
Source: Employment and output data are from GGDC 10 sector database for all countries except Bangladesh, while the land data for all come from World Development Indicators (WDI), the World Bank. Employment and output data for Bangladesh are from Asian Productivity Organization (APO) database .

agriculture. For example, in 2000, land productivity in several GR-adopting countries was 39% that of several non-adopting countries, while labour productivity was only 11% that of non-adopting countries. During the period 1965 to 2000, agricultural employment increased on average by 1.85% per year in adopting countries, by contrast it decreased by 1.65% per year in non-adopting countries (see Table 3.3). I use the diffusion of Green Revolution (GR) to study this issue. Green

Figure 3.2: Major objectives of Green Revolution



Revolution refers to fertilizer efficient high yielding varieties (HYVs) of rice and wheat. It was introduced in the 1960s as a potential solution to food-population imbalance in developing countries. It was popular among many developing country policy makers as a way to save scarce land and encourage more labour intensive production technique based on family labour. Figure 3.2 shows these two prime objectives of the GR: increased crop production and hence, minimize the food insecurity, and enhanced employment in agriculture. The first channel implies that GR would increase yield, defined as output per unit of land and thus increase labour productivity which, all else equal, would stimulate structural change. Yet, the second channel implies that GR would also increase employment per hectare of land. The second channel can also be seen as an unintended consequence of GR if it ends up slowing down agricultural labour productivity growth and the reallocation of labour out of agriculture.

In this paper, I empirically test whether the second channel has dominated the first, and whether the Green Revolution slowed down the labour reallocation process. To fix ideas, I first develop a two-sector model with factor-biased technical change in agriculture, and derive its predictions pertaining to agricultural labour reallocation. The model predicts that in a small open economy, factor-neutral (Hicks-neutral) technical change in agriculture slows down the labour reallocation from agriculture (as in Matsuyama, 1992). Land-augmenting technical change also slows down structural change. However, even in a small open economy, labour augmenting technical change expedites the labour reallocation process in agriculture, when land and labour are complements in agricultural production (Bustos et al., 2016).

In the empirical analysis, I test the predictions of the model using data on the adoption rates of HYV seeds of eight crops (rice, maize, wheat, barley, millet, sorghum, cassava, and potatoes) in 33 countries and for the period 1965-2000. I use two measures of land augmenting technical change. The first measure is the adoption rate of HYV seeds which is the area planted with HYV seeds of a given crop relative to the total area planted with either modern or traditional varieties of the specific crop. Not all of the countries in the sample have adopted HYV seeds at the same time or at the same pace; there are variations across countries in adoption rates and timing of adoption. The main idea is to use the variation in adoption rates across countries and over time. Second measure of land-augmenting technical change is the difference between the potential yield under high and low inputs calculated by the FAO-GAEZ, where a high input level corresponds to modern farming like adoption of HYV seeds, while low input refers to a traditional technique. FAO calculates potential yields by incorporating local soil and weather characteristics into an agro-production model. Thus, the difference in yields between the high and low technology captures the profitability of moving from traditional agriculture to a technology that uses improved seeds and chemicals.

I find that countries where the HYV seeds technology is predicted to be relatively more land-augmenting as captured by the FAO potential yields, also experienced a higher increase in the area planted with HYV seeds. In addition, I find that countries with larger expansion of the area with HYV seeds experienced a positive effect on agricultural employment and labour intensity, defined as labour per unit of land in agriculture. By contrast, in the HYV seeds adopting regions agricultural land-labour ratio decreased. The point estimates on agricultural labour productivity is found to be negative, yet not statistically significant. However, the point estimate on yield per unit of land is positive and statistically significant. The estimated coefficient for agricultural employment suggests that GR accounts for 28% of the increase in total agricultural employment in 33 adopting countries over the period 1965-2000. The counterfactual without GR suggests that on average agricultural employment share would have declined by 6 percentage points more in those 33 countries. These findings are robust to different estimation procedures and specifications.

The remaining of the chapter is organized as follows. Section 2 discusses the relevant literature. Section 3 gives background information on the diffusion of green revolution technology. Section 4 develops a two-sectors model with factor-biased technical change in agriculture. Section 5 describes the data. Section 6 describes the empirical results and presents an analysis on the findings. Section 7 concludes.

3.2 Related Literature

There is a large literature on the relationship between agricultural productivity and industrial development. Agricultural productivity growth has long been seen as an essential precondition for industrial revolution (see, for example, Rosenstein-Rodan, 1943; Nurkse, 1953; Rostow, 1960). Development economists have long emphasised the role of agricultual productivity in economic development, yet there is substantial uncertainty about the link between agricultural productivity and agricultural labour reallocation. In classical models of structural transformation, agricultural productivity growth can be viewed as one of the major drivers of the process of structural change (Kongsamut et al., 2001; Ngai and Pissarides, 2004). For example, Dennis and İşcan (2009) in a general equilibrium set up show that mainly agricultural productivity growth accounts for the structural change in the USA in the pre-World War II period, while in Alvarez-Cuadrado and Poschke (2011), they find that agricultural productivity had been a dominant determinat for structural change in USA and 11 other industrial countries in the post-World War II period. Üngör (2013) shows that growth of output per worker in agriculture combined with low income elasticity of demand for agricultural goods is able to explain most of the secular declines in the agricultural employment share in several countries around the world.

In the literature there are two distinct mechanism to explain the structural change: (i) productivity growth in agriculture, and (ii) unbalanced productivity growth across sectors. The first mechanism states that improvements in agricultural technology (combined with the fact that the income elasticity of demand for food is less than one) release labour from agriculture (Kongsamut et al., 2001; Gollin et al., 2002; Gollin, Parente, and Rogerson, 2007). The second mechanism states that if productivity growth in agriculture is faster than that in non-agriculture and these goods are complementary in consumption, then the demand for agricultural goods does not grow as fast as productivity and agriculture releases labour towards non-agriculture (Baumol, 1967; Ngai and Pissarides, 2004). In a recent work, Alvarez-Cuadrado et al. (2016) has proposed an other mechanism, namely, 'factor rebalancing effect' that works through the sectoral differences in the degree of capital-labor substitutability.

Yet others argue that there is a negative link between agricultural productivity and structural change driven by the law of comparative advantage. See for example, Mokyr (1976) for a comparative study of industrialization in Belgium and the Netherlands; Wright (1979), and Field (1978) for industrialization in New England and the U.S. south.

Matsuyama (1992) argues these two views are not necessarily incompatible: wheares the positive link approach rests on the implicit assumption of a closed economy, the negative link approach requires a small open economy. In a small open economy, since prices are mainly determined in world markets, high productivity and output in agricultural sector may, without offsetting changes in relative prices, squeeze out manufacturing sector. In a two-sector endogenous growth model, Matsuyama (1992) points to only Hick-neutral or factor-neutral technology as a sources of agricultural productivity, yet Bustos et al. (2016) argue that even in a small open economy agriculture may release labour depending on the technology; agriculture sheds labour towards non-agriculture if technology is land-biased, while structural change process might be slow if technology is either Hicks-neutral (as in the case of Matsuyama, 1992) or labour-biased.

There is also a literature which argues that adoption of labour-biased (land-augmenting) technology, like HYV seeds can increase labour demand in agriculture and hence slowe down the labour reallocation from agriculture. For example, Hayami and Ruttan (1970) show that starting from 1880s till 1930s, Japan experienced higher yield per hectare than the United States as during that period Japan adopted biological techniques, while the United States adopted mechanical technology and as a result had higher output per worker than Japan. During this period Japan also experienced high employment in agriculture. Since the 1930s, Japan started to adopt mechanical technology like the United States followed by declining yield as well as employment in agriculture. Recent studies along this line include Foster and Rosenzweig (2004, 2008), who study the effects of the adoption of HYVs of corn, rice, sorghum, and wheat during the GR in India. They find that villages with higher improvements in crop yields experienced lower manufacturing growth.

However, GR was successful to enhance food production in developing countries and thus, mitigate the food shortages (see among others Otsuka, 2000). Pingali (2012) and Renkow and Byerlee (2010) are two recent survey on the literature considers social, economic and environmental impacts of GR. In their review of the evidence, Evenson and Gollin (2003) conclude that the GR accounted for 21% of the growth in yields and about 17% of production growth during the 1961-1980 period in all developing countries, mainly in Asia and Latin America. GR stimulated the rural non-farm economy, which in turn grew and generated significant new income and employment (IFPRI, 2002). More recently Gollin, Hansen, and Wingender (2016) show that the GR had a positive effect on GDP per capita as well as negative effect on population growth in a sample countries over the period 1965-2000. The current paper also examines the impact of Green Revolution, yet, the major focus is on the agricultural labour reallocation. In this paper, I do not have a maintained hypothesis that Green Revolution had a negative effect on population growth, though, I control for population growth in the empirical study.

The closest precedent to my paper is Bustos et al. (2016) who study the effects of Genetically Engineered (GE) soy and the adoption of second-harvest maize on structural change in Brazil. They argue that second-harvest maize production is labour-biased, while GE-soy is land-biased, and find that in those municipalities where the area planted with GE soy increased, agricultural output per worker increased and land-labour ratio increased too. By contrast, in those regions where second-harvest maize increased, land-labour ratio deceased, industrial employment decreased and wages increased. The conclusions of this paper are thus consistent with my findings that HYV seeds adoption is labour-biased. However, this paper differs from Bustos et al. (2016) in the following ways. First, I study a group of countries that adopted a common technique of production in agriculture-the green revolution in agriculture. Second, I account for the effects of this common technology on agricultural employment and through that on productivity in agriculture by taking advantage of the variation of adoption rates of HYV seeds both across countries and over time.

3.3 Green Revolution: an overview

The Green Revolution attempts to increase the rate of growth of agricultural productivity, through the application of modern crop breeding techniques (Evenson and Gollin, 2003). At its early development stage, the GR was identified by the spread of fertilizer-efficient high yielding variety (HYV) seeds of rice, maize and wheat. As a result, in the literature, GR and HYV seeds adoption are used interchangeably. Scientific development of HYV seeds were led by Norman Borlaug, an American biologist, in the 1940s. The term "Green Revolution" was first used by William Gaud, an USAID administrator in 1968, and the technology also refers to a set of research and development projects and technology transfer initiatives that took place between the 1930s and 1960s. In particular, in the mid-1960s scientists developed HYV seeds of rice and wheat that were subsequently released to farmers in Asia and Latin America (Evenson and Gollin, 2003). Such initiatives of HYV seeds were quickly adopted in tropical and subtropical regions under conditions of good irrigation or reliable rainfall.

By the late 1960s, HYV seeds were associated with two international agricultural research centres: the International Center for Wheat and Maize Improvement in Mexico (CIMMYT) and the International Rice Research Institute in Philippines (IRRI). The CIMMYT grew out of a

Table 3.1: Yield and input use for major rice varieties in Bangladesh

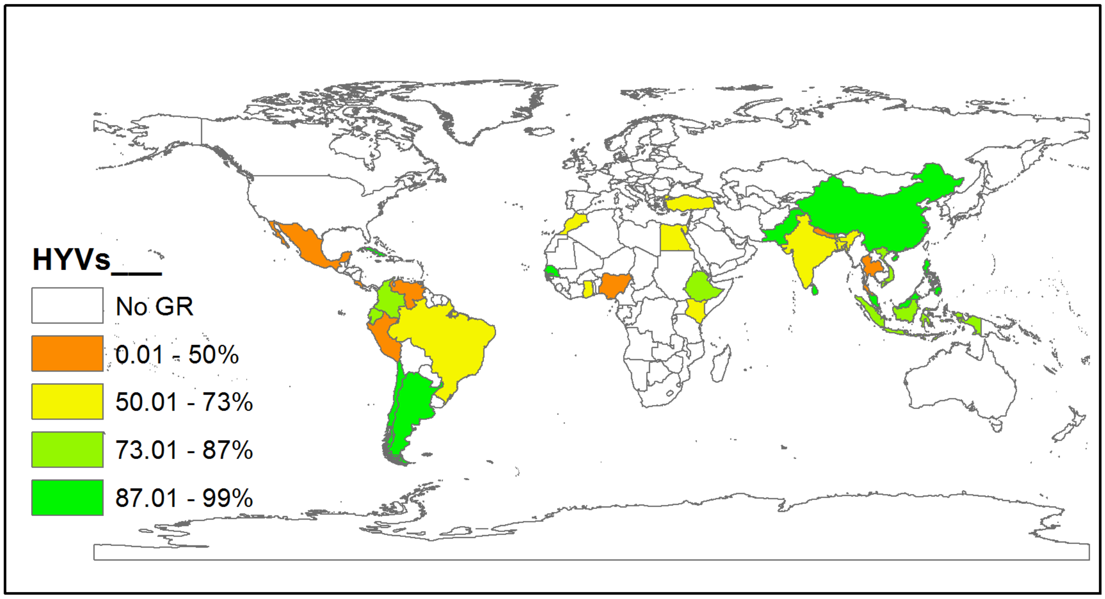
Rice varieties	Yield/ha (ton)	Fertilizer/ha (kg)	labour hours/ha (hour)
HYV Aman (34%)	2.16	294	858
HYV Boro (35%)	3.64	455	1,076
LV Aman (15%)	1.40	203	683

Note: LV stands for Local Variety. Percentage shows the total land use under each rice variety.
Source: Data are from Regmi, Oladipo, and Bergtold (2016).

pilot program sponsored by the Mexican government and the Rockefeller foundation in the 1940s and 1950s. And the IRRI was established in 1959 under the auspices of the Rockefeller and Ford foundations.

The technology of the GR involved bio-engineered seeds that worked in conjunction with chemical fertilizers and heavy irrigation to increase crop yields. HYV seeds are land substituting, and more labour using innovations. Table 3.1, as an example, documents the input requirements for rice production in Bangladesh, one of the pioneer countries that adopted GR. In Bangladesh three varieties of rice account for almost 84% of the land used for rice production (which is 68% of the arable land). For example, HYV of Aman and Boro rice together account for 69% of the land used for rice production, while local variety of Aman rice is planted in 15% of the land under rice cultivation. While the two HYV Aman and Boro produce more per hectare of land, they also need more inputs than the traditional variety Aman. The HYV seeds are less resistant to droughts and floods and need an efficient management of water, chemical fertilizers, insecticides, and pesticides. Any lapse on the part of the cultivator in the application of inputs reduces output and productivity substantially.

Figure 3.3: Green Revolution across countries: rice, wheat, and maize

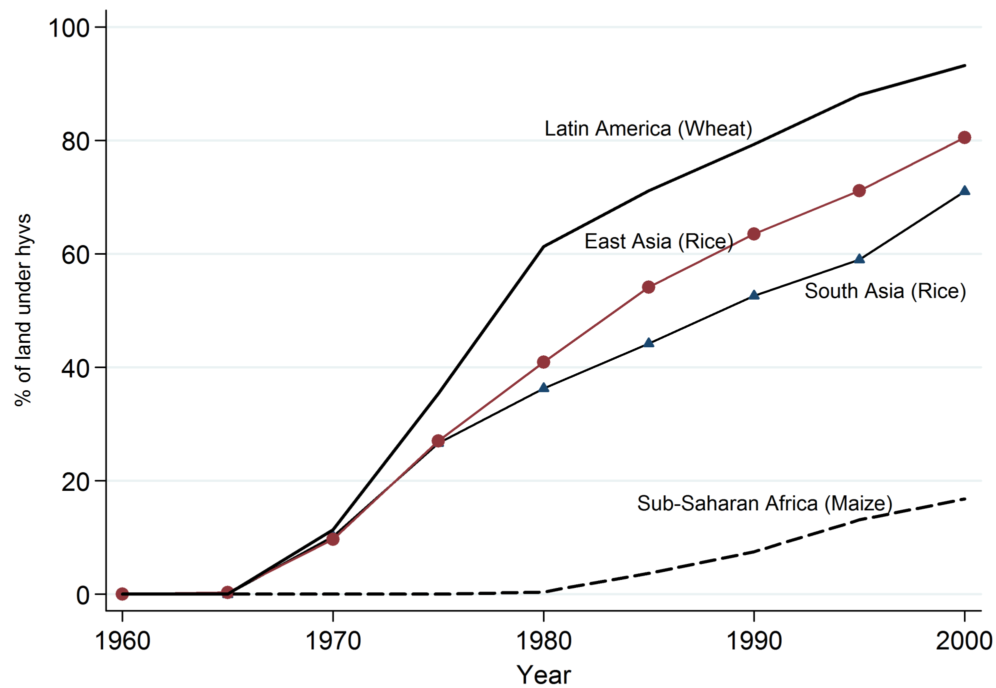


Note: Original data on HYV seeds adoption rates is from Robert Evenson. Accessed from Douglas Gollin's website: https://sites.google.com/site/douglasgollin/doug-gollin/research. The dataset includes HYVs adoption rates for several crops. The map only contains information on rice, wheat and maize.

Figure 3.3 shows the adoption rates of HYV seeds for three major crops, rice, wheat, and maize for 33 countries as of 2000. The adoption rates of HYV seeds differ across countries, which range between 35% and 99% (in case of these major crops). In Figure 3.4, I document the adoption rates over time for these three crops. As of 1965 no region had adopted HYV seeds. While the adoption rate in these three regions reached an average rate of 10% at the onset of 1970, in Sub Saharan-Africa there was little adoption by farmers until 1980. As of 2000, Latin America had the highest adoption rates of HYV seeds followed by East Asian countries, and at slightly less than 20%, Sub Saharan Africa had the lowest adoption rate than any other region.

The prime objective of the GR was to enhance food production in

Figure 3.4: Distribution of HYV seeds adoption rates by regions, selected crops



Note: Originally data were collected by Robert Evenson. Accessed from Douglas Gollin's website: https://sites.google.com/site/douglasgollin/doug-gollin/research.

developing countries (see among others Otsuka, 2000). To some extent, the GR has been successful in achieving this goal.[4] In their review of the evidence, Evenson and Gollin (2003) conclude that the GR accounted for 21% of the growth in yields and about 17% of production growth during the 1961-1980 period. However, during the 1980-2000 period, GR accounted for almost 50% of the yield growth and 40% of production growth in all developing countries (Evenson and Gollin, 2003, Table 1). In this study, I use data on 33 countries that adopted GR from 1965 to 2000. See Appendix Table B.1 for the list of countries, their major crops, and the time period for which there is data.

Figure 3.5, panel (a) shows the change in agricultural employment

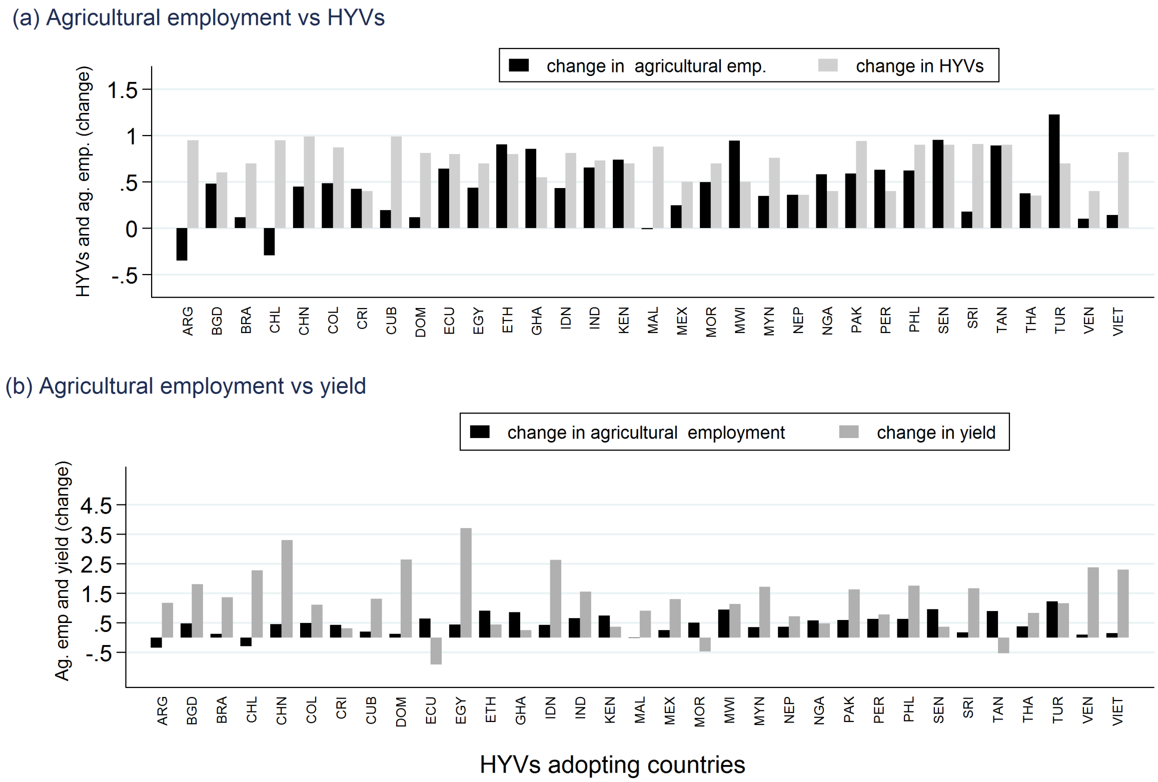
[4]There are, however, skeptics. See Dalrymple (1979) and the references therein.

and the change in the rates of adoption of HYV seeds and panel (b) shows the change in agricultural employment and change in yields. The figure shows that the countries that have experienced higher positive change in the adoption of HYV seeds also experienced higher positive change in agricultural employment barring three countries, Argentina, Chile and Malaysia. Alongside the increases in agricultural employment, these countries also experienced increases in agricultural yields (panel b of Figure 3.5).

I also decompose output per labour in agriculture as a product of yield per hectare and hectare per labour ratio.[5] In Table 3.2, I report both output per hectare for rice, maize and wheat alongside the hectare per labour for countries under different categories. For example, the upper panel of the table shows that the difference of rice yield per hectare between the richest 10% and the poorest 10% countries is more than two fold, while this gap for hectare per labour ratio is 30 fold. Thus, output per labour gap between countries in the top 10% and bottom 10% is 60 fold (2×30), where the main contribution is coming from the hectare per labour ratio gap. The lower panel of the table, however, shows that among the HYV seeds adopting countries, those with higher HYV adoption rates experienced both high yield per hectare as well as low land-labour ratio. For example, among those countries, where the adoption rate is higher than 50%, rice yield is approximately 36% higher, while land-labour ratio is about 50% lower compared with countries where adoption rate of HYV seeds is less than 50%.

[5]Agricultural output per worker ($\frac{Y_a}{L_a}$) can be decomposed into land-productivity ($\frac{Y_a}{T}$) and land-labour ratio $\frac{T}{L_a}$. If $\frac{Y_a}{T}$ increases, output per worker increases, but the magnitude of this increase depends on $\frac{T}{L_a}$. If it decreases, labour productivity grows at a slower rate.

Figure 3.5: HYV seeds adoption rate, agricultural employment and agricultural output



Note: Percentage changes over the period 1965-2000 are reported. Data for HYVs are from Douglas Gollin's website: https://sites.google.com/site/douglasgollin/doug-gollin/research. Employment data are from GGDC 10-sector database, Asian Productivity Organization (APO) database, FAO database. Yields are from FAOSTAT.

Overall the data are suggestive of a positive relation between the

Table 3.2: Yield per hectare and land per labour for top 10% and bottom 10% countries, 2007

% of countries	Yield per hectare			Land-labour ratio
	Rice	Wheat	Maize	(Ha per labour)
Top 10%	8.1	4.9	9.2	44.6
Bottom 10%	2.9	2.0	2.0	1.4
Ratio of top to bottom 10%	2.8	2.5	4.7	31.2
Adoption $\leqslant$50%	2.8	2.6	2.7	1.07
Adoption > 50%	3.8	2.3	3.0	0.58

Notes: The upper panel of the table is extracted from Gollin, Lagakos, and Waugh (2014). Data are from GGDC 10-sector database, Asian Productivity Organization (APO) database, and FAO database.

adoption rate of HYV seeds and agricultural employment. Before I explore this issue in a multivariate setting, in the next section, I develop a model incorporating factor-biased technology in agriculture. The model provides predictions on several agricultural outcomes. Then in the subsequent section I empirically test those predictions using data on 33 GR-adopting countries.

3.4 A conceptual framework

To show the effects of factor-biased technical change in agriculture on the labour reallocation from agriculture, I develop a small open economy model with two sectors and two factors of production: agriculture and non-agriculture, and land and labour. The economy takes the world price as given, and labour is not mobile across borders. While, most of the literature on structural change has assumed a close economy, I believe the small economy assumption has important implication. This chapter undertakes a cross-national study, where several developing countries adopted a common technology and hence, domestic agricultural price might be exogenous to agricultural productivity. In a closed economy, an increase in land productivity (i.e. Green Revolution) will tend to depress agricultural prices and hence shift labour out of agriculture. By contrast, in an open economy relative prices are determined by the world market, and hence relative price is exogenous to domestic productivity. Under this condition, an increase in land productivity, if land and labour are complements, shifts labour into agriculture. Matsuyama (1992) also makes this point.

4.1 Production

The economy has a unit mass of residents, each endowed with 1 unit of labour. The economy produces two goods, agricultural and non-agricultural. Agriculture uses both land and labour and the production function takes the CES form:

$$A_a\left(\gamma(A_L L_a)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_T T)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{3.1}$$

where A_a represents factor neutral technology; A_L stands for labour-augmenting technology, and A_T is land-augmenting technology. The parameter $\gamma \in (0,1)$ determines the relative importance of the two factors and the parameter $\sigma > 0$ stands for the elasticity of substitution between land and labour. Production function in non-agricultural sector is:

$$A_n L_n, \tag{3.2}$$

where, A_n stands for productivity in the non-agricultural sector. Equation (3.1) can be used to obtain the marginal product of labour in agriculture:

$$MPL_a = A_a\left[\gamma(A_L L_a)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_T T)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \gamma(L_a)^{-\frac{1}{\sigma}} A_L^{\frac{\sigma-1}{\sigma}}. \tag{3.3}$$

The above expression shows that both factor-neutral, A_a, and land-augmenting, A_T, technical change in agriculture increase the marginal product of labour in agriculture. However, the effect of labour augmenting, A_L, technical change on marginal product of labour depends on the value of σ. If $\sigma < 1$, an increase in A_L tends to reduce the marginal product of labour in agriculture. Furthermore, the ratio of marginal product of labour to marginal product of land in agriculture is:

$$\frac{MPL_a}{MPT_a} = \left(\frac{A_T}{A_L}\right)^{\frac{1-\sigma}{\sigma}} \left(\frac{T}{L_a}\right)^{\frac{1}{\sigma}} \left(\frac{\gamma}{1-\gamma}\right). \tag{3.4}$$

If land and labour are complements ($\sigma < 1$), an increase in land-augmenting technology A_T raises the marginal product of labour relative to land for a given amount of land per agricultural worker ($\frac{T}{L_a}$). For a given wage rate, employment in agriculture would increase, which would bring the marginal product of labour back to its equilibrium. Thus, any change in agricultural technology affects the employment in agriculture through a change in the marginal product of labour relative to land. However, whether agriculture releases or gains labour in response to a land-augmenting technical change depends on the value of σ: if the elasticity of substitution between land and labour is less than one, a higher A_T results in higher labour in agriculture.

4.2 Partial equilibrium

Profit maximization requires that the value of the marginal product of labour must equal in both sectors:

$$P_a MPL_a = P_n MPL_n$$

As a result, in equilibrium, the marginal product of labour in agriculture is determined by relative prices and non-agricultural productivity. $MPL_a = (P_n/P_a)A_n$. Using the expression for MPL_a and MPL_n, the above equation can be written as:

$$A_a \left[\gamma(A_L L_a)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_T T)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \gamma(A_L L_a)^{-\frac{1}{\sigma}} A_L = \left(\frac{P_n}{P_a}\right) A_n. \tag{3.5}$$

solving for the equilibrium level of employment L_a^* gives:

$$L_a^* = A_T A_L^{\sigma-1} T \left[\left(\frac{1}{\gamma}\frac{P_a}{P_n}\frac{A_a}{A_n}\right)^{1-\sigma} - 1\right]^{\frac{\sigma}{1-\sigma}} \left(\frac{\gamma}{1-\gamma}\right)^{\frac{\sigma}{1-\sigma}}. \tag{3.6}$$

In turn, the equilibrium level of employment in non-agriculture, L_n^* can be determined by using the labour market clearing condition, $L_a^* + L_n^* = L$. From Equation (3.6) I have the following predictions:

- An increase in A_T increases employment in agriculture: $\frac{\partial L_a^*}{\partial A_T} > 0$. Elasticity of substitution, σ does not have a direct impact on agricultural employment here. However, σ affects L_a^* indirectly through its affect on the ratio of marginal product of labour and land. Thus, land-augmenting technology increases agricultural employment if land and labour are complements, by contrast would tend to decrease agricultural employment if land and labour are substitutes.

- If the elasticity of substitution between land and labour is less than one($\sigma < 1$), an increase in A_L decreases employment in agriculture. Conversely if $\sigma > 1$, then an increase in A_L increases employment in agriculture.

- An increase in factor-neutral technology A_a increases employment in agriculture regardless of the value of σ. Notice that this is true only when P_a and P_n are exogenous. But, if P_a decreases when A_a

increases, then agriculture may shed labour.

So, countries that invested in A_L should have lower employment in agriculture if elasticity of substitution between land and labour is less than one, and countries that invest in A_T should have higher employment in agriculture.

4.4 Available estimate on σ

The above model predicts that if land and labour are complements in agricultural production, a land-augmenting technical change increases labour demand in agriculture. Thus, being a land-augmenting technology the Green Revolution is likely to increase employment and the ratio of agricultural employment to land ($\frac{L_a}{T}$). Therefore, this technology may adversely effects the growth of agricultural labour productivity through increasing employment in agriculture.

Empirical studies find a low elasticity of substitution between land and labour ($\sigma < 1$). For example, Binswanger (1974) using USA data find elasticity of substitution between land and labour 0.20; Vincent (1977) with Australian data between 1920 and 1970 estimate this elasticity of substitution as .19; and in recent work, Bui, Hoang, and Thi Minh Hang (2012) by estimating a nested CES model for Vietnam rice production in 2012 find that elasticity of substitution between land and the nest (labour, capital) lies between .44 to .46.

3.5 Empirical strategy

3.5.1 The model

I consider the effects of the adoption of HYV seeds on four agricultural outcomes. The first is agricultural employment, measured as persons employed in agriculture in a given year. The second is labour productivity, measured as the output per worker in farms. The third outcome is the land productivity, measured as the yields per hectare of land. The forth one is the land available for each worker i.e. land-labour ratio. Later I also discuss whether non-agricultural employment was effected by the Green Revolution.

I control for labour-biased technology (A_T in the model) in two ways: i) the area planted with HYV seeds; and ii) difference between yields under techniques that employ modern technology including HYV seeds and traditional techniques. I expect this difference to be a good predictor of the technological change due to adoption of HYV seeds, as the difference in yields between the high and low technology captures the profitability of moving from traditional agriculture to a technology that uses improved seeds and chemicals. I control for land-biased (A_L in the model) technology by tractor use per capita. The basic from of the equations to be estimated are:

$$y_{it}^{a} = \alpha_i + \beta_t + \psi_1 \left(A_T\right)_{it} + \psi_2 \left(A_L\right)_{it} + \varepsilon_{it}, \tag{3.7}$$

where y_{it}^{a} is one of the four outcome variables that varies across countries and time, i represents countries, t stands for year, α_i are country-fixed effects, β_t are year-fixed effects, and $\left(A_T\right)_{it}$ is either $\frac{\text{Land for HYV}}{\text{Agricultural land}}$, total area cultivated with HYV seeds divided by the total agricultural land in country i and in year 1965 and 2000, or $\text{Potential yield}_{it}$. $\text{Potential yield}_{it}$ is equal to the potential yield under high inputs from 2000 onwards and to the potential yield under low inputs before 2000. $(A_L)_{it}$ is the tractor use per capita in country i in year t. Finally, ε_{it} is the residual term (a measure of factor-neutral technology) and these are county-specific. The variables span the period from 1965 to 2000.

The fixed effects model and the first difference estimates are identical when I consider only two periods (1965 and 2000). Thus, I estimate equation (3.7) in first differences:

$$\Delta y_i^a = \Delta\beta + \psi_1 \Delta \left(A_T\right)_i + \psi_2 \Delta \left(A_L\right)_i + \phi \mathbf{X}_{i,1965} + \Delta\varepsilon_i. \tag{3.8}$$

where $\mathbf{X}_{i,1965}$ are a set of control variables in the initial year that might have impact on the outcomes that I observe.

Identification. In equation (3.8), I regress the outcome variables on the technology adoption in agriculture. In order to obtain unbiased estimates, technology and its adoption need to be exogenous. First, in the case of HYV seeds, as the technology was invented elsewhere and not necessarily in the adopting countries, this technology is independent of the level of economic development of the adopting countries. However, technology adoption is likely to be endogenous. I use estimates of potential yields for each country from the FAO-GAEZ database. Since, potential yields are calculated as a function of weather and soil characteristics, not of actual yields of any country, this is a source of exogenous variation in land augmenting technology.

A potential concern with my identification strategy is that the outcome variables respond to many country-specific macro events (omitted variable bias). For instance, it might be that differences in initial urbanization rates across countries differently effect the outcomes that I consider. Thus, I also control for the share of rural population in 1965, GDP per capita income in 1965, population density in 1965, population growth in 1965, literacy rates in 1965 and annual rainfall in 1965.[6]

3.5.2 Data

Table B.2, lists the variables with the associated source of the data. I collected data on agricultural and non-agricultural employment, agricultural production, actual relative to potential yields. The main data sources are the GGDC 10-sector database, FAOSTAT, and FAO-GAEZ database. I study 50 countries of which 33 countries adopted HYV seeds and the remaining 17 did not. Selection of countries is based on data availability. The sample includes countries from across the world and altogether consists of 81% of the world population in 2000. Out of the 50 countries, 15 are from Asia, 13 from Africa, 12 from Latin America, while 13 countries are from Europe and 1 from North America. There are 33 HYVs adopting countries (GR=1), and 17 HYVs non-adopting countries (GR=0). Table 3.3 reports the within group and between group comparisons. Columns 2-3 compare the countries that adopted HYV seeds over the time from 1965 to 2000. Columns 4-5 do the same

[6] At least one concern remains untreated, agricultural openness. This might be important given the very different predictions of the close/open economy model for the question I am addressing. Since, I control for country and time fixed effects, to some extent they should control for the degree of openness and trends in globalization. However, incorporating this issue into the analysis seems to be interesting which I keep for future study.

Table 3.3: Summary statistics

Variables	Mean (GR=1)		Mean (GR=0)		Difference	
	1965	2000	1965	2000	1965	2000
Log agriculture employment	15.11	15.56	13.9	13.12	1.21*	2.44***
					(0.48)	(0.50)
Log non-agricultural employment	14.7	16.02	15.15	15.97	−0.43	0.06
					(0.39)	(0.43)
Ag employment share	0.59	0.42	0.29	0.09	0.30**	0.33**
					(.07)	(.06)
Non-agricultural employment share	0.41	0.58	0.71	0.91	−0.30**	−0.33**
					(0.07)	(0.06)
Area planted with HYVs, %	0.0	52	0.0	0.0	0.0	52***
						(0.05)
Min of HYV adoption %	0.0	0.20	0.0	0.0		
Max of HYV adoption %	0.0	0.87	0.0	0.0		
Tractor in use per capita	0.01	0.03	0.27	0.80	0.26***	0.77***
					(0.04)	(0.13)
Potential yield (ton per hectare)	2.60	7.76	2.23	6.35	0.37	1.41**
					(0.22)	(0.60)
Actual yields (per acre in 2004-06 constant US $)	204	491	1005	1245	−801*	−753*
					(464)	(483)
Output per worker (in 2004-06 constant US $)	116	218	489	1932	−372**	−1713**
					(109)	(394)
Land-labour ratio	2.58	2.12	6.29	11.86	−3.71*	−9.74**
					(2.26)	(3.24)
Share rural population	0.71	0.53	0.43	0.27	0.29**	0.26***
					(0.09)	(0.06)
GDP per capita (in 1990 international GK $)	1968	3626	4436	16755	−2468**	−13128** -
					(701)	(1437)
Log Population density (per km)	3.59	4.40	4.42	4.86	−0.88**	−.46
					(0.41)	(.38)
Literacy rate	0.50	0.75	0.79	0.93	−.29**	−.18***
					(.07)	(.05)
Annual rainfall (mm)	1419	1298	1110	1024	308	274
					(232)	(191)
Births per woman	6.25	3.35	3.6	1.88	2.65***	1.46**
					(0.27)	(.39)

Notes: GR=1 represents the countries that adopted the Green Revolution and in the sample 33 countries fall under this category. GR=0 are the binary variables for countries that did not adopt the Green Revolution. The last two columns show the difference between GR=1 and GR=0. The figure in the parentheses shows the standard error. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

for countries that did not adopt HYV seeds. Column 6-7 present the difference between adopting and non-adopting countries for 1965 and 2000 separately with the associated standard-errors in parentheses. The outcome variables of interest are: employment in both agriculture and non-agriculture, output per hectare of land (yield or land productivity), output per worker in agriculture (labour productivity in agriculture), and land per worker ratio.

Employment. Employment in agriculture and non-agriculture is one of the major outcomes in this study. Employment data mostly comes from GGDC 10 sector database and in addition, for several Asian countries I gather employment data from Asian Productivity Organization (APO, 2014) database. Employment data for Bangladesh and Vietnam are available from 1970 and 1975 respectively. Table 3.3 shows that from 1965 to 2000 the employment in agriculture in the adopting countries increased on average, whereas it decreased in non-adopting countries over the same period, and the increase in the gap between the two groups was statistically significant. By contrast, the employment share in agriculture decreased in both group of countries: in the case of adopting countries employment share in agriculture decreased by 17 percentage points (from 0.59 to 0.42) and in the case of non-adopting countries it decreased by 20 percentage points. Both employment and employment share increased in non-agriculture in both group of countries.

Productivity. I calculate both agricultural land productivity and labour productivity using data from the FAOSTAT database. FAOSTAT reports production data for various crops in 2004-2006 constant US dollars. I calculate the gross production value for each of the eight crops that I study in this chapter, weighting by the proportion of land devoted to that specific crop. Then, to calculate land productivity, I divide the weighted gross production value (for eight crops) by the arable land, while to calculate labour productivity data, I divide the weighted gross production value by the person employed in agriculture.

Table 3.3 shows that the market value of yields in 33 adopting countries increased from \$204 per acre in 1965 to \$491 per acre in 2000 with a 141% change over 35 years, while in 17 non-adopting countries it increased 24% over the same period, from \$1003 per acre in 1965 to \$1245 per acre in 2000. Thus, the adopting countries performed better than the non-adopting countries in terms of percentage change in yield. As a result, the gap in yield per acre between these two group of countries decreased over the year 1965-2000 from \$802 in 1965 to \$753 in 2000.

As for labour productivity (measured by output per worker), it increased from \$116 in 1965 to \$218 in 2000 in adopting countries, about a 87% change over 35 years. By contrast, in non-adopting countries labour productivity in agriculture increased by about 300% over the same period. What is worth mentioning here is that the gap between the two groups of countries widened during this period. The labour productivity gap between adopting and non-adopting countries was \$372 in 1965, but increased to \$1713 in 2000, almost a five fold increase in the gap.

Land area planted with HYV seeds as a % of total cultivated land. The key variables capture actual adoption of HYV seeds and potential yield difference as a measure of land-augmenting technology. The data on the diffusion of HYV seeds come from Douglas Evenson and Gollin (2003). I study eight crops: rice, wheat, barley, millet, sorghum, cassava, potatoes and maize. However, I find that the crop choice is systematically distributed over regions: in Asian countries rice is the main crop and most land is used to produce rice, in Latin America it is wheat, while in Africa it is mostly maize.[7] Figure 3.3 presents the distribution of the percentage of land under HYV seeds for rice, wheat and maize across 33 countries and the summary statistics for all eight crops are presented in Table 3.3. In 1965, neither group of countries adopted HYVs technique, while in 2000 the adopting countries on average employed 52% of the land under HYVs technology. I construct an index of HYV seeds adoption rate using crop-specific adoption rates and total harvested area (both HYVs and local varieties):

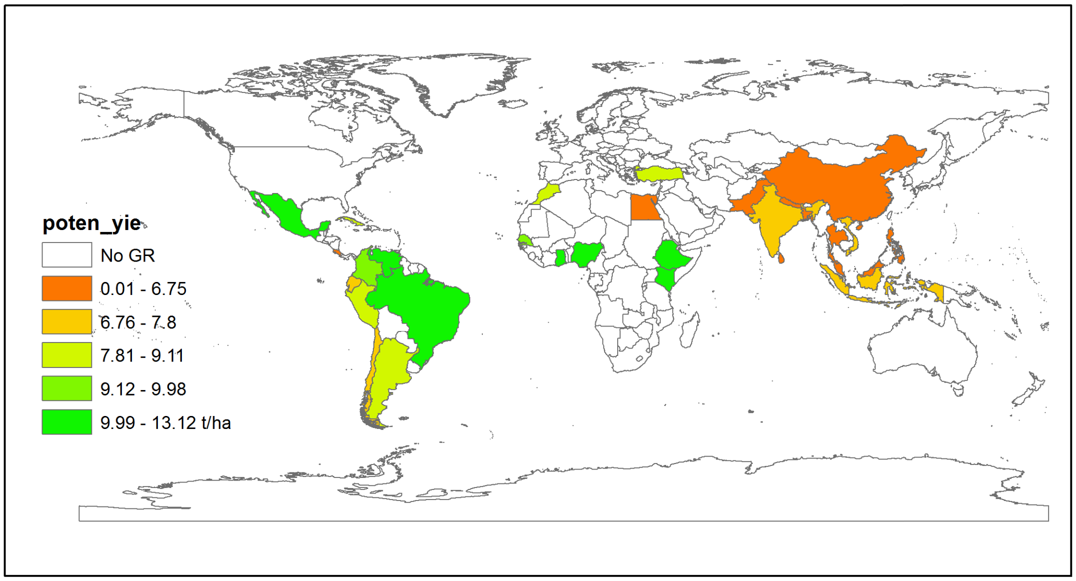
$$\text{HYV seeds}^{\mathrm{j}}_{\mathrm{i},2000} = \frac{\sum_{j=1}^{8} \text{HYV seeds}^{j}_{i,2000} \times \text{harvested area}^{j}_{i,2000}}{\sum_{j=1}^{8} \text{harvested area}^{j}_{i,2000}}$$

where i indexes countries in 2000; and j indexes crops. $\text{HYV seeds}^{j}_{i,2000}$ is the crop-specific adoption rate in country i and thus, $\text{HYV seeds}^{j}_{i,2000} \times \text{harvested area}^{j}_{i,2000}$ is the land in hectare/acre under HYV seeds technology for a specific crop in a specific country. So, the above index, as a whole, shows the crop-wise proportion of land under HYV seeds relative to total arable land of a country.

Potential yields. I obtain potential yields data for all eight crops under study from the FAO-Global Agro-Ecological Zones (GAEZ) database. FAO calculates these yields by incorporating local soil and weather characteristics into an agro-production model and then by estimating

[7]According to FAO statistics, in 2000, those countries that produced mainly rice, devoted 66% of the cultivable land to rice, maize producing countries devoted 53%, while wheat producing countries devoted 58% of cultivable land to wheat.

Figure 3.6: FAO-GAEZ potential yield for Green Revolution adopting countries, selected crops



Source. Potential yields for rice, wheat and maize are shown in the above map. The data of the above map come from FAO-GAEZ database.

the maximum attainable yields for each crop across the world. These potential yields do not depend on the actual yields of any country. Figure 3.6 shows the potential yields for 33 countries across the world that adopted HYV seeds technology in agriculture. The figure depicts potential yields of rice, wheat and maize based on the maximum land used for the respective crops.

The FAO-GAEZ database reports potential yields under two different input combinations. Low-level input technology is described as those obtained using traditional seeds with no or little use of nutrients or chemicals for pest and weed control. When the level of technology is "high", production is mechanized, and it uses HYV seeds and applies nutrients and chemicals pest, disease and weed control. FAO reports the potential yields data in raster format under each technology for a worldwide grid. To match the potential yields data across countries, I superimposed each of the potential yields' raster data-based map with the boundaries of the World map. Next, I compute the average potential yield of all cells falling within the boundaries of every country. Based on this mapping, I construct a measure of technical change for each country by deducting the average potential yields under low inputs from the average potential yield under high inputs.

Tractor use per capita. I control for capital intensity by data on agricultural machineries and tractors from the World Bank, WDI. Agricultural machinery refers to the number of wheel and crawler tractors (excluding garden tractors) in use in agriculture at the end of each calendar year. On average, tractor use per person increased from .01 to .03 in GR-adopting countries, while it increased from .27 to .80 in non-adopting countries.

A decomposition of data

Table 3.3 shows that over the period 1965-2000, HYV seeds-adopting countries experienced a faster growth of agricultural employment compared to the non-adopting countries. Alongside, the gap of labour productivity in agriculture between these two groups of countries has also widened over the same period. For example, in 2000, land productivity in GR-adopting countries was 39% that of non-adopting countries, while labour productivity was only 11% that of non-adopting countries. Note that a change over time in labour productivity in agriculture, may stem from either a change in yield or a change in land-labour ratio or a combination of these two factors:

$$\Delta\frac{Y_a}{L_a} = \Delta\frac{Y_a}{T} \times \frac{T}{L_a}_{1965} + \Delta\frac{T}{L_a} \times \frac{Y_a}{T}_{1965} + \Delta\frac{Y_a}{T} \times \Delta\frac{T}{L_a}, \qquad (3.9)$$

where, Y_a is agricultural output; T is arable land; L_a is agricultural employment; and Δ stands for change over time. The first component on the right-hand side measures the yield effect: the change in agricultural labour productivity due to a change in yield holding land-labour ratio constant at its 1965 level. The second component measures the effect of land-labour ratio: change in agricultural productivity with respect to a change in land-labour ratio holding yield constant at its 1965 level. The third component captures the changes in labour productivity resulting from the interactions of yield and land-labour ratio. When yields and land-labour ratio move in the same direction, this component amplifies the agricultural labour productivity. By contrast, if they move in the opposite direction, the growth of labour productivity slows down. Thus, the contribution of the interaction term depends on the size and sign of the changes in yield and land-labour ratio.

Table 3.4 shows the above decomposition results for both GR adopting and non-adopting countries by region. The upper panel of Table 3.4 shows that the growth rate of agricultural labour productivity in non-adopting countries is more than double that of the growth rate in adopting countries. And this is despite the fact that the contribution from the growth of land productivity is almost half that of the adopting countries. For example, in adopting countries the contribution of the yield growth is 2.36% which was pulled down 1.01 percentage points by the negative contribution of the growth rate of land-labour ratio

Table 3.4: Decomposition of labour productivity growth; 1965 - 2000

	Growth of output/worker	Contribution from (1) Yield	(2) Land-labour ratio	(3) Interaction
GR-adopting countries	1.35	2.36	−0.47	−0.54
Non-adopting countries	2.92	1.41	0.80	0.71
Asia	0.78	2.97	−0.99	−1.20
Latin America	2.66	1.55	0.53	0.58
Sub Saharan Africa	−0.14	1.42	−1.02	−0.54

Notes: The above calculation has been weighted by population. see Equation (3.9) for the method that decomposes agricultural labour productivity growth into yield per hectare growth, land-labour ratio growth, and an interaction term. All data are in percent.
Source: Land and output data are from FAOSTAT, while the labour data come from GGDC 10-sector database, FAOSTAT database and APO database (for several Asian countries). Data for Bangladesh and Vietnam are available from 1970 and 1975 respectively.

and combined effect. By contrast, in non-adopting countries of 2.92% growth of labour productivity, 1.51 percentage points came from the land-labour ratio and the interaction term.

In Table B.3 through B.6, I document the decomposition results by countries. For non-adopting countries, all the three effects- yield effect, land-labour ratio effect and the interaction term, are positive and hence, agricultural labour productivity growth is faster than land productivity growth. By contrast, in almost all countries in Africa and Asia, the contribution of land-labour ratio is negative, resulting in a relatively lower agricultural productivity growth. Moreover, the interaction term has material impact on the growth of agricultural labour productivity. In almost all GR-adopting countries, there is a negative co-movement between yield and land-labour ratio. By contrast, in non-adopting countries the co-movement between yield and land-labour ratio is positive and large. Finally in non-adopting countries the major contribution to agricultural labour productivity growth comes from land-labour ratio growth, whereas in adopting countries this is not the case.

To summarise, the aforementioned decomposition suggests that even though the GR-adopting countries had higher growth rates in land productivity relative to non-adopting countries, they registered relatively a poor performance in terms of labour productivity in their agriculture which mostly came from the negative growth rate of land-labour ratio. Given land is a quasi-fixed factor, this can be attributed to an increase in agricultural employment- consistent with the predictions of the model in Section 4. In the next section, I test this hypothesis using a multivariate regression model and data on 33 GR-adopting countries.

3.6 Estimation results

3.6.1 Estimation results

I start by reporting the estimation results concerning the impact of the expansion of the area planted with HYV seeds on agricultural and non-agricultural labour market outcomes. I report the OLS estimates in Table 3.5. Column 1 shows that those countries where adoption of HYV seeds increased relatively more also experienced an increase in agricultural employment. Next I show the effects of the change in HYV seeds adoption on agricultural production per worker, yield per hectare of land and land-labour ratio. Columns 2 through 4 show that countries with a relatively larger increase in HYV seeds adoption rate experienced a decline in output per worker and land-labour ratio, and also an increase in output per unit of land. The estimated coefficient

Table 3.5: Green Revolution and agricultural outcomes

Variables	Dependent variables			
	Δ Log agricultural employment	Δ Log labour productivity	Δ Log yield	Δ Log land-labour ratio
	(1)	(2)	(3)	(4)
Δ HYV seeds	0.36^{**}	-0.07	0.64^{**}	-0.42^{*}
	(0.17)	(0.35)	(0.29)	(0.25)
Tractor use per capita in 1965	0.16	-0.23	1.34^{**}	-0.19
	(0.23)	(0.20)	(0.52)	(0.21)
Birth per women in 1965	0.18^{**}	-0.18^{**}	0.06	-0.16^{**}
	(0.08)	(0.05)	(0.13)	(0.06)
Log GDP per capita in 1965	-0.09	0.15	0.19	0.11^{*}
	(0.07)	(0.10)	(0.22)	(0.06)
Literacy in 1965	-0.43	-0.22	0.62	0.17
	(0.41)	(0.53)	(0.91)	(0.4)
Log population density in 1965	$.09^{**}$	0.18^{**}	0.61^{**}	0.04
	(0.04)	(0.08)	(0.17)	(0.05)
Share rural population in 1965	0.13	-0.74^{**}	-0.58	-0.04
	(0.18)	(0.22)	(0.41)	(0.19)
Log rainfall (mm) in 1965	0.01	0.05	-0.35	-0.005
	(0.07)	(0.11)	(0.28)	(0.07)
Observations	48	48	48	48
R^2	0.80	0.69	0.78	0.59

Notes: ΔHYV seeds is the change in the adoption of HYV seeds between 2000 and 1965. Robust standard errors are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

implies that a 1 percentage point increase in HYV seeds area share corresponds to a 0.36 percent increase in agricultural employment, and to a .42 percent decrease of agricultural land-labour ratio and these estimates are statistically significant. Moreover, the estimated coefficients in column 3, implies that a 1 percentage point increase in HYV seeds area share leads to 0.64 percent increase in yield, which is significant at the 5% level. The point estimate on labour productivity is negative suggesting that the change in HYV seeds has a negative impact on agricultural labour productivity, however this relation is statistically insignificant.

In Table 3.6, I report the results of the OLS regression on the

Table 3.6: GR, mechanization, and agricultural outcomes

Variables	Dependent variables: Δ Log agricultural employment	Δ Log labour productivity	Δ Log yield	Δ Log land-labor ratio
	(1)	(2)	(3)	(4)
Δ Tractor use per capita	-0.81^{**}	0.68^{*}	-0.20	0.71^{**}
	(0.21)	(0.44)	(0.30)	(0.21)
Δ HYV seeds adoption	0.52^{*}	0.55	0.93^{**}	-0.58^{*}
	(0.29)	(0.38)	(0.44)	(0.39)
Birth per women in 1965	0.11^{**}	-0.17^{**}	-0.05	-0.09^{*}
	(0.02)	(0.05)	(0.05)	(0.05)
Log GDP per capita in 1965	-0.07	0.28^{*}	0.04	0.10
	(0.06)	(0.14)	(0.14)	(0.10)
Literacy in 1965	-0.07	-0.20	0.02	0.05
	(0.22)	(0.52)	(0.49)	(0.35)
Log population density in 1965	0.03	0.10	0.17	-0.08
	(0.04)	(0.08)	(0.10)	(0.07)
Share rural population in 1965	0.07	0.06	-0.01	0.02
	(0.11)	(0.30)	(0.21)	(0.25)
Log rainfall (mm) in 1965	-0.04	-0.15	-0.06	0.04
	(0.06)	(0.12)	(0.14)	(0.11)
maize	0.46^{**}	-0.15	0.29	-0.41^{*}
	(0.17)	(0.43)	(0.39)	(0.23)
wheat	0.01	-0.31	0.25	-0.22
	(0.18)	(0.39)	(0.41)	(0.28)
Observations	36	36	36	36
R^2	0.92	0.79	0.75	0.72

Notes: Robust standard errors are in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

same outcome variables, while the variable of interest is tractor use per capita. I also control for change in adoption of HYV seeds. The results indicate that Tractor use is positively associated with land-labour ratio and agricultural labour productivity but negatively associated with agricultural employment and yield per hectare of land. However, coefficient estimate on land productivity is not statistically significant.

Column 1 of Table 3.6 shows that a one unit increase in tractor use per capita decreases agricultural employment by 0.81% with a significance level of 5%. Columns 2 and 4 indicate that a one unit increase in tractor use is associated with 0.68% increase in labour productivity and 0.71% increase in land-labour ratio and both estimates are statistically significant. However, agricultural land productivity is not statistically significantly related to tractor use per capita. The coefficient estimates for the ΔHYV seeds adoption are consistent with earlier results reported in Table 3.5.

IV estimates

Next, I use change in FAO-GAEZ potential yield as an instrument for the adoption of HYV seeds and employ two separate specifications: (i) interaction between instrumented changes in the area cultivated by HYV seeds by changes in potential yields and GR=1 (ΔPotential yield $\times$ GR=1), and (ii) changes in the area cultivated by HYV seeds by changes in potential yield (ΔPotential yield). Note that under the second specification, I pool GR-adopting and non-adopting countries. I estimate the model by 2SLS and report the results in Table 3.7.

Examining the first stage regressions, I find that changes in potential yield is a good predictor of the adoption of HYV seeds technology (the bottom panel of Table 3.7). However, under the second specification, I do not find any statistical significant relation between ΔHYV seeds and ΔPotential yield. Table 3.7 shows that compared to a non-adopting country, in an adopting country, a 1% increase in ΔPotential yield lead to an increase in the adoption of HYV

Table 3.7: Green Revolution and agricultural outcomes: IV estimates

Variables	Second stage			
	ΔLog agricultural employment	Δ Log Ag. labour productivity	Δ Log yields	Δ Log land-labour ratio
	(1)	(2)	(3)	(4)
ΔHYV seeds	1.02***	-0.27	1.02**	−1.25**
	(0.24)	(0.40)	(0.48)	(0.45)
Other controls	Yes	Yes	Yes	Yes
Kleibergen and Paap (KP)(2006) test of underidentification				
p-value	0.003	0.003	0.003	0.003
R^2	0.74	0.69	0.43	0.64
		First stage Dependent variable: ΔHYV seeds		
ΔPotential Yield $\times$ GR $= 1$		0.49***		
		(0.08)		
Other control	Yes	Yes	Yes	Yes
F-test of excluded instrument		34.0		
R^2		0.61		
Observations	48	48	48	48

Notes: The null hypotheses of the Kleibergen and Paap (2006) test is that the structural equation is underidentified. And, the null hypothesis of Stocky and Yogo (2005) test is that the set of instrument is weak. Other control includes share of rural population, GDP per capita, population density, literacy rate, annual rainfall and birth per woman, tractor use per capita, all in 1965. Robust standard errors are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

seeds by .49% and this is significant at the 1% level. Moreover, the F-statistic reported in Table 3.7 suggests that the interaction term (ΔPotential yield $\times$ GR $= 1$) is not a weak instrument (here the F-test for excluded instrument 34 is higher than the standard rule of thump of 10 used in the applied literature). By contrast, the F-test reported in Table B.7 suggests that ΔPotential yield is a weak instrument. The point estimates in Table 3.7 are larger than the estimates in Table 3.5. These estimates are not due to weak- or under-identification: the Kleibergen and Paap (2006) test of underidentification indicates that the model is identified ($p < .01$), while as stated the F-test of

Table 3.8: GR, mechanizations and agricultural outcomes: IV estimates

Variables	Second stage			
	ΔLog agricultural employment	Δ Log agricultural labour productivity	Δ Log yields	Δ Log land-labour ratio
	(1)	(2)	(3)	(4)
ΔHYV seeds	0.57^{**}	0.15	1.05^{**}	-0.95^{*}
	(0.28)	(0.38)	(0.47)	(0.56)
ΔTractor per capita	-0.85^{***}	0.244	-0.07	0.52^{***}
	(0.16)	(0.34)	(0.30)	(0.18)
Other controls	Yes	Yes	Yes	Yes
Kleibergen and Paap (2006) test of underidentification				
p-value	0.01	0.01	0.01	0.01
R^2	0.88	0.78	0.74	0.66
	First stage Dependent variable: ΔHYVs			
ΔPotential Yield × GR = 1		0.47^{***}		
		(0.11)		
Other control	Yes	Yes	Yes	Yes
F-test of excluded instrument		18.0		
R^2		0.61		
Observations	48	48	48	48

Notes: Robust standard errors are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

excluded instrument suggests that the IV (ΔPotential yield $\times$ GR $= 1$) is not weak. So, I can not reject the hypothesis that the IV estimates are valid.

Examining the second stage regressions, compared to non-adopting countries I still find that adoption of HYV seeds led to increase in agricultural employment and yield per unit of land. The point estimates on labour productivity, and land-labour ratio are negative but the estimate on labour productivity is not statistically significant. The first column of Table 3.7 shows that a 1 percentage point increase in the adoption of HYV seeds (instrumented by ΔPotential yield $\times$ GR $= 1$)

leads to a 1.02% increase in agricultural employment relative to no-adopting countries. And these finding is statistically significant at the 1% level. Columns 3 and 4 show that a one percentage point increase in the adoption of HYV seeds, lead to an increase in yield per hectare by 1.02% and a decrease in land-labour ratio by 1.25%. Agricultural labour productivity decreases by .27% due to a one percentage point increase in HYV seeds adoption, but this point estimate is not statistically significant.

In Table 3.8, I present the results of the IV estimation, when I allow for both adoption of HYV seeds and change in tractor per capita over time. In the baseline estimation, I fixed the tractor use per capita in 1965. This specification thus considers all three sources of technological change; labour, land biased, and factor neutral. Table 3.8 shows that the results are not sensitive to the inclusion of changes in tractor use. Column 1 shows that a one percentage point increase in HYV seed adoption leads to a .57% increase in agricultural employment, while a one unit increase in the tractor use is associated with a .85% decrease in the agricultural employment. The effect of change in HYV seeds adoption on yield is positive and statistically significant, while the effect of change in tractor use is negative but not significant. HYV seeds and tractor use have no statistically significant impact on agricultural labour productivity (column 2). Finally, land-labour ratio decreased by .95% due to one percentage point increase of HYV seeds adoption, while it increased by .56% due to a one unit increase of tractor use.

Table 3.9: Green Revolution and structural change; OLS estimates

	Δ Log agricultural employment	Δ Log non-agricultural employment	Δ agricultural employment share
Δ HYVs seeds	0.36**	−0.25	0.05
	(0.16)	(0.23)	(0.07)
Tractor use per capita in 1965	0.23	−0.31	0.19**
	(0.22)	(0.30)	(0.07)
Birth per women in 1965	0.19**	0.16**	−0.004
	(0.08)	(0.05)	(0.01)
Log GDP per capita in 1965	−0.06	−0.17	0.04
	(0.11)	(0.16)	(0.05)
Literacy in 1965	−0.33	0.43	−0.07
	(0.36)	(0.39)	(0.10)
Log population density in 1965	−0.09*	−0.16**	0.02
	(0.05)	(0.04)	(0.01)
Share rural population in 1965	0.35*	0.28	0.09*
	(0.23)	(0.23)	(0.05)
Log rainfall (mm) in 1965	0.06	−0.05	0.009
	(0.06)	(0.09)	(0.02)
Observations	48	48	48
R^2	0.80	0.93	0.80

Notes: ΔHYV seeds area is the change in the percent of area cultivated with HYV seeds. Robust standard errors are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

3.6.2 Structural change

To study the effects of Green Revolution on structural change, I estimate equation (3.8), where the dependent variables are employment in non-agriculture and agriculture and share of employment in agriculture. I report the OLS results in Table 3.9 and IV results in Table 3.10. While the OLS point estimate indicates that HYV seeds adoption rates have a positive impact on the share of employment in agriculture, the point estimate is not statistically significant. The point estimate on non-agricultural employment is negative but not statistically significant. The IV point estimates are statistically significant. Compared to non-adopting countries, in GR-adopting countries, a one percentage point increase of the adoption of HYV seeds leads to a .26% increase of

Table 3.10: Structural change :IV estimates

Variables	Second stage		
	Δ Log agricultural employment	Δ Log non-agricultural employment	Δ agricultural employment share
	(1)	(2)	(3)
Δ HYVs seeds	1.02***	−0.50*	0.26**
	(0.24)	(0.31)	(0.08)
Other controls	Yes	Yes	Yes
R-squered	0.76	0.93	0.75
Kleibergen and Paap (2006) test of underidentification			
$p - value$	0.004	0.004	0.004
		First stage Dependent variable: Δ HYVs	
Δ Potential Yield		0.50***	
		(0.09)	
Other controls	Yes	Yes	Yes
F-test of excluded instruments		33.0	
R^2		0.75	
Observations		48	48

Notes: Robust standard errors are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

the agricultural employment share, while non-agricultural employment decreases by -.50% due to a one unit increase of the adoption of HYV seeds and these estimates are statistically significant (Columns 2 and 3 of Table 3.10).

3.6.3 Crop effects

Are the results driven by idiosyncratic crop effects? Crops may have differential labour requirement which may be responsible for the results. Moreover, the production method could be different across countries and regions as well. While the first difference estimation method takes care of country-specific time invariant heterogeneity, potential crops effects remain untreated. To address this issue, I re-estimate equation (10) controlling for three major crop types: rice, wheat, and maize. Rice is the reference crop.

Using the variation across crops, I continue to find the effect of GR on agricultural outcomes with similar sign, and with higher magnitudes, as well as lower standard errors. I present the results in Table 3.11. Columns 1 and 4 show that HYV seeds adoption rates have a positive and statistically significant association with agricultural employment and statistically significant negative association with land-labour ratio in agriculture in adopting countries. Column 3 shows that change in HYV seeds adoption rates have positive and significant effects on yield; a one percentage point increase in HYV seeds adoption leads to a 1.01% increase of yield. However, adoption of HYV seeds does not have a statistically significant association with agricultural labour productivity. Table 3.11 also suggests that compared with rice producing countries the magnitudes of the impact of ΔHYV rates on log agricultural employment, agricultural labour-land ratio and land-labour ratio are higher in maize producing countries. And the estimates for wheat are all statistically insignificant, and thus that suggests virtually there is no differential impact between rice and wheat producing countries on agricultural outcomes. These results are consistent if I use changes in both HYV seeds adoption and tractor use per capita (Table 3.6).

Table 3.11: The effects of Green Revolution with crop effects

Variables	Δ Log agricultural employment (1)	Δ Log labour productivity (2)	Δ Log yield (3)	Δ Log land-labour ratio (4)
Δ HYVs seeds	0.75***	0.26	1.01**	−0.81**
	(0.18)	(0.35)	(0.35)	(0.31)
Maize	0.43**	−0.05	0.48*	−0.51**
	(0.15)	(0.32)	0.29)	(0.22)
Wheat	−0.09	0.28	0.13	−0.21
	(0.17)	(0.38)	(0.37)	(0.26)
Other control	Yes	Yes	Yes	Yes
Observations	48	48	48	48
R^2	0.85	0.70	0.69	0.63

Notes: Other controls include: share of rural population, GDP per capita, Population density, literacy rate, annual rainfall, tractor use per capita and birth rate per woman, all in 1965. Robust standard errors are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

3.6.4 A Difference-in-Difference (DiD) model

In this section I estimate the effects of GR on the same outcomes using a difference-in-difference (DiD) technique. In my sample 33 countries adopted HYV seeds (treatment group) and remaining 17 countries did not adopt it (control group). Relative to the non-adopting countries, the adopting countries had more people employed in agriculture, less land and labour productivity in agriculture and also lower land-labour ratio in 1965 (see Table 3.3). This gap between adopting and non-adopting countries increased by 2000. For example, on average adopting countries had 13.8 million more employment in agriculture in 1965, while this gap increased to 26.1 million in 2000. Not all of this increase in agricultural employment in adopting countries is due to the GR and the difference-in difference estimator helps to estimate the impact of the

Table 3.12: Green revolution and agricultural outcomes: Difference-in-Difference estimates

Variables	Dependent variables: Δ Log agricultural employment	Δ Log labour productivity	Δ Log yield	Δ Log land-labour ratio
GR=1	1.27**	0.63*	0.03	0.60**
	(0.63)	(0.37)	(0.45)	(0.23)
year 2000	−0.71*	1.21**	0.56*	0.65***
	(0.42)	(0.32)	(0.35)	(0.15)
HYV seeds×year 2000	1.13**	−0.72**	0.25	−0.98***
(DiD estimates)	(0.54)	(0.37)	(0.41)	(0.22)
Tractor use per capita	1.81**	1.79**	−0.22	2.0***
in 1965	(0.57)	(0.41)	(0.48)	(0.21)
Birth per women	−0.36**	−0.21**	−0.04	−0.16**
in 1965	(0.13)	(0.071)	(0.08)	(0.05)
Log GDP per capita	−0.92**	0.12	0.07	0.06
in 1965	(0.40)	(0.26)	(0.26)	(0.17)
Literacy in 1965	−1.38	0.16	0.18	−0.02
	(1.08)	(0.57)	(0.60)	(0.40)
Log population density	0.13	0.17**	0.33	−0.16**
in 1965	(0.14)	(0.07)	(0.08)	(0.05)
Share rural population	−0.07	−0.86**	−0.34	−0.51*
in 1965	(0.42)	(0.35)	(0.41)	(0.26)
Log rainfall in 1965	−0.08	0.09	0.08	0.01
	(0.28)	(0.14)	(0.22)	(0.19)
maize	−1.06**	−0.33	−1.02**	0.69**
	(0.54)	(0.32)	(0.33)	(0.20)
wheat	−0.47	0.32	−0.81**	1.13***
	(0.59)	(0.37)	(0.39)	(0.27)
Observations	48	48	48	48
R^2	0.50	0.72	0.52	0.79

Notes: GR=1 represents the countries that adopted HYV seeds. year 2000 is a year dummy for 2000. The figures in the parentheses show the robust standard errors. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

GR. I estimate the following difference-in-difference regression model:

$$y_{it} = \alpha_i + \beta_1 \text{GR} + \beta_2 \text{year 2000} + \delta(\text{GR} \times \text{year 2000}) + \phi \mathbf{X}_{i,1965} + \varepsilon_{it} \quad (3.10)$$

where, GR=1 if a country adopted HYV seeds and zero otherwise. In 1965 no country adopted it. Therefore, the difference between GR=1 and GR=0 in 2000 reflects the difference between the adoption rates of HYV seeds technology. year 2000 is a year dummy variable and equal to one if the year is 2000, and zero otherwise. The interaction term GR $\times$ year 2000 provides the difference-in-difference estimator.

Table 3.12 reports the OLS estimates of equation (3.10) for four agricultural outcomes. The first and forth columns show that in countries where GR technology expanded, agricultural employment increased and land-labour ratio in agriculture decreased. Columns 2 and 3 show that in adopting countries GR leads to an increase in agricultural land productivity, and a decrease in agricultural labour productivity. However, the point estimate on yield is not statistically significant. The estimated coefficients on the effect of GR expansion on employment imply that due to the adoption of HYV seeds an adopting country on average had an increase of 1.13% in agricultural employment and .98% decrease in agricultural land to labour ratio. The effect on yield per hectare is positive, but not statistically significant. Overall, the sign and magnitudes of DiD point estimates are consistent with the IV and OLS estimates.

Summary of the results

To summarise, I find that after controlling for country, crops, and time-specific effects, adoption of HYV seeds has increased agricultural employment, while it decreased agricultural labour productivity as well as land-labour ratio relative to non-adopting countries. I obtain similar results with the IV estimates. Thus, these findings are robust to different estimation procedures and specifications. This evidence is consistent with the conceptual framework in Section 4, in which a land-augmenting technical change increases agricultural employment. The point estimate on land-labour ratio is negative and statistically significant, meaning an increase in adoption of HYV seeds leads to decrease in land-labour ratio. Point estimate on agricultural labour productivity is negative, while it is positive on land productivity, yet the result on agricultural labour productivity is not statistically significant. Given, land is a quasi-fixed factor, land-labour ratio is decreasing because of the increases in agricultural employment. Thus, the empirical findings are consistent with the model prediction that labour-biased technical change in agriculture lead to increases in employment in agriculture.

The estimated coefficient can be utilized to infer to what extend changes in adoption of HYV seeds can explain the increase in agricultural employment between 1965 and 2000.

–Based on the OLS point estimate (0.36 from Table 3.5), the change in area devoted to HYV seeds can explain 28% of the aggregate increase in agricultural employment between 1965 and 2000, which amounted to approximately 101 million workers together for 33 countries. (see Appendix B, where I show the brief calculation procedure).

– Based on the IV point estimate (1.02 from Table 3.7), the change in area devoted to HYV seeds can explain 80% of the aggregate increase in agricultural employment between 1965 and 2000, which amounted to approximately 284 million workers for 33 countries.

– Based on the DiD point estimate (1.13 from Table 3.12), the change in area devoted to HYV seeds can explain 88% of the aggregate increase in agricultural employment between 1965 and 2000, which amounted to approximately 313 million workers together for 33 countries

As for agricultural employment share, according to data these 33 countries had on average 50% of their labour force in agriculture in 2000. Using more conservative estimates (i.e. the one I obtain from OLS estimation), the counterfactual without Green Revolution suggests that employment share in agriculture would have declined 6 percentage points more in those 33 countries on average.

3.7 Conclusion

This paper argues that the effect of agricultural productivity on agricultural labour reallocation crucially depends on the factor-bias of technical change. If technical change in agriculture is land-augmenting (i.e. labour-biased), agriculture gains labour, if instead technical change is labour-augmenting (i.e. land-biased), agriculture sheds labour. Green Revolution was meant to increase output per unit of land and represents a land-augmenting technology. After its introduction in the mid 1960s, many developing countries across the world adopted this technology.

The results show that there is a systematic difference in various agricultural outcomes between GR-adopting and non-adopting countries. The econometric estimates using a variety of method all suggest that the GR substantially increased agricultural employment in adopting countries leading to declining land-labour ratio and hence slower labour productivity growth in agriculture.

Chapter 4

Share Tenancy and Agricultural Productivity: Evidence from Bangladesh

4.1 Introduction

Inefficiency in agricultural share contracts refers to an incentive problem where a tenant undersupply effort compared to a fixed rent contract. Is share tenancy in agricultural land rental market inefficient? In this chapter, I study the impact of share tenancy on agricultural productivity, measured as yield per acre, in Bangladesh.[1] Bangladesh is an interesting case study because agriculture employs approximately 50 percent of its labour force and 88 percent of the households are rural based (Raihan, 2012). Apart from that, there is high incidence of poverty, for example in 2008 the poverty rate was 32 percent. Moreover, among the rural farm households, 10 percent do not own land, and 32 percent of farm households cultivate under share tenancy contract. Why do we observe such a high tenancy rate in Bangladesh, despite ample evidence pointing to high levels of inefficiencies in share tenancy? Is the high incidence of share tenancy indicative of inefficiency in agriculture in Bangladesh?

The practice of share tenancy has been wide-spread and historically has been a persistent form of lease in the land rental market. However, whether share tenancy is efficient, is far from settled in both

[1] In empirical literature, yield per unit of land is used to measure efficiency; see for example, Shaban (1987); Jacoby and Mansuri (2009); Arimoto, Okazaki, and Nakabayashi (2010).

theoritical and empirical literature (Otsuka and Hayami, 1988). In the theoritical literatre, two competing approaches have been proposed on the efficiency of share tenancy. According to the first approach tenant's labour effort is unobservable and non-enforceable, which would discourage efficient methods of production. According to the second approach landlords have inexpensive and effective monitoring ability to extract the optimal intensity of labour per acre, and hence share tenancy will be an efficient way to organize agricultural production; in Johnson (1950) duration of lease is a monitoring device, and in Cheung (1968) it is contractual agreement.

The empirical literature on the efficiency of share tenancy is also inconclusive. However, there is general agreement that the 'agency problem' looms large in agriculture: tenant shirks in work and employs less efforts than potential. The fundamental difference between the two theoretical approaches lies in the ability of the landlord to monitor the activities of the tenant effectively. According to the monitoring approach agency problems can be eliminated. For examples, comprehensive contract (what the tenant must do) in pre-War China. One way to mitigate the 'agency problem' faced by the landlords is to use credible threats, such as termination of the lease, if tenant's performance is not satisfactory to the landlord. Landlords can grant a short-term lease, and if the non-farm job option for the tenant is limited, the agency problem is likely to be less severe.[2]

[2]Short term leasing policy does not involve much supervision or transaction costs. Other methods of enforcing proper cultivation such as inputs and cost sharing, however, entail considerable transaction and enforcement costs.

A short term contract coupled with limited non-farm job options, will expose a tenant to a credible threat of eviction. This incentivizes the tenant to cultivate the leased land with an efficiency at least sufficient to secure a renewal of the lease (Johnson, 1950). In this chapter, I test this hypothesis using data from Bangladesh, and ask the following question; is there any negative association between agricultural land productivity and share tenancy in Bangladesh? I argue that under the conditions of short-term contract and limited non-farm job options for the tenants, share tenancy is not inefficient. In Bangladesh, there is a reserve army of landless labour: more than 80% of the farms are small (less than 2.44 acres) and the land-labour ratio is low. Moreover, the share tenants face a short-term contract, usually one year or less (Hossain and Hussain, 1977; Rahman and Rahman, 2009). This combined with limited non-farm job options expose share tenants to a credible threat of eviction. Under these circumstances, each tenant has an incentive to use the land intensively to extract a minimum output to meet his subsistence requirement as well as to continue with the contract.

To test the productivity of share tenancy, this study draws upon a district-level data set from rural Bangladesh. I use five different agricultural census reports conducted in Bangladesh between 1977 and 2008 to construct a panel encompassing 64 districts. One feature of using a panel of districts survey is that it allows tracking a particular district over time and therefore it provides an opportunity to observe the source of the within - district variation of share tenancy. The data allow me to follow the distribution of tenant cultivators across districts and the same district over time. There is substantial variation in tenancy share across districts and within a district over time. I use these district level variations of tenancy to control for both time invariant district level heterogeneity and factors that vary over time but are constant across districts. The fact that the data come from one country with similar data collection strategies in each district, and the relatively long time period is one of the advantages of these data.

Using yield per acre of land as a measure of agricultural productivity, I find that a one percent increase in share tenancy, on average, leads to 0.6 percent increase in yield of rice in Bangladesh. Thus, I conclude that land productivity is not necessarily lower among share tenants relative to owner cultivators in rice cultivation. The reason is that, in Bangladesh both land and non-farm jobs for farm households are scarce, about ten percent of the farm households are landless. Under this condition, competition for scarce land among landless farmers would increase the value of land and would thus increase land productivity. This finding is consistent with Kassie and Holden (2007), where they find that under the eviction threat land productivity on sharecropped plots is higher than the share cropper's own plots in the case of Ethiopia.

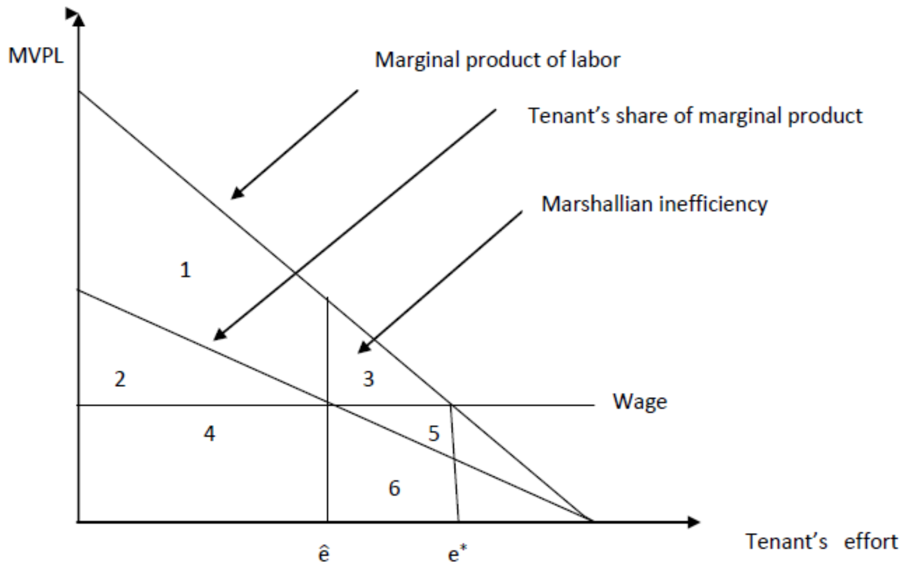
The rest of the paper is organised as follows. Section II reviews the related literature. Section III summarises the land tenure history of Bangladesh. Section IV provides a conceptual framework and motivates the empirical strategy. Section V presents the data and contains the main empirical results. Section VI concludes.

4.2 Related literature

In the economic development literature both the causes and the consequences of share tenancy have been extensively studied. At least since Adam Smith, many have argued that share tenancy is an inefficient contract (Hallagan, 1978). The inefficiency refers to the fact that since tenants are not the full claimant of residual income, they exert less effort. If share tenancy is inefficient, then why is it so prevalent in both time and space? The optimal contract choice literature considers whether fixed or share rent is more efficient. A fixed rent contract maximises the tenant's incentives and would always be chosen if the tenant is sufficiently wealthy (Banerjee, Gertler, and Ghatak, 2002; Laffont and Matoussi, 1995) or there is no random variability of agricultural output (i.e. a risk-free environment) (Cheung, 1968). When moral-hazard in effort and risk aversion by the tenant are prevalent, both landlord and tenant may choose share tenancy.

Theoretical literature on efficiency of agricultural tenancy has followed two basic approaches to modelling a share tenancy contract: a) the 'Marshallian model', assumes a prohibitively high cost of monitoring the tenant's activities and predicts lower input intensities on rented land than on own land; and b) the 'monitoring model', first proposed by Johnson (1950) and later developed by Cheung (1968, 1969), which argues that landlords can stipulate the intensity of labour in a contract, and they have a sufficiently inexpensive and effective monitoring ability to ensure that their stipulation is fulfilled. Therefore, empirical studies on share tenancy-productivity debate has focused on the following

Figure 4.1: Marshallian inefficiency of share tenancy



Note: MVPL stands for value of marginal product of labour. Under share tenancy, landlord's income is the area 1, while share tenant's income is the area 2+4, and area 3 is a dead weight loss. Under fixed rent contract, landlord gets the area 1+2+3 and tenant gets the area 4+5+6, no dead weight loss.

questions: a) whether tenant effort is prohibitively costly to monitor, thereby leading to moral hazard; or b) whether underprovision of tenant effort is obviated by landlord supervision (Jacoby and Mansuri, 2009).

To get an idea regarding the inefficiency associated with share tenancy, I present the traditional model geometrically in Figure 4.1. Landlord's rent under fixed rent contract is attained according to the marginal condition whereby the marginal product of labour is equal to wage. Under fixed rent, tenants supply e^* labour and the area 1+2+3 constitutes landlord's rent under fixed rent contract. Under share tenancy, the tenant provides $\hat{e}$ effort whereby the tenant's share of marginal product is equal to wage, not e^* and under this system landlord's rent is the area 1 and hence landlord loses area 2+3: 2 to tenant and 3 is a dead weight loss (the Marshallian inefficiency). Hence, the marginal product of labour is higher under share tenancy but the optimum labour effort is less in share tenancy than under the two alternative contracts.

The efficiency issue of share tenancy dates back to Adam Smith (1776) and was later formalized by Marshall (1890a). Appealing to share tenancy system in French and fixed rent system in England, Marshall (1890b) argues that "..if a French metayer is free to cultivate as he chooses, he will cultivate far less intensively than on the English plains". Mill (1894) took a more favourable view of the sharecropping (French metayage) system and argued that most of the defects pointed out by earlier writers were due to imperfections of the metayer system as practiced (see also Johnson, 1950). Adam Smith argued that share tenancy would prevent desirable land improvements and encourage inefficient methods of production, and most subsequent writers have agreed (Reid Jr, 1976). For instance, Heady (1955) using data from Iowa, USA; Bhagwati (1966) and Bardhan and Srinivasan (1971) using Indian data, Bell (1977) using data from Bihar, India; Shaban (1987) using village level data from India; and Jeon and Kim (2000) using macro level data from Korea find that share tenancy contracts result in inefficiencies. By inefficiency they mean lower yield per unit of land under share tenancy than fixed rent or owner cultivation.

Johnson (1950), by contrast notes that share tenancy has not always resulted in the gross inefficiency of production. He suggested three possible solutions to the potential inefficiency in share tenancy: by specifying in detail what the tenant must do; sharing the costs of cultivation in the same proportion as the landlord shares in gross output; and by granting a short-term lease which would be renewed only upon satisfactory performance. Johnson discussed the third method and this result holds up in the presence of risk (Newbery, 1975; Bell, 1977)

Cheung (1968, 1969) later formalized this argument. Using wheat as a risky crop which was frequently sharecropped, and rice as less risky crops which tended to be rented and data from Taiwan, Cheung (1968) argues that whereas risk is shared by landlords and tenants under a share tenancy contract, it is not shared under other forms of contracts. Cheung, then, argues that share tenancy would be used in risky environment despite higher negotiation and enforcement costs. Subsequently, Jacoby and Mansuri (2009) using data from rural Pakistan, Huang (1975) using data from Malaysia, among others, find supportive evidence to argue that share tenancy is efficient.

Therefore, empirical findings on share tenancy-productivity debate are rather inconclusive. However, there is general agreement between both approaches that agency problem looms large in agriculture: tenants tend to employ less efforts on sharecropped land, and due to high supervision/monitoring costs effort can not be contracted (Banerjee, 1999). But, the 'monitoring approach' points to the mitigating devices of this incentive problems and to the conditions under which share tenancy can be efficient. For example, Cheung (1969) shows using the data of Taiwan that if the comprehensive contract is able to enforce the minimum labour input of the tenant in per acre, the adverse incentive problem will be eliminated. And thus share tenancy becomes as efficient as other alternative contracts. 'operation borga'-a comprehensive tenancy reform in West Bengal, India that gives tenants more secure right to the land and an increased share of output, enhanced agricultural productivity in West Bengal compared to other states of India (Banerjee et al., 2002). kinship relation between tenants and landlords in Philippines, and non-kinship relation between tenants and landlords in Ethiopia. Sadoulet, De Janvry, and Fukui (1997) find using data from Philippines that kinship networks provide an efficient mechanism of contract enforcement (cooperative behaviour and make share tenancy efficient). By contrast, Kassie and Holden (2007) using village level data from Ethiopia find higher productivity on share-cropped plots of non-kin than of kin tenants.

Why is share tenancy chosen as a contract despite the fact that it is a less efficient tenure arrangement? A number of factors like risk (Newbery, 1977), supervision problems (Lucas, 1979), capital constraints (Jaynes, 1982), moral hazard, and screening problems (Hallagan, 1978) may render share cropping cultivation more attractive and profitable than the other forms of cultivation. The common theme about the existence of share tenancy is that it is a response to uncertainty that stems from random variability of output in agriculture and asymmetric information. It is also viewed as a response to market failure in labour, insurance, credit, and capital markets. Typically, however, these market failures can be traced back to imperfect or incomplete information (Singh, 1987).

The most obvious explanation of share tenancy is that it provides a method in which the inevitable risks of agricultural production can be shared between the tenant and landlord (Newbery and Stiglitz, 1977). The idea that share tenancy might have a risk-sharing advantage over fixed rent and wage contract was suggested by Cheung (1968, 1969), who postulates that share tenancy offers the advantage of risk sharing while the other two contracts involve lower transaction costs. In the absence of insurance markets or other means for diversifying risk, the tenant bears all the production risk under fixed-rent contract. If the tenant is risk-averse, fixed-rent contract is not profitable to him and it is not an optimal contract choice by landlord either if the tenant is poor and output is uncertain -the tenant maybe be unable to pay the required rent if crop fails- limited liability (see e.g., Hurwicz and Shapiro, 1978; Shetty, 1988). A share contract, on the other hand, assign some risk to each of the contracting parties and might be preferable. A sequence of papers by Newberry and Stiglitz (1974, 1975, 1977) have contributed to the literature by generalizing Cheung's basic results of uncertain world.

But, what is the rationality for existence of the share tenancy under certainty? The self-selection or screening model represents an approach to rationalize the existence of share tenancy under certainty. Hallagan (1978) and Newbery and Stiglitz (1979) independently introduced similar models of screening or self-selection by contractual choice. The basic idea behind this model is that landlord can not directly observe some characteristics of tenants such as entrepreneurial or other ability. Then by offering a menu of contracts, the landlord can induce individuals with abilities to select different contracts. Tenants are thus screened according to ability, and the lowest-ability individual might not receive a contract at all.

But, the assumption that the landlord is ignorant about tenants' abilities may not be appropriate for most rural communities. Typically, there is little mobility, thus information about abilities and assets is easily available. Moreover, screening models cannot explain why a certain contractual form might predominate in one area while quite another form predominates elsewhere (Eswaran and Kotwal, 1985). Alternative theories of share tencny argue it pools unmarketed resources, and act as a partnership arrangement in which both agents have incentives to self-monitor. Bliss and Stern (1982), for example, view share tenancy as an arrangement that involves the pooling of managerial and cultivating skill.

In recent year it has been recognized that the empirical work should also consider the fact that the data come from the market that consists of heterogeneous landlords and tenants. Particular types of landlords may look for particular types of tenants or particular types of tenants may choose certain types of crops i.e. there might be a matching process. When the landlords are heterogeneous with respect to riskiness of their assets as well tenants are heterogeneous with respect to their degree of risk aversion, then both of the contracting parties may have incentive to match with each other (for example Ackerberg and Botticini, 2002; Serfes, 2005; Aggarwal, 2007,deal with this issue).

4.3 Land tenure in Bangladesh

Bangladesh was a British colony up until 1947 for nearly 200 years. Under the British colonial rule, about 80% of the land was cultivated by share tenant type farmers with a per farm holding between .69 and 1.91 acres (Table 4.1). When the British left in 1947, it became part of Pakistan (East Pakistan) and became independent in 1971. The economic progress of Bangladesh is mainly depended on the development of the agrarian sector which contributes around 20% to the country's GDP and provides employment to around 50% of the labour force (Bangladesh Census of Agriculture, 2008). The present agrarian system in Bangladesh is the out growth of an act legislated in 1950. But the system also has a close connection with long colonial history. At least three dates are important to understand the history of agrarian system in Bangladesh: 1793, 1950 and 1971.

In 1793, Lord Cornwallish enacted 'Permanent Settlement Act' in the then Bengal presidency. According to this Act, large feudal landlords (*zamindars*) received the rights to collect tributes from peasants in exchange for a land tax to the state which was fixed (Ghatak and Roy, 2007). Around 1938-40, more than 80% of the land in British East Bengal was under permanent settlement with the landlords and remaining 20% was owned by either government estates or British landlords. No land was owned by the tiller of the soil.

In 1950, after the British left India, the major agricultural land reform abolished the permanent settlement. All tenants under permanent settlement would have permanent, heritable, and transferable rights on their lands and would be entitled to use their land in any way they like. Thus the Act effectively created a land market where the real cultivators were allowed to buy and sell land. This marked a huge policy shift in land related property rights regime. All cultivated lands in excess of

33.3 acres per family or 3.3 acres per member of the family, whichever was larger, plus homestead land up to a maximum of 3.3 acres, were to be acquired by the government. Later on, this ceiling was raised from 33.3 acres to 124.80 acres. As against this ceiling, the average size of holdings was 2.6 acres. Thus, while this law eliminated intermediaries between the state and the cultivators, the ownership of land was still concentrated in the hands of few; the feudal middleman (*zamindars*) during British rule converted into large land owners under new law.

In 1971, when Bangladesh became independent, the question of land reform has assumed crucial importance. This was not surprising given the very high man-land ratio: 1867 people per square mile. The country became independent in December 16, 1971, and Starting from that point on, the government of Bangladesh has been undertaking land reforms almost continuously while two main land reforms that were enacted in Bangladesh are in 1972 and 1984 respectively (for a brief history of land reforms in Bangladesh see Table C.2):

- The land reform in 1972 is, in fact, the amendment and continuation of State acquisition act of 1950. This reform reset the landownership ceiling and brought it back to 33.3 acres from 124.8 acres.

- 'Land Reform Ordinance enacted in 1984 reset the ceiling of maximum land holding at 21 acres (60 bighas). It gave the tenants the rights to have a written contract with the landowners for share-cropping. Products grown by share-cropping (bargha system) were to be divided into 3 parts where both the owner and the share-cropper share one-third of the product and remaining one-third

Table 4.1: Extracts from various agricultural censuses in Bangladesh

	1951	1961	1983-84	1996	2005	2008
Total farm holdings (in million)	n/a	n/a	10.05	11.80	14.33	14.87
Cultivated area (in million acres)			20.16	17.77	18.26	18.82
Average farm size (in Acres)	.69 to 1.91		2.00	1.50	1.26	1.26
Farm size	% of total	% of total	% of total	% of total	% of total	% of total
.05 - 2.44 acres	51.64	56.63	70.34	79.87	88.49	84.27
2.5 - 7.49 acres	37.69	35.52	24.72	17.61	10.34	14.16
7.50 acres & above	10.67	7.85	4.94	2.52	1.17	1.54
Landless agricultural labor	15.3	17.5	8.67	10.18	10.65	9.58

Note. n/a stands for data not available. Total farm holdings show farm households out of total households in rural area. In British India average farm size was in between .69 and 1.91 acres.
Source: Bangladesh Census of Agriculture 2008, National series, Vol. 1, Bangladesh Bureau of Statistics (BBS).

will be shared by the person who supplies inputs for cultivation. However, evidence suggests that there is no written share contract and still it is an oral contract. And for share tenancy in the case of Bangladesh, 50:50 is a rule rather than an exception.

Table 4.2: Distribution of households; rural Bangladesh, 1984 - 2008

Division	1983/84			1996			2008		
	Total HHs	Farm HHs	%	Total HHs	Farm HHs	%	Total HHs	Farm HHs	%
Barisal	1.1	.85	76.82	1.33	1.03	75.89	1.6	1.1	67.79
Chittagonj	2.69	1.97	73.16	3.17	2.13	67.01	4.31	2.4	55.66
Dhaka	3.70	2.84	71.63	4.94	3.22	65.18	7.66	3.9	51.36
Khulna	1.57	1.19	75.80	2.18	1.52	69.87	3.12	1.98	63.53
Rajshahi	3.6	2.53	70.60	5.08	3.2	63.02	7.2	4.2	58.45
Sylhet	.91	.67	73.93	1.11	.70	63.56	1.4	.77	52.99
Bangladesh	13.81	10.05	**72.70**	17.83	11.80	**66.18**	25.35	14.39	**56.74**

Note. HHs stands for households (in million) and % represents farm as a % of total. All information compiled in the table shows only farm holdings in rural areas over six divisions in Bangladesh.
Source: Report of Agriculture Census, 2008, Bangladesh Bureau of Statistics (BBS).

The salient features of Bangladesh agriculture are increasing and high prevalence of small scale farming, and a high percentage of landless households. The lower panel of Table 4.1 shows that as of 2008, 84% of the rural agrarian farms were less than 2.44 acres and about 10% of the rural households were landless. In Table 4.2, I document number of total households and farm households as a percentage of total. It appears from the table that share of farm household is gradually decreasing while the absolute number of farm households is increasing over the years. For example, between 1984 and 2008, share of farm households in rural Bangladesh declined at a rate of 1.03% per year, by contrast absolute number of farm households increased from 10.05 million to 14.39 million at an annual rate of 1.50% per year.

4.4 Conceptual framework

Here, to fix ideas, I present a model of contractual forms. Following Otsuka and Hayami (1988), suppose the return to a tenant, Y is assumed to be expressed by the following linear function:

$$Y = \alpha Q + F$$

where, α is a parameter representing an output sharing rate, and F is a fixed payment that corresponds to a fixed wage component if $F > 0$ and to a fixed rent component if $F < 0$. Typical form of contracts, then, can be written as following:

1. Fixed rent contract. if $\alpha = 1$ and $F < 0$; the tenant gets the output, pays a fixed amount of rent to landlord. Here, all the risk is with tenant. Note that risk here represents random variability of output in agricultural production.

2. Share tenancy contract. if $0 < \alpha < 1$ and $F = 0$. The tenant gets α fraction of output and the rest remains for the landlord. Notice that risk is shared here.

3. Fixed Wage contract. if $\alpha = 0$ and $F > 0$. The output is collected by the landlord while the tenant gets a fixed wage F. All risk is with landlord.

All of the above contractual forms are observed throughout the world; in Latin America fixed rent is most popular, while it is mostly share tenancy in Asia. As for the efficiency (i.e. yield per unit of land), fixed rent contract is argued to be efficient as tenant receives whole of the extra output, while share tenancy is viewed as inefficient as tenant gets a fraction of the marginal benefit from putting more effort (i.e. incentive disadvantage problem). If effort is unobservable fixed wage contract also confers inefficiency as tenant is paid the same no matter how much he works (moral hazard problem). Thus, a fixed rent contract seems perfect in terms of incentives but it will not be preferred by the tenant if he is a risk averse, and the landlord will not choose it either if the tenant is poor and output is subject to uncertainty like pest, weather (limited liability). Under fixed rent, the landlord would wait until after product but production is uncertain and crops may fail. This situation sets the bound on the fixed rent so that tenant be able to pay it even when his crop fails. If this bound is low enough, the landowner may not want a fixed rent. So, if both the tenant and landlord are risk-averse, share tenancy appears to be an optimal contract as a compromise between risk and incentives.

However, if the incentive disadvantage problem can be solved, share tenancy might be efficient. Johnson (1950) has proposed three possible ways to solve the potential inefficiency of share tenancy and he emphasised that by granting a short-term lease which will only be renewed after the satisfactory performance, the inherent incentive problem in share tenancy can be solved. This sort of short-term contract imposes an eviction threat on the tenants and improve his performance in terms of gross output to get a renewal of the contract. Notice that the threat of eviction will only be credible if the tenant is earning rent (i.e. his utility in the tenancy contract is higher than his best outside alternative) - thus eviction may be more credible under limited liability problems - i.e. for poorer tenants.

To summarize, the agency problem inherent in share tenancy will be solved if the fraction of landless farmers in a region is high, because competition for scarce land among landless farmers would increase the value of land and would thus increase land productivity. For example, on average, market price of land in Bangladesh is 17 fold higher than the annual value of the net output of the land (Griffin, Khan, and Ickowitz, 2002). I documented in section 3 that historically, in Bangladesh the fraction of landless labour is high, e.g. in 1951 fraction of landless labour was 15%, which was still approximately 10% in 2008 (see the lower panel of Table 4.1). Apart from this, the share tenancy contract in Bangladesh is of short duration, usually one year or less (Hossain and Hussain, 1977; Rahman and Rahman, 2009). Moreover, the reserve of landless labour is pushing down the land available for each labour. This combined with limited non-farm job options expose share tenants in Bangladesh to a credible threat of eviction. In this backdrop, share tenants in Bangladesh must try to ensure a minimum yield per smaller parcel of land rented to meet their subsistence requirements and to continue with the contract, thus increasing the land productivity. In what follows, I will empirically test this hypotheses drawing on the data from rural Bangladesh.

4.5 Empirical analysis

Data sources and variables

I construct a dataset using Agricultural Censuses (1977 to 2008). I use rice yield per acre as an index of agricultural productivity for three reasons. First, in Bangladesh, around 80% of the cultivated land is used for rice production. Second, while agriculture in Bangladesh includes livestock and poultry, forestry and fishing, share tenancy has direct effects only on farming. Third, Bangladesh is a land scarce but labour abundant country and hence measuring agricultural productivity by yield per acre rather than yield per labour seems appropriate. The data on rice yield per acre come from the Yearbook of Agricultural Statistics of Bangladesh and Statistical Yearbook of Bangladesh . The data on the percentage of share tenancy come from the Report of Agriculture Census conducted in Bangladesh between 1977 and 2008.

Four agricultural censuses have been carried out in Bangladesh; 1977, 1983/84, 1996 and 2008. An agriculture sample survey was also conducted in 2005.[3] The censuses of agriculture in both 1977 and 1996 covered only rural areas while the censuses in 1983/84 and 2008 and the sample survey in 2005 covered both rural and urban areas.[4] For the purpose of comparability I use the rural data only. Slightly less than 90% of the households in Bangladesh live in rural areas, while most of these households also have farm holdings.[5]

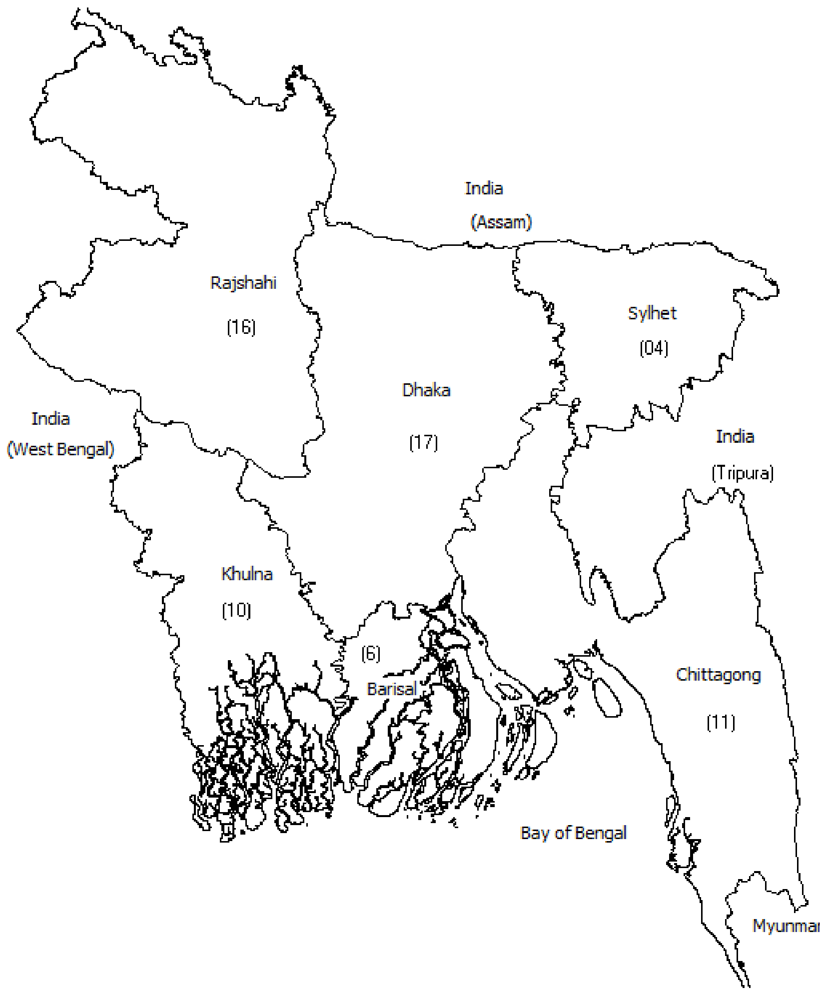
The data are collected at the district level (names of the districts are given in Table C.1 in appendix). Before 1984 Bangladesh had 19 districts, which increased to 64 in 1984 in six divisions. Figure 4.2 shows the map of Bangladesh and districts are shown in parentheses under six divisions in Bangladesh. In Bangladesh, districts are an administrative unit, with an average area of 2305 square kilometres and population of roughly 2.34 million. Districts only implement policies legislated centrally and have no legislative power. I use district-level data for all censuses by dividing the old districts along the post-1984 administrative borders (see Appendix). The data from 1977 is the earliest available for independent Bangladesh. I use data from all censuses and surveys available: 1977, 1983/84, 1996, 2005 and 2008. Thus, 19 districts in 1977 and 64 districts in the remaining four years provide altogether 275 observations.

[3]The agriculture sample survey was conducted during the period 17-31 May 2005. This sample covered a fixed number of clusters (10% mauza/mahalla (small local area)) in each zila(district)/city and the selected agricultural households were interviewed in each selected cluster. A total of 13539 enumeration areas were selected for enumeration. The census schedule-1 used in the 1996 agriculture census was taken as the basis for developing the 2005 sample survey . Thus, this sample survey is deemed nationally representative.

[4]Censuses in Bangladesh are conducted dividing the whole country in to two parts: rural and urban. The definition of the rural and urban is different in different censuses. For example, in 1983/84, there were only 79 municipalities. Its number increased to 147 in 1996. Agriculture sample survey 2005 rural area includes some 80 urban areas at upazila (sub-district) level which were treated as rural in agriculture census 1996.

[5]A farm household is defined as a holding whose net cultivated area is 0.05 acre or more. For example, in 2008, 88% of the total 28.70 million households in Bangladesh were rural and of these about 57% had farm holdings.

Figure 4.2: Administrative map of Bangladesh

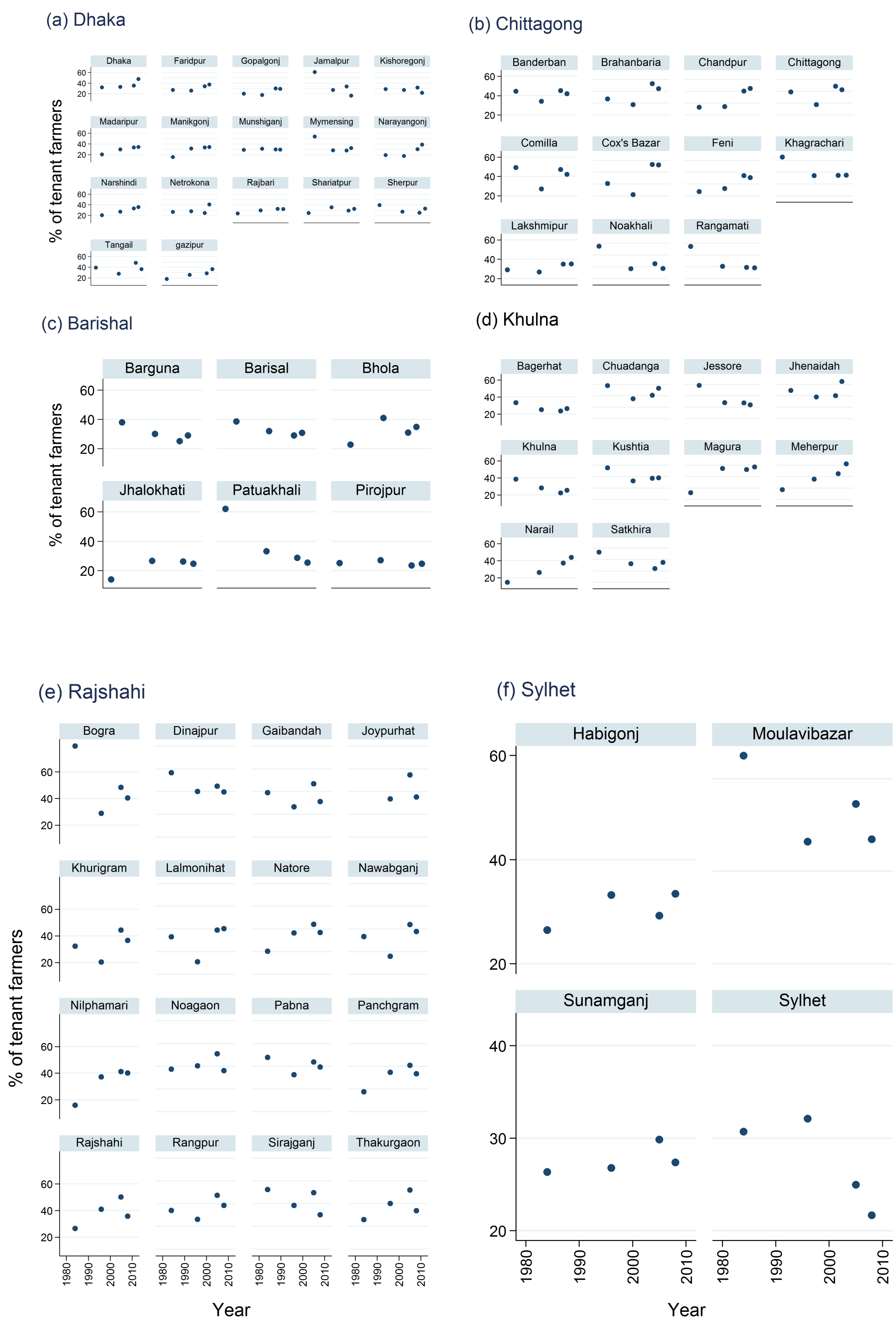


Note. There are 64 administrative districts in Bangladesh under 06 divisions. Each cell represents one division and the number in parenthesis under the division name is the number of districts in the corresponding division.

Tenant holdings. The agricultural land in Bangladesh is cultivated by three categories of cultivators: i) owners, ii) tenants, and iii) owner cum tenants. The last category cultivates both own and rented land. Bangladesh Bureau of Statistics (BBS) defines tenant households as those who pay (either in cash or kind) to use or occupy land for cultivation or other purposes owned by others. Tenants as a percentage of rural farm households constitutes the variable of interest and I measure this in two ways: i) I add up both tenants and owner cum tenants to find the tenant households (mixed tenancy), and ii) only tenants households as a percentage of rural farm households (only tenancy). However, I base my analysis on the first category and show the second category as a sensitivity analysis. More than 80% of owner cum tenants own land less than .99 acre and they are dependent on large and absentee land-owners for their livelihood (Abdullah, 1981). Also, in Bangladesh top 10% owners of land control about 50% of total land while they cultivate only 30% of it (Hossain et al., 1980). Thus, considering all factors, the land cultivated under tenancy is approximately 27% of total cultivable land (Alamgir 1981).

The data on tenant households come from various years' agriculture census. As per census of 2008, Bangladesh had approximately 34% farmers who were tenants. Table 4.3 documents the percent of tenant holdings in Bangladesh corresponding to five agriculture census years. Table 4.3 suggests that tenancy in Bangladesh has varied over the years: tenants as a percent of cultivators was 28.78% in 1977 reached 36% in 2005 and then again declined to 34% in 2008. Figure 4.3 shows the distribution of tenancy share across six divisions and over time. There are variations of tenancy share both across different administrative divisions, within the same division across time, and across districts within a division as well as the same district across time.

Figure 4.3: Distribution of tenancy across districts, 1984 - 2008



Note: The figure shows the distribution of tenant holders across 64 districts over four census years. Each panel in above figure represents a division.

Source: Reports of Bangladesh Agriculture Census, various issues.

Table 4.3: Tenancy by years, 1977 - 2008

Year	Mean	Median	St. Deviation	Max	Min
1977	28.78	28.76	4.95	37.7	21.7
1983/84	30.90	28.92	11.42	62.06	11.01
1996	31.32	30.38	4.64	40.96	17.66
2005	36.19	33.65	8.40	54.49	22.28
2008	33.66	33.60	5.74	47.86	16.67
overall	32.74	32.08	8.11	62.06	11.01

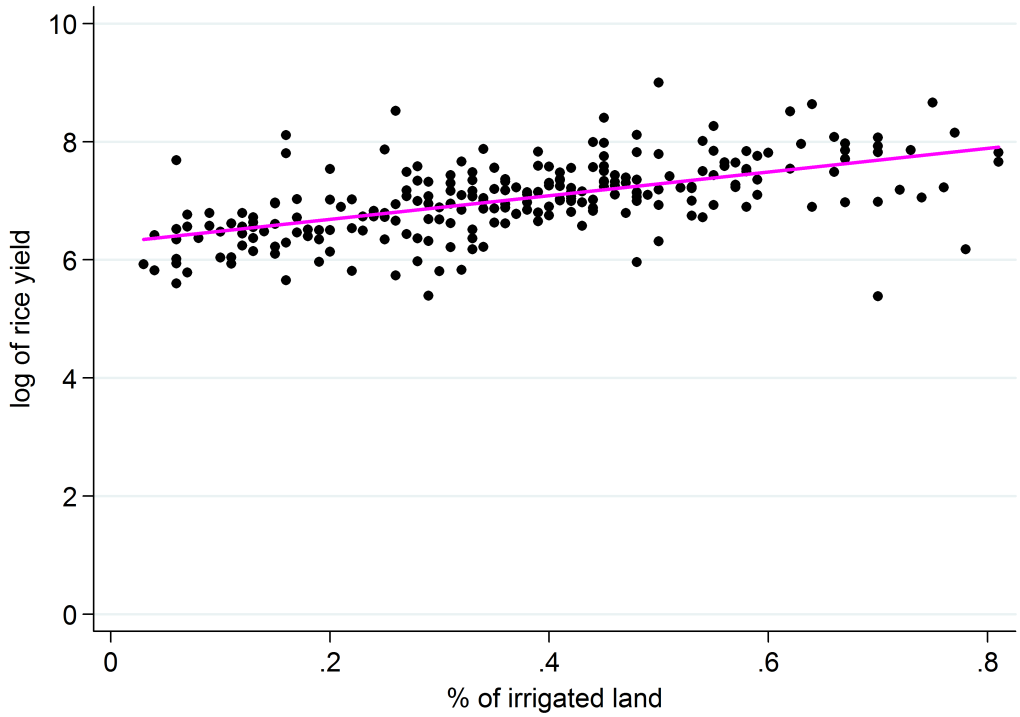
Source: The statistics above show the tenants plus tenants cum owner farm households across all available districts. The number of districts is 19 in 1977 and 64 thereafter. Bangladesh Census of Agriculture, various years, Bangladesh Bureau of Statistics.

Control Variables

Irrigation. Boyce (1987) finds a strong complementary among fertilizer, high-yielding varieties (HYV) and water control/irrigation for agricultural productivity in Bangladesh. In a broader sense, the combination of these constitutes the 'green revolution'. water control/irrigation is essential- it is also a fixed investment. I calculate the 'percent of land under irrigation' from two sources: i) land used for rice production (both local varieties and high yielding varieties) in each district, and ii) area used for rice production which is under irrigation at the district-level. Then I take the ratio of (i) over (ii) to construct 'percent of land under irrigation' variable. The data for (i) come from Yearbook of Agricultural statistics (respective years) and the remaining data is from various Agriculture Census reports. Figure 4.4 shows the strong association between irrigation and rice yield per acre in my data set.

High Yielding Varieties (HYV). High Yielding Varieties (HYV) of rice seeds was introduced in Bangladesh in the early 1970s. In 1977, about 28% of cultivated land was brought under HYV which increased to

Figure 4.4: Rice yield per acre and irrigation, 1977 - 2008



Note. The figure shows the distribution of rice yield in logs against % of irrigated land by district-year pair.

slightly less than 60% of cultivated land by 2008. Agricultural census reports provide information on the areas of cultivated land used both for HYV seeds and also for local varieties.

Educational attainment. I control for the average educational attainment of farms households in a district by calculating literacy rates by district. Literacy rate for those seven years old and above has been defined as the ratio of literate persons of age seven and above to total population of the same age and expressed in percentage. The data on literacy rates come from Population Censuses. Unfortunately, the timing of population censuses do not coincide with Agriculture Censuses and so I rely on the Population Census that was conducted to the nearest time of a particular Agriculture Census. In particular I match Population Census, 1974 to Agriculture Census, 1977, 1981 with 1984, 1991 with 1996 and 2001 with 2005 and 2008 with 2011. The global mean of literacy rate over the period 1977-2008 is 36 with a minimum value of 12 and maximum value of 71.

Soil fertility. The data on fertility come form Quddus (2009). This paper divides Bangladesh into 12 Agro-Ecological Zones (AEZ) and defines the fertility conditions of soil of each of the districts. Based on these information, I categorise the land fertility in each district as 'High'; 'Medium'; and 'Low'. The list of the districts according to these categories are shown in Table 4.4. Out of total 64 districts, nine has been categorized as 'high', 23 as 'medium', and the remaining 32 as 'low'. Thus based on this, I generate dummy variables, High fertility=1 if the district falls under high land fertility regions and 0 if it does not; medium fertility=1 if the district falls under medium fertility regions and 0 if it does not. A low land fertility region is the reference category.

Average rainfall. Bangladesh has an uneven topography and a humid tropical climate. This coupled with abundant monsoon rain offers a suitable environment for the rice plant. The overall statistics of annual rainfall during the sample period in Bangladesh is reported in Table 4.6. Over the period from 1977 to 2008, the annual average rainfall across 64 districts was 1755mm with a minimum of 824mm and a

Table 4.4: District-wise land fertility in Bangladesh

Land type	Name of districts
High	Barguna, Jhalokhati, Patuakhali, Pirojpur, Barguna Munshigonj, Dhaka, Noakhali, Chandpur
Medium	Barisal, Bhola, Netrokona, Kishorgonj, Brahambaria, Satkhira Khulna, Nawabgonj, Pabna, Lakshipur, Goalandha, Faridpur Madaripur, Gopalgonj, Shariatpur, Kustia, Magura, Bagerhat Comilla, Feni, Chittagonj, Rajbari, Cox's Bazar
Low	Dinajpur, Gaibandha, Joypurhat, Bogra, Naogaon, Rangamati Sirajgonj, Natore, Habigonj, Nilphamari, Rangpur, Khagrachari Lalmonihat, Kurigram, Rajshahi, Jamalpur, Sherpur Tangail, Manikgonj, Narayngonj, Gazipur, Mymensing Kishorgonj, Narsindi, Netrokona, Panchagarh, Thakurgaon Kurigram, Sylhet, Moulavi Bazar, Sunamgonj, Bandarban,

Note. The information of Table 4.4 comes from Quddus (2009). Bangladesh consists of 30 Agro-ecological Zones (AEZ), which are overlapping with each other. For convenience of analysis, Quddus (2009) combined 2/3 zones for a region and grouped them into 12 mutually exclusive regions. Each AEZ on was an aggregate of a number of administrative districts and this information has been shown in Table 1 of Quddas (2009). I use this table to classify the districts as 'high', 'medium', and 'low' according to the fertility of their land.

maximum of 3993 mm. The highest rainfall is recorded during monsoon period (June-September). The data on annual total rainfall comes from Bangladesh Metrological Department, which collects daily rainfall data and publishes the rainfall statistics on a monthly basis.

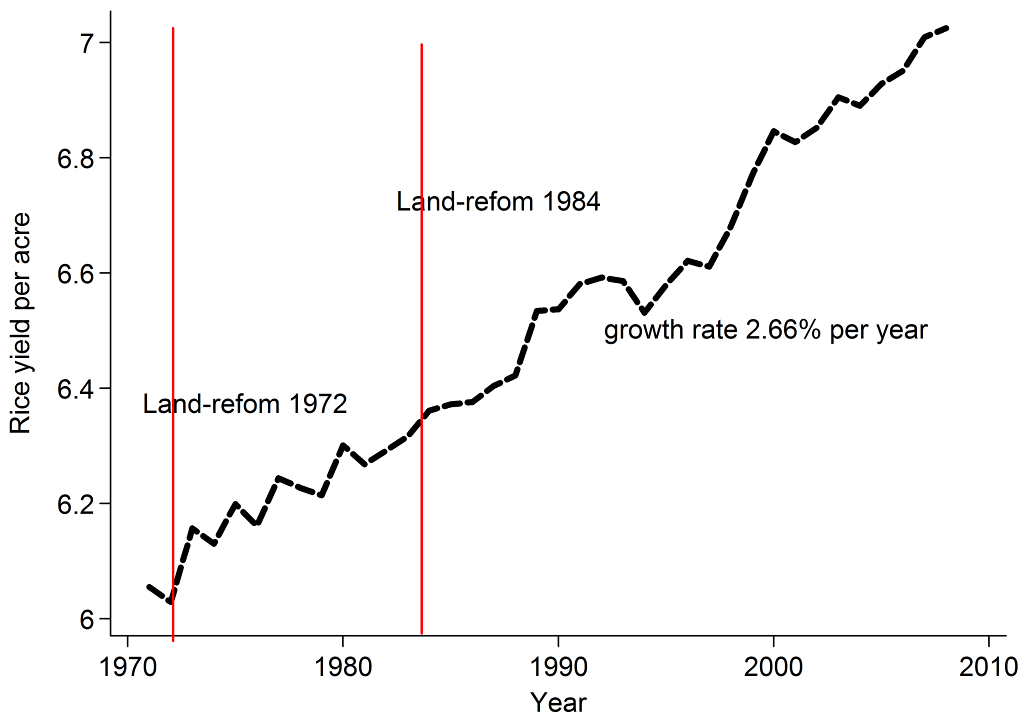
Per cent of land under rice production. Slightly lees than 80% of the arable land in rural Bangladesh is used to produce rice (Bangladesh Bureau Statistics). I construct a variable which is the ratio of land under rice production to total arable land across 64 districts. I include this variable to address possible endogenous crop selection. Almost all land cultivated by tenants are used for rice production. It is possible that some owner cum tenants may cultivate cash crops and in relatively fertile land and also invest more for the improvement of that land, the point estimates might wrongly pick that as an impact of share tenancy on productivity. Including the land ratio variable will control for this effect.

Labour employed in rice production. I have data on rural farm households across 64 districts and over four census years. Unfortunately, in Bangladesh district-wise data on agriculture labour employed in rice production is not available. In the absence of such information, I multiply each census year's farm households data by the respective year's average family size (e.g. for 1984=5.75; 1996=5.25; 2005=4.89, and 2008=4.70).

Rice yield per acre. Data on rice yield per acre come from two sources: i) Yearbook of Agricultural Statistics of Bangladesh, and ii) Statistical Yearbook of Bangladesh (Agricultural chapter). While in the empirical section, I use rice yield data across 64 districts and over five periods, Figure 4.5 documents the time series of rice yield per acre in Bangladesh over the last 40 years. This figure suggests that during the period from 1977 to 2008 rice yield per acre grew at an annualized rate of 2.66% per year. In the figure the 1972 and 1984 land reforms are also indicated by two vertical lines.

The overall mean of rice yield was 1306 KG (Table 4.6) and also there were notable variation across regions and over time (Table 4.5). Rice yield varied across different divisions and across years within the same division. Table 4.5 presents a measures of risk, the CV (Coefficient of Variation) of the average rice yield for each divisions for the period from 1977 to 2008. The CV estimates suggest that there were volatility of rice production during the period 1977 to 2008 in Bangladesh, which might be due to exogenous risks like weather, pest etc.

Figure 4.5: Trend of Rice yield per acre, 1971 - 2008



Note. The vertical axis shows the log of rice yield per acre. The time period is from 1971 to 2008. Since the log number is plotted against year, the above Figure in fact shows the growth path of rice yield per acre over time.
Source: Takashi (2011). Compilation of Agricultural Production Data in Areas Currently in India, Pakistan, and Bangladesh from 1901/02 to 2011/02.

Descriptive statistics

Table 4.6 reports the descriptive statistics for each of the variables of the panel data. Here, I decompose the standard deviations into between (across different districts) and within (within the same district) components which are measured in terms of the deviation from each district's average (i.e. $X_{st} - \overline{X_s} + \overline{X}$). To make results comparable, global mean has been added. Thus, the within number refers to the deviation from each district's average, some of these deviations could be negative. For example, minimum number for rice yield is -815, which

Table 4.5: Coefficient of Variation in rice yield by divisions, 1977 - 2008

Year	overall	Barisal	Chittagong	Dhaka	Khulna	Rahshahi	Sylhet
1977	27	60	71	83	92	54	92
1984	46	51	62	82	91	56	76
1996	47	50	86	75	81	52	62
2005	76	82	82	79	75	76	76
2008	41	54	55	62	60	52	50

Note. Data are collected from Yearbook of Agricultural Statistics of Bangladesh, and Statistical Yearbook of Bangladesh (Agricultural chapter).

is not to say that any district had actually negative yield. The within shows the variation of the yields within district around the global mean 1306.

In case of tenancy share, the overall and within are calculated over 275 (N) district-years pairs. The between is calculated over 64 (n) districts, while the average number of years a district was observed in the tenancy data is 4.30 ($\overline{T}$). Tenancy over the period 1977-2008 varied between 11% and 62%. Average tenancy share over the same period for each district varied between 23% and 41%. Tenancy within each district varied between 13% and 59%. Table 4.6 suggests that there are sizeable variations in both between and within districts. If two different districts were randomly drawn from the data the variation of tenancy is on average 3.9% while the variation over time within a same district is 7.13%.

Correlations

To get an efficient point estimator, I need some degree of correlation between the independent variables as well as a sizeable variation in the

Table 4.6: Summary statistics

Variables		**Mean**	**std Dev.**	**Min**	**Max**	**observations**
rice yield	Overall	1306	972	217	8097	$N = 274$
(in kg)	Between		430	369	2588	$n = 64$
	Within		869	-815	6815	$\overline{T}$=4.28
tenants	Overall	32.74	8.11	11	62	$N = 275$
(in %)	Between		3.9	23	41	$n = 64$
	Within		7.13	13	59	$\overline{T} = 4.30$
irrigation	Overall	.37	.18	.03	.81	$N = 240$
(in %)	Between		.12	.15	.61	$n = 64$
	Within		.15	.09	.81	$\overline{T} = 3.75$
HYVs	Overall	.47	.14	..14	.78	$N = 275$
(in %)	Between		.15	.30	.59	$n = 64$
	Within		.19	.11	.79	$\overline{T} = 4.30$
literacy	Overall	.37	.13	.12	.71	$N = 266$
(in %)	Between		.07	0.23	.55	$n = 64$
	Within		.12	.08	.64	$\overline{T} = 4.55$
rainfall	Overall	1811	652	815	3993	$N = 275$
(in mm)	Between		450	1120	3117	$n = 64$
	Within		474	35	3065	$\overline{T} = 4.31$
Land under rice	Overall	.77	.067	.50	.96	$N = 275$
(in %)	Between		.05	.55	.85	$n = 64$
	Within		.05	.51	.95	$\overline{T} = 4.28$
labour	Overall	13.73	.52	11.92	14.95	$N = 256$
(in logs)	Between		.50	12.15	14.85	$n = 64$
	Within		.14	12.98	14.18	$\overline{T} = 4$

Note. Rice yield per acre; % of land under irrigation; % of land under high yielding varieties (HYV); literacy rate; monthly rainfall; labour employed in agriculture.

explanatory variables. While Table 4.6 exhibits that there is considerable variations both within and between each of the variables, here I document the correlations among the variables. I report the pairwise correlation of the variables in Table 4.7. Based on 5% level of significance, the correlation coefficients suggest that all the variables are worth-including separately in the baseline equation. For example, tenants have a positive correlation with yield per care at 5% significant level. Apart from that, other variables like HYVs, rainfall, irrigation,

Table 4.7: Correlation: pairwise

	rice yield	tenancy	rain-fall	HYV-seeds	irrigation	literacy	land rice	labour	soil-quality
rice yield	1.00								
tenancy	.11*	1.00							
rainfall	.25**	.07	1.00						
HYV seeds	.29**	.35**	.14**	1.00					
irrigation	.49**	.10	.14**	.42**	1.00				
literacy	.47**	.07	.39**	.26**	.52**	1.00			
land rice	.02	−.18**	.06	−.14**	-.12	-.04	1.00		
labour	.18**	.22**	.13**	.30**	.07	.09	.23**	1.00	
soil quality	.12	−.21**	−.04**	−.21**	-.02	.17**	.15**	−.15**	1.00

Note. Levels of statistical significance are indicated by asterisks (one or two asterisks show significance at the ten or five percent level, respectively).

literacy and land under rice have expected correlation with rice yield variable and in most cases this correlations are statistically significant. For example, the correlations between rainfall and rice yield, HYV seeds and rice yield, irrigation and rice yield, literacy and rice yield are .11, .25, .29, .49, and .47 respective and they all are significant. The correlation between land used for rice production and rice yield, soil quality (i.e soil fertility) and rice yield are .02 and .12 respectively, but they are not significant at 5% level.

4.5.1 The regression model

The empirical analysis uses a panel-data regression model of the form,

$$Y_{st} = \alpha_s + \beta_t + \psi \text{ tenancy}_{st} + \gamma \mathbf{X}_{st} + \varepsilon_{st},$$

where, the dependent variable Y_{st} is a measure of agricultural productivity in district s at time t, α_s is a district fixed effect, β_t is a year dummy variable, $\mathbf{X}_{st}$ is a vector of control variables. And the 'tenancy'- the variable of interest- is the proportion of farmers who farm under share tenancy. I measure this variable in two ways: (i) the sum of tenants and tenants cum owners households expressed as a percentage of rural farm households (mixed tenancy), or (ii) tenants as a percentage of all rural farm households (only tenancy). Lastly, ε_{st} is a district-specific error term.

I include control variables that are likely to be correlated with level of agricultural productivity at the district level. These controls include irrigation, rainfall, literacy, HYV seeds, coastal dummy, soil quality, land under rice production and labour. The estimate of ψ measures the effect of share tenancy on agricultural land productivity.

My main identifying assumption is that the observed variations in tenancy share is exogenous and does not, in any way, depend on agricultural productivity. Following factors seem to contribute to these variations: i) functioning of the land reform committee to monitor the ceiling of land holding;[6] ii) periodic re-distribution of *khas land*, (government land) to the landless poor. Thus, the observed variation in tenant households is likely to be exogenous to any factor that may affect yield per acre.

Of course there might still be factors not controlled for here and that may affect land productivity. In general unobserved factors might be of

[6] Since independence in 1971, Bangladesh administered two land reforms, and both the reforms in 1972 and 1984 were implemented by a local level committee comprising of local political members and locally posted civil servants. The reforms were not 'one shot' reform, rather they were on going reform and the local committee continuously monitor the ceiling of land ownership. To the extend the committee monitors the land holding with fairness, any person is barred to own land more than the set ceiling. In this way, the local level committee is working against land concentration, at least to some extend. It is unlikely that all committee across the country monitor the ceiling of land ownership with equal fairness. Thus, if any specific committee is corrupted, land reform law will be loosely implemented in the area under their jurisdiction. Thus, the observed variation of tenancy both across districts and over time might be contingent upon the degree of monitoring of the ongoing reform.

two types: a) time invariant, and b) time variant. If those variables are not correlated with any of the regressors, then these will be absorbed in the random error term and the estimated parameters confer causal relation. But if they are correlated with any of the right hand side variables, then the estimated parameters will be biased.

These problems can be overcome if there is a panel data in place. The approach used here has the advantage of controlling for district fixed effects (i.e., unobserved district-heterogeneity that captures all unobserved, time-constant factors that may affect agricultural productivity), and year-fixed effects (i.e., unobserved factors that vary over time but are invariant across districts). In the baseline regression, I allow for different intercept both across district, α_s, and across time, β_t, to account for these time-invariant and district-invariant heterogeneity. I also estimate the same model with division fixed effects and in that case standard errors are clustered around six divisions instead of 64 districts. Therefore, to the extent that fixed district-specific factors (e.g., geographical factors that are fixed for a specific district and do not vary over time) matter for agricultural productivity, I control for them and do not incorrectly attribute their impact on agricultural productivity to share tenancy. Similarly, to the extent that there are time-varying shocks that are common to all the districts and that affect agricultural productivity, by controlling for year-fixed effects, I do not incorrectly attribute their impact on agricultural productivity to share tenancy.

4.5.2 Empirical results

Share tenancy and land productivity. I examine the effect of share tenancy on the rice yield per acre of land. The results are presented in Table 4.8 and Table 4.9: pooled regression model and unobserved effects model respectively. To begin, I estimate a pooled regression model without district and year effects. In the first column of Table 4.8, I report the regression results for tenants plus owner cum tenants farmers and in column 3, I report the result for tenants only. In columns 2 and 4, I also report the standardized beta-coefficient. The standard errors in this estimation are clustered around 64 districts, later I cluster the standard errors at six divisions level and report the result in Figure C.3. Holding all other factors constant, the point estimate shows that if share tenancy increases by one percent then agricultural productivity increase by 0.8% ([exp(.008)-1]) and this estimate is significant at the 5% level. This result does not change significantly when I estimate the regression model using tenants only (see column 3): using tenant farmers only the magnitude of the point estimate is higher with a lower standard error. When I control for year fixed effects, and use the interaction of tenancy with both divisions and year and estimate the same pooled regression model there is still a positive impact of share tenancy on rice yield (see Table C.3 in the appendix). Thus the point estimate suggests that this is an economically significant effect, given the fact that 32% of the farm households are share tenants.

Examining the standardized beta-coefficient, gives a different interpretation of the point estimates. The standardized estimates show that the change in the dependent variable in a standardized unit due

Table 4.8: Tenancy and agricultural productivity: pooled regression results

	Dependent variable: ln(rice yield)			
	Mixed tenants		only tenants	
	coefficients	beta-coefficients	coefficients	beta-coefficients
	(1)	(2)	(3)	(4)
tenancy	0.008**	0.11**	0.02***	0.20***
	(0.003)	(0.004)	(0.005)	(0.006)
irrigation	1.20***	0.34***	1.14***	0.32***
	(0.27)	(0.21)	(0.25)	(0.20)
HYVs	0.54**	0.11*	0.64**	0.13**
	(0.23)	(0.30)	(0.24)	(0.29)
Rainfall	0.24*	0.12**	0.19*	0.09*
	(0.13)	(0.11)	(0.12)	(0.11)
Literacy	0.01**	0.23**	0.01**	0.20**
	(0.003)	(0.003)	(0.003)	(0.003)
Land under rice	0.48	0.06	0.43	0.05
	(0.70)	(0.47)	(0.66)	(0.45)
Labour	0.23**	0.19**	0.21**	0.17**
	(0.08)	(0.07)	(0.08)	(0.06)
High fertility	−0.17	−0.09	−0.20	−0.11*
	(0.15)	(0.12)	(0.14)	(0.11)
Medium fertility	0.24**	0.19**	0.21**	0.16**
	(0.08)	(0.07)	(0.07)	(0.07)
coastal dummy	−0.09	−0.05	−0.08	−0.04
	(0.12)	(0.10)	(0.11)	(0.10)
District & year effect	No	No	No	No
R^2	0.49		0.52	
$Adj\,R^2$		0.46		0.52
Observations	220	220	220	220

Note. Mixed tenants include both tenants and tenants cum owners. Robust standard errors clustered at 64 districts levels are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

to a one-standard deviation change in any of the independent variables. Here, effects of any variables is not measured in terms of the original units, but in standard deviation units and hence by putting all independent variables on equal footing. For example, using tenants and owner cum tenans, Table 4.8 implies that a one standard deviation increase in the share tenancy is associated with a .11 standard deviation increase in log of rice yield.

In the data, both using either tenants plus owner cum tenants or only tenants, in explaining the variation of agricultural productivity in Bangladesh, irrigation appears to be the most important variable followed by literacy. That is, a one standard deviation increase in irrigation increases agriculture productivity by a 0.34 standard deviation and a one standard deviation increase of literacy increases production by a 0.23 standard deviation and these estimates are statistically highly significant. While the main purpose of this study is to identify the impact of share tenancy on agricultural land productivity, Table 4.8 suggests that infrastructure and education has considerable impact on agriculture in Bangladesh.

Baseline results

Share tenancy and yield per acre for unobserved effects

The results reported in Table 4.8 are based on a pooled regression model which assumes that all 64 districts are the same, and does not control for district-specific heterogeneity and time-varying factors that also affect agricultural productivity. To address this concern, I estimate two different unobserved effects models and report the results in Table 4.9. I conducted a Hausman test, and a Breusch-Pegan LM test. In both cases I can not reject the null hypothesis that there is no correlation between unobserved district fixed effects (α_s) and the independent variables (i.e. Cov(α_s, X_{st})=0). Thus, the Hausman test suggests that the random effects model is appropriate while the Breusch-Pegan test indicated that the random effects is better than pooled OLS model. Now if $\mathrm{Cov}(\alpha_s, X_{st})$ =0, then under random effect model unobserved district effects (α_s) will be absorbed in idiosyncratic error, u_{st} and the error will be serially correlated. Thus I estimated the random effects model by GLS.

I report the results obtained from the random effects model in Table 4.9. The results suggest that tenancy has a positive impact on agricultural productivity. In column 2 of Table 4.9 I report the results only for tenant farmers, while column 1 shows the results for tenants plus tenants cum owner farmers. Both show a positive impact of tenancy on productivity e.g. column 1 shows that a one percent increase in share of tenancy leads to 0.6% ([exp(.006)- 1]) increase in rice yield per acre and it is significant at the 10% level.

Thus, the results reported in column 1 and 2 of Table 4.9 strongly and statistically significantly support the hypothesis that share tenancy in Bangladesh does not have a negative effect on agricultural productivity, holding all other factors constant. The results also suggests that in the agricultural productivity equation, factors like irrigation, labour, soil quality etc are statistically significant and practically important.

In the above unobserved effects estimation, I dropped 1977 as I do not have data on 'Labour' for this year. I re-estimate the same panel data regression with full sample; but dropping 'Labour' and report the estimated results in Table C.4 in the appendix. Still, the random effects is the appropriate model to estimate the model. The results are shown in column 2 of Table C.4. Still tenancy has a positive effect on rice

Table 4.9: Tenancy and agricultural productivity: unobserved effects model results

Dependent variable: ln(rice yield)

	Mixed tenants	only tenants
	(1)	(2)
tenancy	0.006*	0.02**
	(0.003)	(0.005)
irrigation	0.95**	0.88**
	(0.29)	0.27)
HYVs	0.20	0.27
	(0.22)	(0.24)
Rainfall	0.13	0.06
	(0.14)	(0.13)
Literacy	0.0005	0.006
	(0.005)	(0.005)
Land under rice	0.40	0.35
	(0.58)	(0.55)
Labour	0.25**	0.24**
	(0.08)	(0.08)
High fertility	−0.02	−0.03
	(0.15)	(0.14)
Medium fertility	0.26**	0.24**
	(0.08)	(0.07)
coastal dummy	−0.12	−0.09
	(0.11)	(0.10)
District effects	Yes	Yes
Year effects	Yes	Yes
R^2 (within)	0.54	0.55
R^2 (Between)	0.46	0.53
R^2 (Overall)	0.51	0.54
ρ	0.12	0.09
Observations	220	220

Note. Levels of statistical significance are indicated by asterisks (one, two or three asterisks show significance at the ten, five or one percent level, respectively). Robust standard errors clustered at the district level are reported in parentheses and as such standard error adjusted for 64 clusters in districts. Here, the ρ-statistic indicates the fraction of variance in dependent variables that is due to district-specific variation, e.g. with random effect model ρ= 0.12 which suggests that 12% of variation comes from individual effect and the remaining 88% is captured by unobserved idiosyncratic error term.

yield per acre; but here it is significant at 5% level. In this estimation with time fixed effect, irrigation, land under rice, and soil quality are significant.

4.5.3 Robustness

In the baseline equation, I estimate an unobserved effect regression with clustered standard errors at both the district-level and the division-level. When I control for both district and year fixed effect, still I get positive impact of share tenancy on agricultural productivity at conventional levels of significance and the result is not at odds with the result from a pooled regression. Thus, armed with these results I can conclude that share tenancy in Bangladesh is not negatively associated with land productivity. To strengthen my claim, I will estimate regression involving interaction terms and I will do this in two steps; first, I interact tenancy and year with districts and report the results in the text below, later, I interact the same variables with divisions id and report the results in Table C.5 in the appendix. I estimate the following three models:

$$Y_{st} = f(\text{tenancy, districts} \times \text{year}, \mathbf{X}) \tag{4.1}$$

$$Y_{st} = f(\text{tenancy, districts} \times \text{tenancy, year}, \mathbf{X}) \tag{4.2}$$

$$Y_{st} = f(\text{tenancy, tenancy} \times \text{irrigation}, \mathbf{X}) \tag{4.3}$$

where, Y_{st} is the rice yield per acre in district s in year t, $\mathbf{X}$ is a vector of control variables. Equation (4.1) shows the effect of tenancy on productivity after controlling for district-specific time effects. Without the interaction terms, the coefficient with tenants would have been interpreted as the unique effect of tenants on rice yield. But in equation (4.1) the interaction means that the effect of tenants on rice yield is different for each district and year pair. In equation (4.2)

Table 4.10: Mixed tenancy and agricultural land productivity: interaction with districts

	Model 1	Model 2	Model 3
Mixed tenants	.004	0.02	0.03**
	(.004)	(0.02)	(0.01)
Districts × year	Yes	No	No
Districts × tenancy	No	Yes	No
tenancy × irrigation	No	No	Yes
Other controls	Yes	Yes	Yes
District effects	Yes	Yes	Yes
Year effects	No	Yes	Yes
R^2 (Robust)	0.72	0.83	0.72
RMSE	0.40	0.41	0.40
observations	220	220	220

Note. Tenancy is the tenants plus tenants cum owner. Robust standard errors are reported in parentheses. RMSE stands for root mean squared errors of the model prediction.

the effect of tenancy is given by the coefficient of tenants plus coefficient of the interaction term tenancy × district. This means that the effect of tenants now depends on the district. So, there is a direct effect from tenants and also an indirect effect from the interaction with districts, its different for each separate district. If some district is more productive than the other and has higher tenancy rate, the interaction term District×tenancy soaks up that productivity impact on tenancy, if any. In Equation (4.3), I interact tenancy with irrigation. The beta-coefficient in Table 4.8 suggests that irrigation is the most important factor to determine agricultural land productivity in Bangladesh. Thus, interacting tenancy with irrigation is likely to take care of any productivity-driven variation in share tenancy. Table 4.10 shows the results of the models with interaction terms for tenants plus tenants cum owners, while Table 4.11 shows results for tenants only. All the coefficients are still found to be positive but with less precision, which means with higher standard errors. However, the point estimates in three models are positive and statistically significant if I interact district, year and irrigation with only tenants. Moreover, if I interact the variables with divisions id, all the point estimates are positive and statistically significant at conventional levels (see Table C.5).

Columns 1 of Table 4.10 shows that a one percent increase of tenancy is associated with 4% increase in yield when I control for the effect of district and year pair, but this is not statistically significant. After controlling for district and tenancy interaction, a one percent increase in tenants leads to 2% increase in yield, yet this is not statistically significant. Column 3 shows that after controlling for tenancy and irrigation interaction, a one percent increase of tenancy is associated with 3% increase of yield and this is significant at the 5% level. Table 4.11 shows that under only tenants, point estimates in all three models are positive and statistically significant. Thus, the findings are consistent with the baseline estimates.

4.6 Conclusion

The principal controversy in the productivity related findings of share tenancy concerns the problem of contract enforceability. While, the researchers inspired by the insight of the modern or monitoring approach indicate to the circumstances which enforce the contract; followers of the insight of the traditional approach are silent in this regard. There is no denying of the fact that enforceability problem is embedded in

Table 4.11: Only tenancy and agricultural land productivity: interaction with districts

	Model 1	Model 2	Model 3
Only tenants	.02*	0.02**	0.02**
	(.01)	(0.01)	(0.008)
Districts × year	Yes	No	No
Districts × tenancy	No	Yes	No
tenancy × irrigation	No	No	Yes
Other controls	Yes	Yes	Yes
District effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
R^2 (Robust)	0.83	0.84	0.72
RMSE	0.40	0.41	0.40
observations	220	220	220

Note. Tenancy is only tenants. Robust standard errors are reported in parentheses. RMSE stands for root mean squared errors of the model prediction.

the share tenancy as the share tenant is not the sole claimant of the residual. Following Adam Smith, all economists until Johnson (1950) have argued that share tenancy is inherently inefficient. Since Johnson (1950), the empirical findings of the impact of share tenancy on agricultural land productivity is far from settled.

In this chapter, I study the impact of the share tenancy contracts on agricultural land productivity in the case of Bangladesh. Two observed facts: i) short term contracts; and ii) limited non-farm options of the tenants, stem from low land-labour ratio (0.84 acre per labour) and high landless labourers (10% of rural households), in Bangladesh give me an opportunity to study the productivity aspect of share tenancy. Using rice yield per acre as an index of agricultural productivity, my empirical results do not find any negative association between share tenancy and agricultural land productivity in Bangladesh. Thus, this chapter's findings refute the idea proposed by traditional approach but complement the argument advanced by the so called modern approach.

One shortcoming of this chapter is that I was not able to identify the separate effects of punishments by landlords of those farmers who shirk and also the competition among landless farmers. One possible way to address this issue is to include district-level controls for unemployment and farm-nonfarm relative wage. Unfortunately, district-level data on unemployment and farm-nonfarm relative wage are not available for Bangladesh. Hence, using micro-level survey data could be an option, which remains as a future study.

A number of questions can be raised on the basis of this study. Why are so many people still employed in agriculture, amid the fact that land productivity is increasing? why is land-labour ratio persistently decreasing against the fact that share of agricultural households is decreasing? These are quiet related and interesting issues and are left to be explored in future study.

Chapter 5

Conclusion

This dissertation studies the process of reallocation of labour from agriculture to non-agricultural sectors in developing countries. Along the long-run development path, all currently industrialized countries have undergone a process of reallocation of resources, mainly significant reallocation of labour from agriculture to non-agricultural sectors. In economic development literature, this process is widely known as structural change. Since Nineteen century, economists have attempted to understand the underlying determinants of this process. Two main forces have been proposed in literature: i) Engel's law effect, as productivity in agriculture increases, agriculture sheds labour due to the low income elasticity of demand for farm goods; and ii) Baumol's effect, higher productivity growth in agriculture relatively to non-agriculture pushes farm workers to produce complementary non-farm goods.

I consider population growth as a determinant of structural change and provide a decomposition of the changes in agricultural employment due to both population and per worker productivity growth. I develop a two-sector general equilibrium model where land is a quasi-fixed factor, and population growth constrains the reallocation of labour from agriculture. Productivity growth in agriculture can alleviate this constraint. The quantitative analysis shows that during the 1970-2010 period, population growth accounted for most of the changes in employment in agriculture in developing countries, while the attenuating contribution of productivity growth was negligible.

While classical models of structural transformation show how productivity growth in agriculture can release labour from agriculture, there is relatively less empirical evidence on the differential effect of land-versus labour-biased technological change in agriculture on the reallocation of labour from agriculture. I provide empirical evidence on the effects of technical change in agriculture on the agricultural labour reallocation by studying the widespread adoption of a common agricultural technology-'Green revolution' by several developing countries in the late 1960s. Green Revolution is a form of land-augmenting technical change which increases labour-intensity and hence, slows down the reallocation of labour out of agriculture. I present a model with land-augmenting technical change. Using cross-national data on the adoption of high yielding varieties technology, I find that the Green Revolution can explain 28 percent of the increase in agricultural employment in the adopting countries over the period from 1965 to 2000.

Finally, as a case study, I provide an empirical study on the the impact of share tenancy on the agricultural land productivity. Using district-level data from rural Bangladesh, this study finds no evidence of negative association between farm output per unit of land and share tenancy. The reason is that while, in Bangladesh share tenancy is highly prevalent, land is scarce, about ten percent of the farm households are landless, contracts are short term, and non-farm jobs are limited.

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Appendix A

Demographics and Structural Change

A.1 Derivation of the agricultural employment equation

Let production functions for agriculture and non-agriculture are:

$$Y_{at} = A_{at} L_{at}^{\alpha} T^{1-\alpha} \quad , \tag{A.1}$$

$$Y_{nt} = A_{nt} L_{nt} \quad , \tag{A.2}$$

The representative family maximizes the following instantaneous utility function:

$$\sum_{t=0}^{\infty} \beta^t (L_t.c) \tag{A.3}$$

subject to $(p_{at}c_{at} + c_{nt}).L_t = Y$

where, $c = \left[\eta_a (c_{at} - \overline{c}_a)^{\frac{\varepsilon-1}{\varepsilon}} + \eta_n (c_{nt} - \overline{c}_n)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}$. The F.O.C. are as following:

$$c_{at} : \frac{\varepsilon}{\varepsilon - 1} [.]^{\frac{1}{\varepsilon-1}} . \frac{\varepsilon - 1}{\varepsilon} . \eta_{at} c_{at}^{\frac{-1}{\varepsilon}} - \lambda P_{at} = 0 \tag{A.4}$$

$$c_{nt} : \frac{\varepsilon}{\varepsilon - 1} [.]^{\frac{1}{\varepsilon-1}} . \frac{\varepsilon - 1}{\varepsilon} . \eta_{nt} c_{nt}^{\frac{-1}{\varepsilon}} - \lambda = 0 \tag{A.5}$$

Where, [.] refers to the bracketed term in the utility function. Divide equation (A.4) by equation (A.5), I get,

$$\frac{\eta_a}{\eta_n} \left(\frac{c_{nt}}{c_{at} - \overline{c_a}} \right)^{\frac{1}{\varepsilon}} = \frac{P_{at}}{1} \tag{A.6}$$

From equation (A.6), I get the optimal consumption of agricultural goods in term of non-agricultural goods:

$$c_{at} = \left(\frac{\eta_a}{\eta_n}\right) P_{at}{}^{-\varepsilon}(c_{nt}) + \overline{c_a} \tag{A.7}$$

Now, I need an expression for P_{at}, which I get from production efficiency conditions: setting value of marginal product of labour in two sectors equal, I get

$$P_{at} = \left(\frac{A_{nt}}{A_{at}}\right)\left(\frac{1}{\alpha(\frac{T}{L_{at}})^{1-\alpha}}\right) \tag{A.8}$$

Since, goods market clearing requires, $L_t.c_{it} = Y_{it}$, I can write equation (A.6) replacing c_{at} by Y_{at}:

$$Y_{at} = L_t\left[\left(\frac{\eta_a}{\eta_n}\right) P_{at}{}^{-\varepsilon}(c_{nt}) + \bar{c}_a\right]. \tag{A.9}$$

Imputing P_{at} from equation (A.8) and divide both side of equation (A.9) by Y_{at}, I get

$$1 = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon}\left(\frac{A_{nt}}{A_{at}}\frac{1}{\alpha\left(\frac{T}{L_{at}}\right)^{1-\alpha}}\right)^{-\varepsilon}\frac{Y_{nt}}{Y_{at}} + \frac{\overline{C}_a}{Y_{at}}. \tag{A.10}$$

I can rewrite the above equation using production functions of both sector as following:

$$1 = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon}\left(\frac{A_{nt}}{A_{at}}\frac{1}{\alpha\left(\frac{T}{L_{at}}\right)^{1-\alpha}}\right)^{-\varepsilon}\frac{A_{nt}L_{nt}}{A_{at}L_{at}^{\alpha}T^{1-\alpha}} + \frac{\bar{c}_a.L_t}{A_{at}L_{at}^{\alpha}T^{1-\alpha}},$$

A simple algebraic manipulation gives:

$$1 = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} \left(\frac{A_{nt}}{A_{at}} \frac{1}{\alpha\left(\frac{T}{L_{at}}\right)^{1-\alpha}}\right)^{-\varepsilon} \frac{A_{nt}L_{nt}}{A_{at}L_{at}^{\alpha}T^{1-\alpha}} \frac{L_{at}}{L_{at}} + \frac{\overline{C_a}}{A_{at}L_{at}^{\alpha}T^{1-\alpha}} \frac{L_{at}}{L_{at}}$$

Now, taking the L_{at} term from numerator to denominator to express in terms of land-labour ratio:

$$1 = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} \left(\frac{A_{nt}}{A_{at}} \frac{1}{\alpha\left(\frac{T}{L_{at}}\right)^{1-\alpha}}\right)^{-\varepsilon} \frac{A_{nt}L_{nt}}{A_{at}\left(\frac{T}{L_{at}}\right)^{1-\alpha}} \frac{1}{L_{at}} + \frac{\overline{C_a}}{A_{at}\left(\frac{T}{L_{at}}\right)^{1-\alpha}} \frac{1}{L_{at}}$$

Further simplification gives:

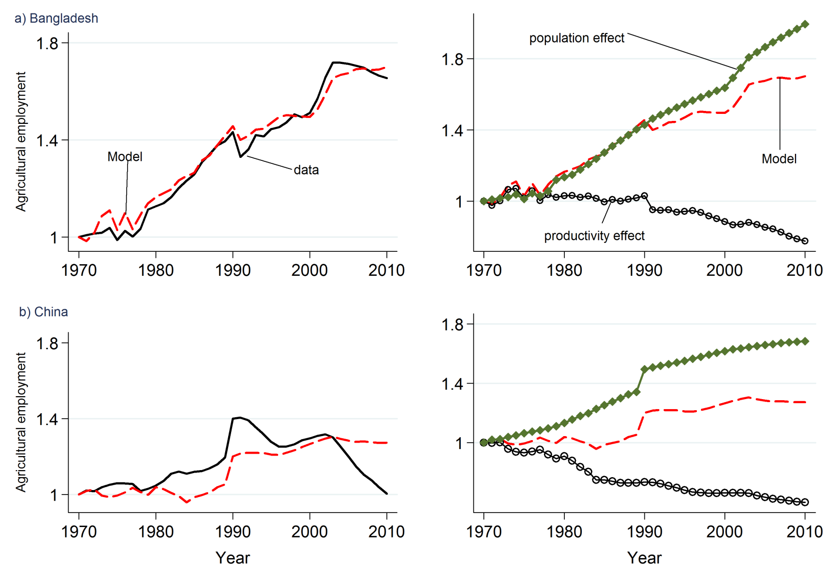
$$1 = \left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} \left(\frac{A_{nt}}{A_{at}} \frac{1}{\alpha\left(\frac{T}{L_{at}}\right)^{1-\alpha}}\right)^{-\varepsilon} \left(\frac{A_{nt}}{A_{at}} \frac{1}{\alpha\left(\frac{T}{L_{at}}\right)^{1-\alpha}}\right) \frac{L_{nt}}{L_{at}} + \frac{\overline{C_a}}{A_{at}\left(\frac{T}{L_{at}}\right)^{1-\alpha}} \frac{1}{L_{at}}. \tag{A.11}$$

Now, multiply both sides of equation (A.11) by L_{at}, I get an expression for agricultural employment, L_{at}:

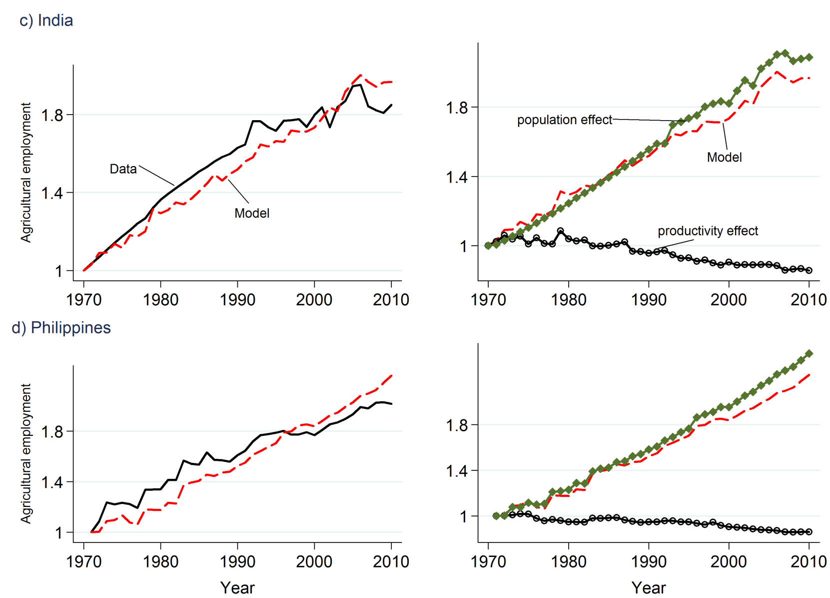
$$L_{at} = \alpha^{\varepsilon} \underbrace{\left[\left(\frac{\eta_a}{\eta_n}\right)^{\varepsilon} \left[\frac{1}{(\frac{T}{L_t - L_{nt}})^{1-\alpha}}\right]^{1-\varepsilon} \left(\frac{A_{nt}}{A_{at}}\right)^{1-\varepsilon} (L_t - L_{at})\right]}_{\text{modified Baumol effect}} + \underbrace{\frac{L_t \overline{c}_a}{A_{at}\left(\frac{T}{L_t - L_{nt}}\right)^{1-\alpha}}}_{\text{modified Engel effect}}. \tag{A.12}$$

Figure B1: Baseline line calibration: Asia

(a) Bangladesh and China



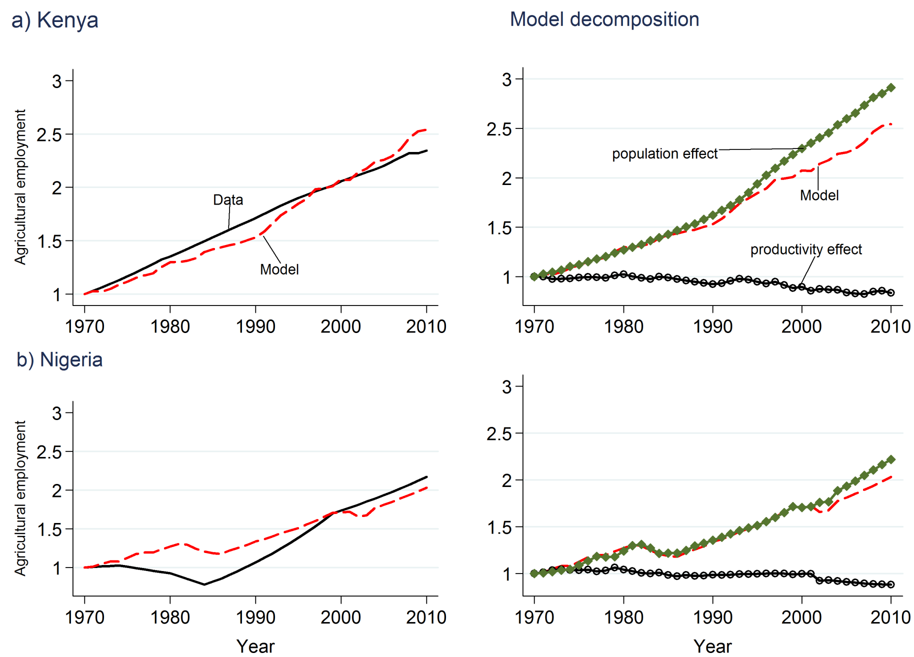
(b) India and Philippines



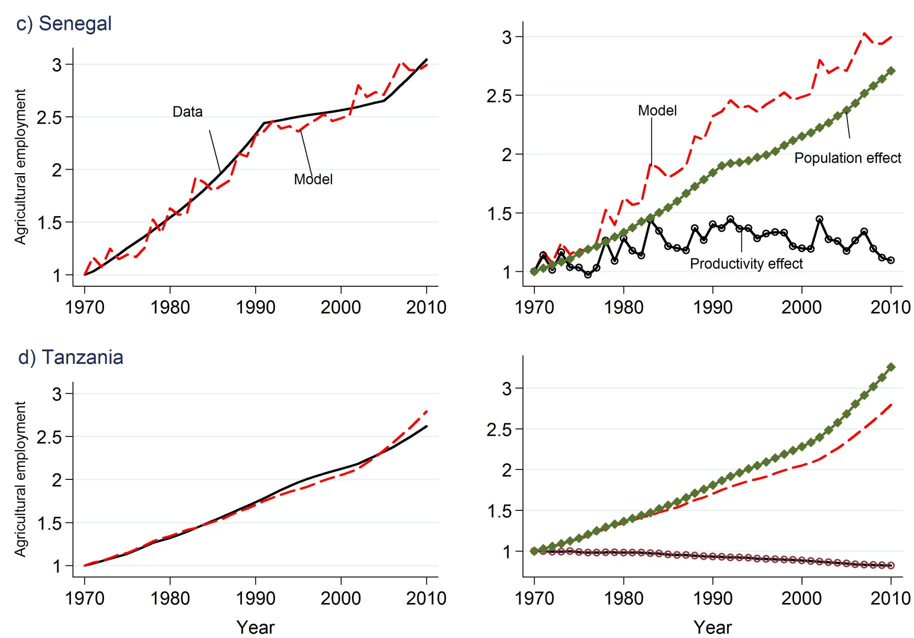
Note: The figures show the baseline calibration results. The solid line denotes data-based and the dashed line shows model-based agricultural employment. The right panel is the decomposition of the model-based agricultural employment in to population effect and productivity effect. All employment data are normalized to initial year i.e. 1970 data.
Source: GGDC 10-Sectors Database and Asian Productivity Organization (APO) database.

Figure B2: Baseline calibration: Africa

(a) Kenya and Nigeria



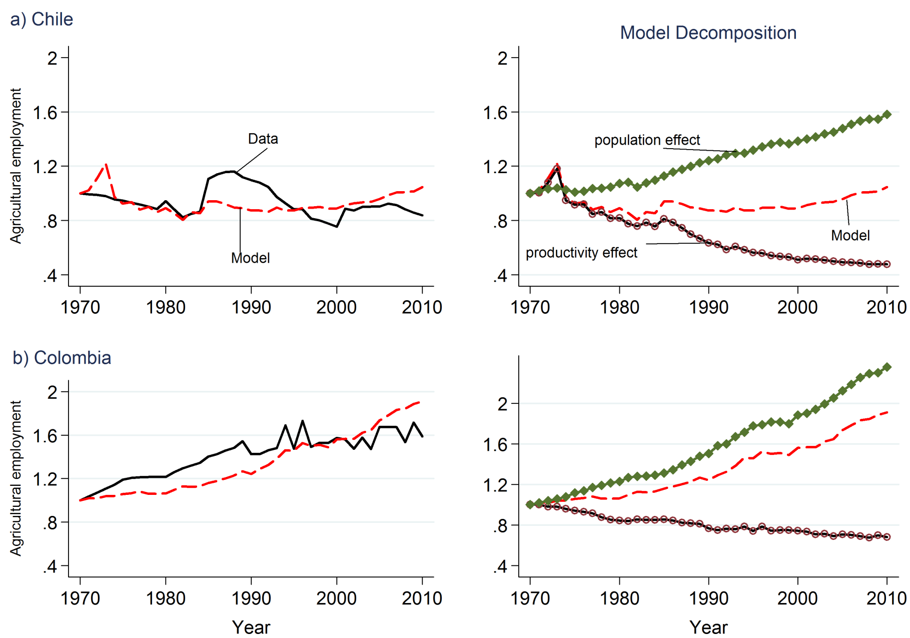
(b) Senegal and Tanzania



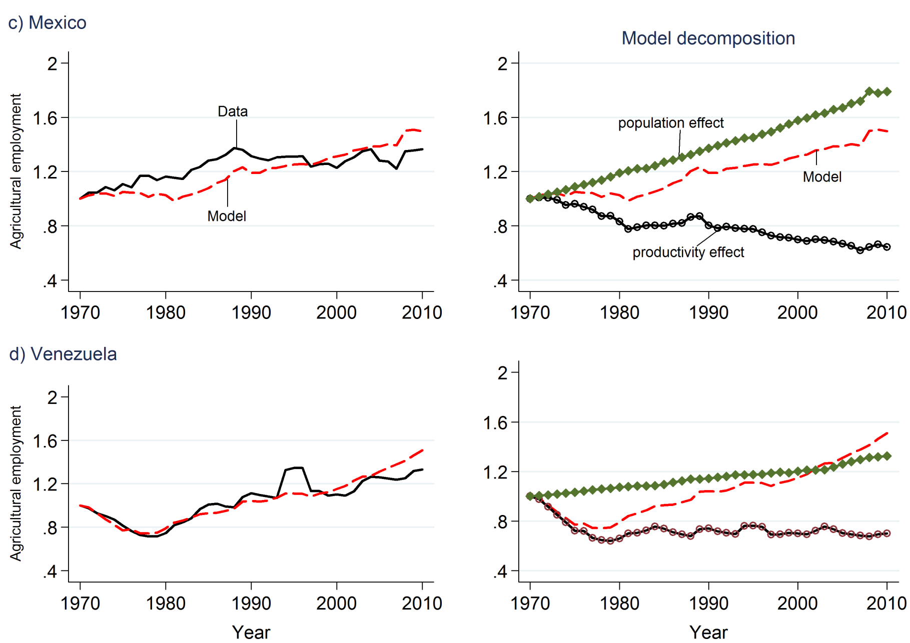
Note: The figures show the baseline calibration results. The solid line denotes data-based and the dashed line shows model-based agricultural employment. The right panel is the decomposition of the model-based agricultural employment in to population effect and productivity effect. All employment data are normalized to initial year i.e. 1970 data.
Source: GGDC 10-Sectors Database.

Figure B3: Baseline line calibration: Latin America

(a) Chile and Colombia



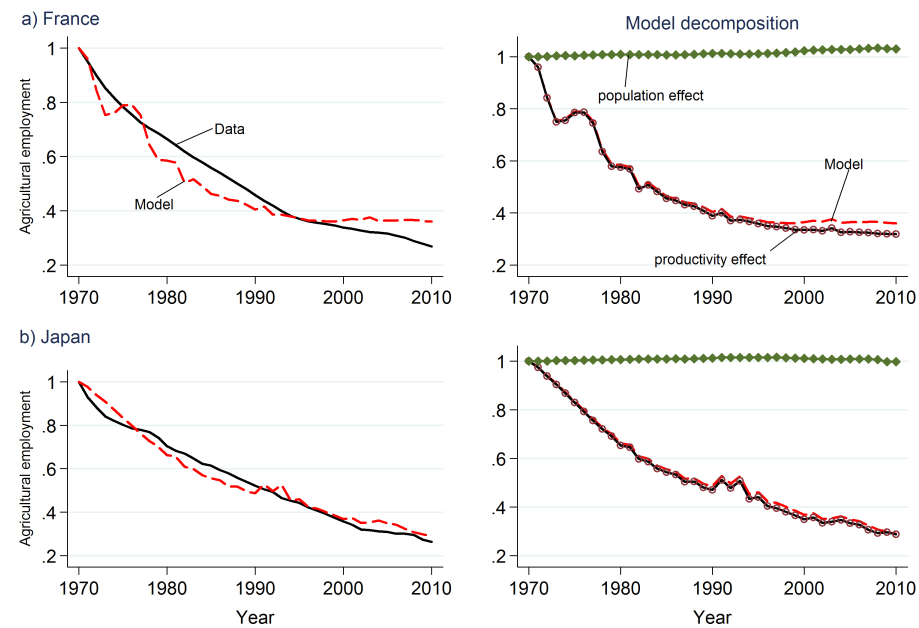
(b) Mexico and Venezuela



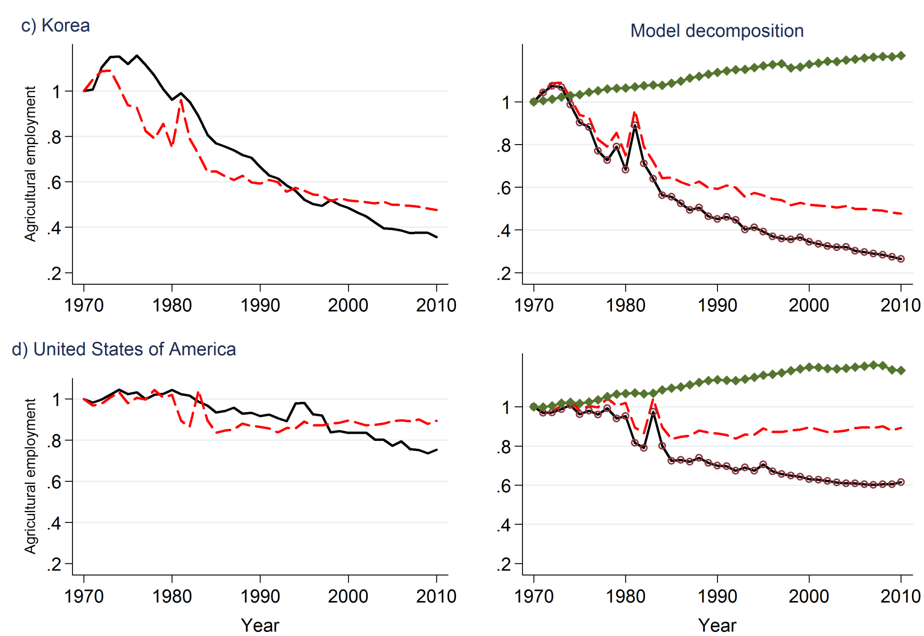
Note: The figures show the baseline calibration results. The solid line denotes data-based and the dashed line shows model-based agricultural employment. The right panel is the decomposition of the model-based agricultural employment in to population effect and productivity effect. All employment data are normalized to initial year i.e. 1970 data.
Source: GGDC 10-Sectors Database.

Figure B4: Baseline calibration: Developed countries

(a) France and Japan

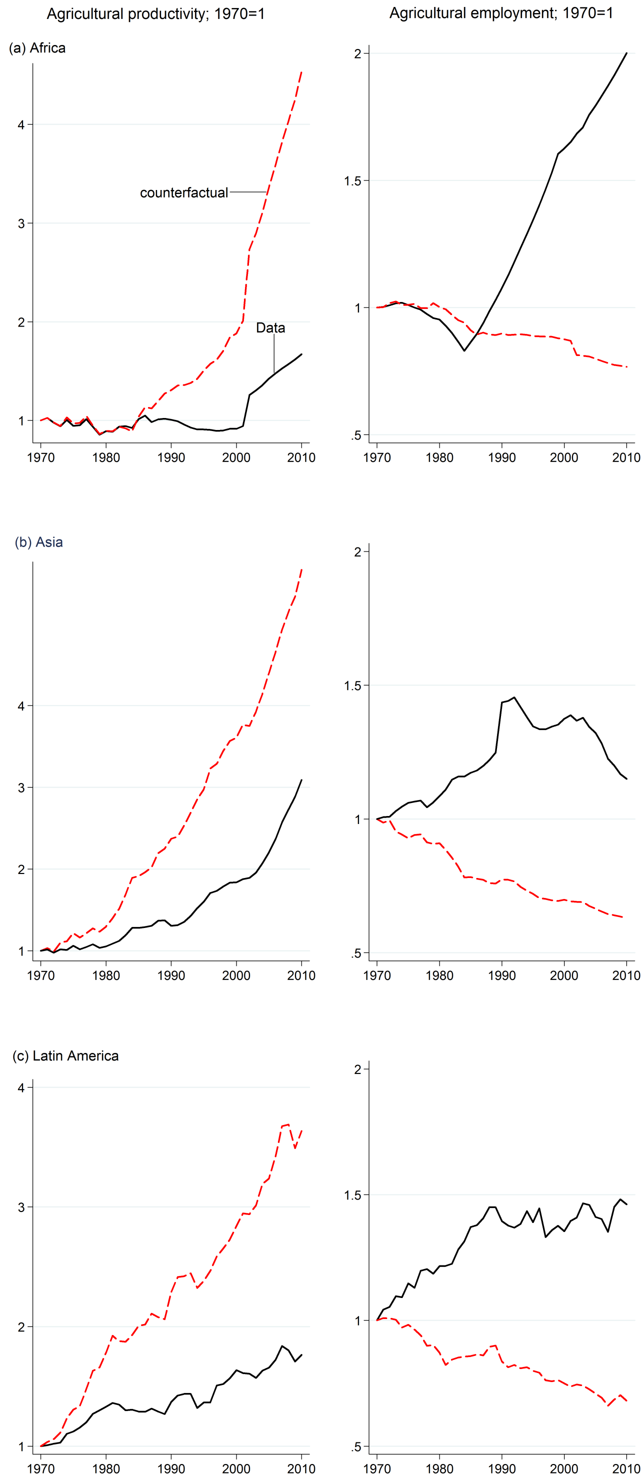


(b) Korea and USA



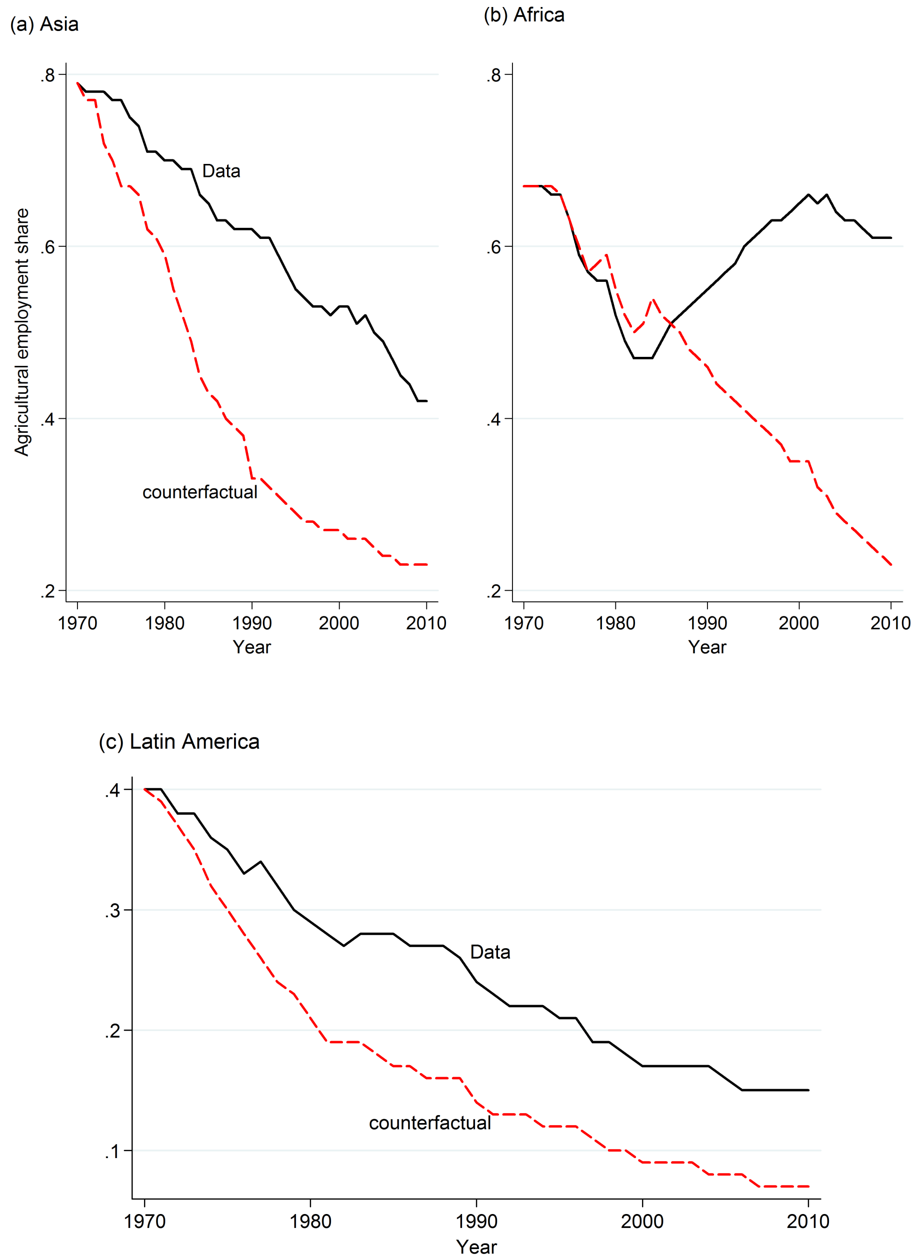
Note: The figures show the baseline calibration results. The solid line denotes data-based and the dashed line shows model-based agricultural employment. The right panel is the decomposition of the model-based agricultural employment in to population effect and productivity effect. All employment data are normalized to initial year i.e. 1970 data.
Source: GGDC 10-Sectors Database.

Figure B5: Region-wise counterfactual results



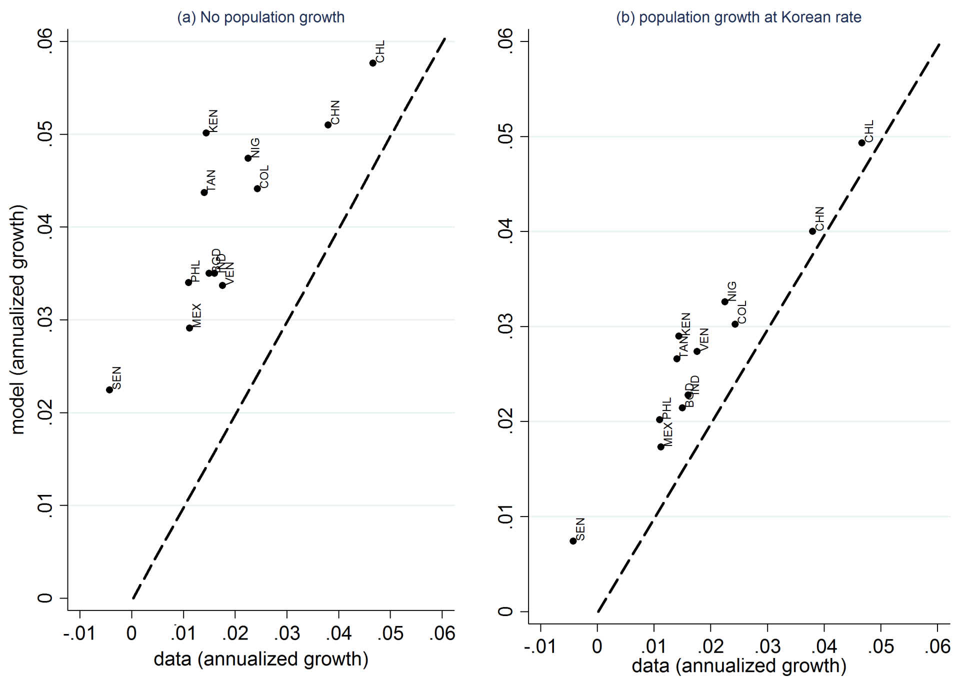
Note: The figures show the region-wise counterfactual results. On the left-panel, agricultural labour productivity is plotted against time, while in right-panel agricultural employment are plotted against year. All data are normalized to initial year i.e. 1970 data.
Source: GGDC 10-Sectors Database and Asian Productivity Organization (APO) database.

Figure B6: Share of agricultural employment; counterfactuals



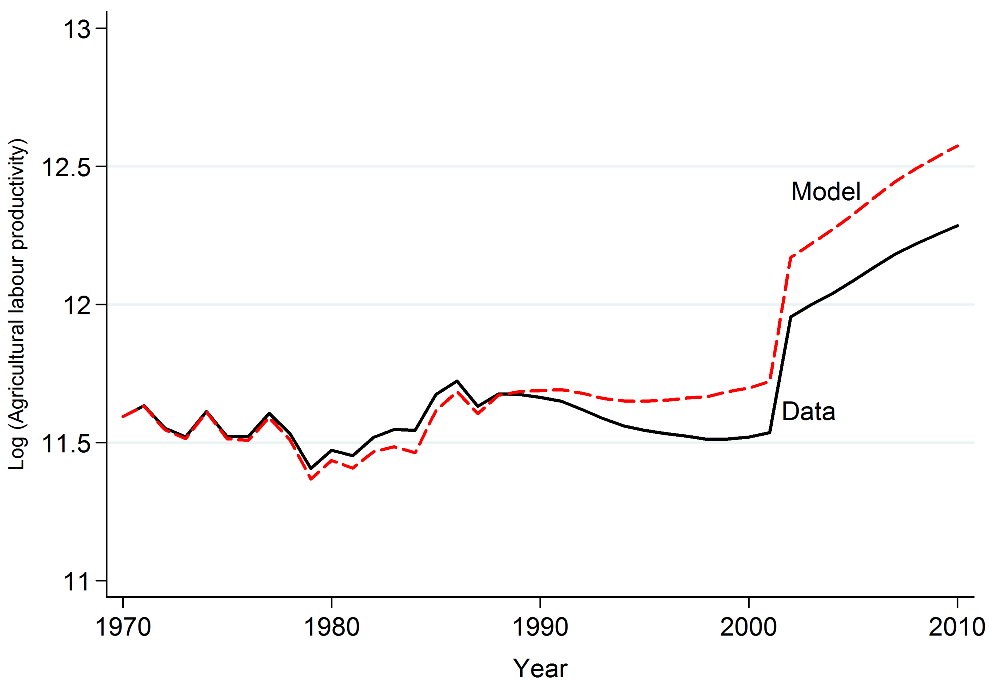
Note: The dashed line is counterfactual and the solid line is the data. Under counterfactual all variables but population are allowed to change.
Source: GGDC 10-Sectors Database.

Figure B7: Agricultural productivity gap in developing countries: counterfactual



Note: Above figure shows the agricultural productivity gap between model generated series and actual data under two counterfactual investigations: i) population is assumed to be constant at initial year i.e. 1970, and ii) population of the selected countries is assumed to grow at the Korean population growth rate (i.e. 1.06%). Panel (a) shows the counterfactual case (i), while panel (b) shows the second case. The Annual average growth rates of the agricultural productivity observed in the data are plotted on the horizontal axis and the vertical axis shows the growth rate of the model generated productivity. The dashed line is a 45^0 line, that indicates the equal growth rates of the model and the data. The population data are from pwt8.0, while other data used in this exercise come from GGDC 10 sectors database.

Figure B8: Agricultural productivity (data and model); Nigeria, 1970 - 2010



Note: Above figure shows the growth rate of agricultural productivity of Nigeria for the period 1970-2010. Since the log numbers are presented against year, the graphs show the growth rate over time. The data used in this exercise come from GGDC 10 sectors database.

Appendix B

Green Revolution and Agricultural Labour Reallocation

B.1 Green Revolution and Agricultural Labour Reallocation

Table B.1: List of countries with major crops

Country	crop
Bangladesh, China, Cuba, India, Indonesia, **Japan, Korea** Malaysia, Myanmar, Nepal, Sri Lanka, Philippines, Thailand, Vietnam	Rice
Botswana, Brazil, Bolivia, Colombia, Costa Rica, Ecuador, Ethiopia, Ghana, Kenya, Malawi, Mexico, Nigeria, Senegal, South Africa, Tanzania Peru, **USA**, Venezuela	Maize
Argentina, Chile,, **Denmark**, Egypt, **France**, **Germany**, **Italy**, Mauritius, Morocco, **Netherlands**, Pakistan, **Spain**, **Sweden**, **Taiwan**, Turkey, **UK**	Wheat

Notes: The above table shows the country-wise adoption of HYV seeds (i.e. proportion of land cultivated using HYV seeds) for selected crops. However, the countries in bold didn't adopt HYV seeds but were included for a comparison. Here, only three major crops, namely rice, wheat and maize are reported.
source: Land use data are from FAO database and the adoption rate data are from Everson-Gollin (2003).

Table B.2: Data sources

Variable	Source	Time period	Accessed date
Employment (agriculture and non-agriculture)	GGDC 10-sectors dataset, FAO, and Asian Productivity Organization (APO) database	1965-2000	GGDC: 18/03/2016 APO: 27/06/2016; FAO 18/05/2016
HYVs area (%)	Douglas Gollin's website	1965-2000	30/03/2016
Potential yields	FAO-GAEZ database	1965-2000	13/06/2016
Actual yields	FAOSTAT	1965-2000	18/05/2016
Arable land	FAOSTAT	1965-2000	18/05/2016
GDP per capita	Maddison Project database	1965-2000	14/12/2015
Population	FAOSTAT	1965-2000	18/05/2016
Country area	FAOSTAT	1965-2000	18/05/2016
literacy rate	Barro R. and J. W. Lee v. 2.1, Feb. 2016	1965-2000	04/07/2016
Annual rainfall	FAO-AQUASTAT	1965	17/06/2016
Births per woman	WDI, The World Bank	1965-2000	26/01/2017

Note: Employment data for Bangladesh is from 1970 and for Vietnam employment data is from 1975.

Table B.3: Decomposition of labour productivity growth; 1965 - 2000: Asia

Countries	Growth of output/worker (in %)	Contribution from (1) Yield (in %)	(2) Land-labour ratio (in %)	(3) Interaction (in %)
Bangladesh	0.58	2.76	-1.05	-1.13
China	1.38	2.47	-0.52	-0.58
India	0.39	3.21	-1.28	-1.54
Indonesia	1.74	3.08	-0.54	-0.80
Malaysia	1.29	0.95	0.24	0.10
Myanmar	1.04	2.46	-0.70	-0.56
Nepal	0.61	0.92	-0.23	-0.56
Pakistan	1.25	4.29	-1.05	-1.98
Philippines	0.83	3.31	-1.06	-1.42
Sri Lanka	1.79	1.94	-0.07	-0.07
Turkey	-1.41	3.91	-2.56	-2.76
Thailand	0.98	1.12	-0.09	-0.04
Vietnam	2.14	2.27	-0.06	-0.07

Notes: The data come from FAOSTAT. In the above table agricultural labour productivity growth over 35 years is decomposed into yield per hectare growth and land-labour ratio growth.

Table B.4: Decomposition of labour productivity growth; 1965 - 2000: Latin America

Countries	Growth of output/worker (in %)	Contribution from (1) Yield (in %)	(2) Land-labour ratio (in %)	(3) Interaction (in %)
Argentina	3.67	1.25	1.28	1.14
Brazil	3.71	1.38	1.17	1.16
Chile	1.28	3.36	-0.84	-1.24
Colombia	0.02	3.14	-1.49	-1.64
Costa Rica	-1.54	0.78	-1.91	-0.40
Cuba	1.73	1.89	-0.08	-0.08
Ecuador	-4.59	-3.42	-2.89	1.72
Mexico	1.97	2.24	-0.13	-0.14
Dominican Republic	2.40	2.19	0.09	0.11
Peru	0.94	1.16	-0.15	-0.07
Venezuela	2.62	3.67	-0.34	-0.71

Notes: The data come from FAOSTAT. In the above table agricultural labour productivity growth over 35 years is decomposed into yield per hectare growth and land-labour ratio growth.

Table B.5: Decomposition of labour productivity growth; 1965 - 2000: Sub Saharan-Africa

Countries	Growth of output/worker (in %)	Contribution from (1) Yield (in %)	(2) Land-labour ratio (in %)	(3) Interaction (in %)
Egypt	1.47	3.06	-0.66	-0.93
Ethiopia	-1.74	2.35	-2.53	-1.56
Ghana	0.51	0.54	-0.03	-0.01
Kenya	-0.31	1.04	-1.01	-0.35
Malawi	1.23	3.30	-0.85	-1.22
Morocco	-2.68	-2.20	-0.96	0.48
Nigeria	0.08	1.62	-0.98	-0.56
Senegal	-1.60	1.79	-2.29	-1.10
Tanzania	-3.74	-2.77	-2.12	1.15

Notes: The data come from FAOSTAT. In the above table agricultural labour productivity growth over 35 years is decomposed into yield per hectare growth and land-labour ratio growth.

Table B.6: Decomposition of labour productivity growth; 1965 - 2000: Non-adopting countries

Countries	Growth of output/worker (in %)	Contribution from (1) Yield (in %)	(2) Land-labour ratio (in %)	(3) Interaction (in %)
Bolivia	3.52	0.93	1.57	1.01
Denmark	4.69	0.76	2.34	1.59
France	5.92	1.01	2.26	2.66
Germany	5.15	1.28	1.72	2.15
Italy	4.24	0.51	2.64	1.08
Japan	3.63	0.50	2.31	0.82
Korea	2.89	1.15	1.03	0.71
Mauritius	5.64	4.02	0.30	1.38
Netherlands	2.75	1.50	0.67	0.59
South Africa	3.69	2.31	0.52	0.86
Spain	5.56	1.67	1.39	2.50
Sweden	4.11	0.73	2.15	1.23
Taiwan	2.82	0.77	1.41	0.65
UK	3.26	1.48	0.90	0.88
USA	2.73	1.45	0.69	0.59

Notes: The data come from FAOSTAT. In the above table agricultural labour productivity growth over 35 years is decomposed into yield per hectare growth and land-labour ratio growth.

Table B.7: IV estimates: (ΔPotential Yield as instrument)

Variables	Second Stage			
	Δ Log agricultural employment	Δ Log of labor productivity	Δ Log Yield	Δ Log land-labor ratio
Δ HYVs seeds	0.08	-2.88	-4.65	2.18
	1.23	4.88	(5.46)	1.87
Other controls	Yes	Yes	Yes	Yes
R-squered	0.79	0.18	-1.17	0.47
Kleibergen and Paap (2006) test of underidentification				
$p - value$	0.165			0.165
	First Stage Dependent variable: Δ HYVs			
Δ Potential Yield		-0.26		
		0.22		
Other controls	Yes	Yes	Yes	Yes
F-test of Excluded Instruments		1.47		
R-squered		0.67		
Observations		48	48	48

Notes: Robust standard errors are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

Total change in agricultural employment: calculation procedure

I obtain the number in the following ways (for OLS estimate):

- Multiply the average change in HYVs area share between the years 1965 and 2000 by the estimated coefficient reported in column 1 of Table 3.5: $0.52 \times 0.36 = 0.1872$.
- Multiply the above number, 0.1872 by the 1965's average level of

agricultural employment (of 33 countries): $0.1872 \times 16,300,000 = 3,05,1360$. This will provide the average increase in agricultural employment due to GR in adopting countries.

- Multiply the above number by the number of adopting countries to obtain the aggregate increase in agricultural employment i.e. $3,05,1360 \times 33 = 100694880$
- In the data aggregate increase in agricultural employment in adopting countries is 356,400,000. Therefore, the model suggested aggregate increase of agricultural employment is 28% of the data.

Appendix C

Share Tenancy and Agricultural Productivity

C.1 Share Tenancy

Table C.1: List of districts, pre-1984 and post-1984

Division	**Pre-1984** (name of districts)	**Post-1984** (name of districts)
Barisal	Barisal, Patuakhali	Barisal, Barguna, Bhola Jhalokhati, Pirojpur, Patuakhali
Chittagong	Chittagong, Noakhali Sylhet, Comilla	Banderban, Chittagong, Cox's Bazar Khagrachari, Rangamati, Noakhali Feni, Lashmipur, Comilla, Brahanbaria Chandpur
Dhaka	Dhaka, Faridpur, Jamalpur Mymensing, Tangail	Dhaka, Gazipur, Kishorgonj, Manikgonj Munshigonj, Narayangonj, Narshindi Faridpur, Gopalgonj, Madaripur, Rajbari Shariatpur, Mymensing, Netrokona, Sherpur Jamalpur, Tangail
Khulna	Khulna, Jessore, Kustia	Khulna, Bagerhat, Satkhira, Jessore Narial, Jhenaidah, Kustia, Chuadanga Magura, Meherpur
Rajshahi	Rajshahi, Dinajpur, Bogra Pabna, Rangpur	Rajshahi, Nawabgonj, Natore, Noagaon Dinajpur, Lalmonihut, Panchgram, Thakurgaon Bogra, Jaipurhat, Gaibandah, Pabna, Sirajgonj Rangpur, Kurigram
Sylhet		Sylhet, Habigonj, Moulavibazar, Sunamgonj
Total	19 districts	64 districts

Note. At present, in Bangladesh there are 64 districts under six divisions. Before 1984, there were 19 districts. Later on, these 19 districts were split in to 64 e.g. after 1984 Faridpur (one of the districts before 1984) was split in to Faridpur, Madaripur, Gopalgonj and Shariatpur etc.

Table C.2: History of land reforms

Period	Year and Title	Descriptions	Land tenure	Outcomes
Colonial 1757-1947	Permanent Settlement Act, 1793	Landlord's revenue commitment to the government to be fixed	No right of tillers on land	Under utilization of land
Pakistan 1947-1971	East Bengal State Acquisition and Tenancy Act, 1950	Abolished landlord System,land should pass to tillers	1950: ceiling 33.3 acres 1961: ceiling 124.8 acres	total land redistributed
Bangladesh 1971- to present	1. State Acquisition and Tenancy Act (Revised) ,1972	Tax exemption for holding less than 8.33 acres	Set ceiling at 33.3 acres	$<1\%$ land redistributed
	2. Land Reform Ordinance, 1984	Sharecropping brought under contract	Set ceiling at 21 acres but existing large farms were exempt	$<1\%$ land redistributed

Source: Compiled from various Government of Pakistan and Government of Bangladesh sources.

Table C.3: Tenancy and agricultural productivity: pooled regression

	Mixed tenants		only tenants	
	ln(rice yield)	ln(rice yield)	ln(rice yield)	ln(rice yield)
	(1)	(2)	(3)	(4)
tenancy	.02***	.02**	.01*	.03**
	(.004)	(.007)	(.006)	(.015)
tenancy × division	Yes	No	Yes	No
tenancy ×year	No	Yes	No	Yes
irrigation	0.89***	0.95***	0.76**	0.83**
	(0.18)	(0.20)	(0.20)	(0.22)
HYVs	0.04	−0.005	0.14	0.17
	(0.31)	(0.31)	(0.29)	(0.28)
Rainfall	0.24	0.15	0.14	0.10
	(0.28)	(0.23)	(0.23)	(0.19)
Literacy	0.004	0.005	0.001	0.002
	(.005)	(.006)	(.005)	(.005)
Land under rice	0.029	0.05	−0.16	−0.06
	(0.54)	(0.51)	(0.49)	(0.41)
Labour	0.25**	0.24**	0.23**	0.24**
	(0.12)	(0.11)	(0.12)	(0.12)
High fertility	0.18*	0.16	0.13	0.12
	(0.12)	(0.14)	(0.13)	(0.13)
Medium fertility	0.28**	0.29**	0.22**	0.23**
	(0.08)	(0.08)	(0.05)	(0.07)
coastal dummy	−0.007	0.03	0.02	0.04
	(0.10)	(0.08)	(0.09)	(0.08)
Division effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
R^2	0.58	0.58	0.61	0.59
Observations	220	220	220	220

Note. Robust standard errors clustered at six division level are reported in parentheses. Significance levels $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

Table C.4: Tenancy and agricultural productivity: within and between effects

	Fixed effect(within) (1)	Random effect (2)
tenants	.005	.008*
	(1.22)	(2.02)
irrigation	.004*	.92***
	(1.65)	(3.59)
HYV	-.33	.05
	(-1.35)	(.28)
rainfall	.04	.11
	(.52)	(0.75)
literacy	.004	-.003
	(.45)	(-.71)
Coastal dummy	omitted	-.13
		(-1.17)
land_rice	-.30	.94
	(-.64)	(1.29)
soil_quality	omitted	.17**
		(2.35)
district effect	Yes	Yes
Year effects	Yes	Yes
R-squared (within)	.62	.59
R-squared (Between)	.05	.30
R-squared (overall)	.43	.49
Rho	.43	.11
Observations	234	234

Note. Levels of statistical significance are indicated by asterisks (one, two or three asterisks show significance at the ten, five or one percent level, respectively). T-statistics from clustered standard errors at the district level are reported in parentheses. Here, the Rho-statistic indicates the fraction of variance in dependent variables that is due to district-specific variation, e.g. with fixed effect model Rho= .43 which suggests that 43% of variation comes from individual effect and the remaining 57% is captured by unobserved idiosyncratic error term.

Table C.5: Tenancy and agricultural productivity: interaction with divisions

	Model 1	Model 2	Model 3
tenancy	.008*	0.02**	0.03**
	(.005)	(.006)	(.009)
Divisions × year	Yes	No	No
Divisions × tenancy	No	Yes	No
tenancy × irrigation	No	No	Yes
Other controls	Yes	Yes	Yes
Division effects	Yes	Yes	Yes
Year effects	No	Yes	Yes
R^2 (Robust)	0.56	0.58	0.59
RMSE	0.43	0.42	0.42
observations	220	220	220

Note. Robust standard errors are reported in parentheses. RMSE stands for root mean squared errors of the model prediction.

Table C.6: Tenancy share and rice yield across six divisions

Division	Mean		St Dev.		Min		Max	
	tenancy	prodkg	tenancy	prodkg	tenancy	prodkg	tenancy	prodkg
Khulna	32	1683	6.93	1356	15	380	50	8097
Sylhet	30	1471	4.02	1147	22	661	37	5031
Barisal	30	875	8.65	536	14	220	62	1979
Chittagong	34	1090	8.21	723	21	217	53	3017
Dhaka	31	1430	7.53	1121	16	337	61	5779
Rajshahi	36	1213	8.89	593	11	375	55	3346