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Beyond Dualism: Agricultural Productivity, Small Towns, and Structural Change in Bangladesh

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ABSTRACT

This paper uses a framework that goes beyond rural-urban dualism and highlights the role of small town economy (STE) in understanding structural change in a rural economy such as Bangladesh. It provides a theoretical and empirical analysis of the role of agricultural productivity in structural transformation in the labor market, with a focus on the differences between a village economy and a small town economy. The empirical work is based on a general equilibrium model that formalizes the demand and labor market linkages: the STE draws labor away from the rural areas to produce goods and services whose demand may depend largely on rural income. The theory clarifies the role played by the income elasticity of demand and the elasticity of wage with respect to productivity increase in agriculture. For productivity growth to lead to a demand effect, the elasticity of wage has to be lower than a threshold. When the demand for goods and services produced in small towns comes mainly from the adjacent rural areas, the demand effect can more than offset the negative wage effect, and lead to higher labor allocation to the production of town good. Using rainfall as an instrument for agricultural productivity, the empirical analysis finds a significant positive effect of agricultural productivity shock on rice yield and agricultural wages. The evidence shows that productivity shock increases wages more in the rural sample when compared to the STE sample. But structural change in employment is more pronounced in the STE sample. In the rural sample, it increases employment only in small scale manufacturing and services. In contrast, a positive productivity shock has large and positive impacts on employment in construction and transport, education, health and other services, and manufacturing employment in larger scale enterprises located in small towns and cities. Agricultural productivity growth is found to induce structural transformation within the services sector in small towns, with employment in skilled services growing at a faster pace than that of low skilled services.

Key Words: Agricultural Productivity, Small Town Economy, Dualism, Employment in Large Firms, Employment Growth, Structural Transformation
JEL Codes: O13, O14, O17, O18

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1. Introduction

A substantial literature in development economics focuses on structural change where economic development is characterized by labor reallocation from a contracting agricultural sector to the expanding manufacturing and services sectors. In much of the literature, agriculture is equated with the rural economy, and manufacturing and services with urbanization. Although such dualistic perspectives have been at the center of a large body of literature starting from Lewis (1954), and Kuznets(1973), the more recent work emphasizes the need for a broader framework, beyond the binary conceptualization of dualistic models, to capture the richness of structural change in a developing economy. In the context of rural-urban dualism, a growing literature underscores the fact that the "rural" and "urban" are two polar cases in a broader spectrum, and many geographic and administrative units are better characterized as partially urbanized. A simple yet useful framework that goes beyond the canonical rural-urban dualism is where the focus is on areas that contain a small town surrounded by significant rural population and agricultural activities. Contrary to popular impression of most urban people being crammed into mega-cities, recent evidence shows that a large share of urban population and rural-migrants live in the smaller cities and towns (Ferre, Ferreira and Lanjouw (2010);Christiaensen, De Weerdt and Kanbur (2015)). In the spatial spectrum from metropolitan cities to villages, the small towns occupy a space in the middle in terms of population and employment density. As suppliers of goods and services and destinations of rural workers, the small towns have ties with both metropolitan cities and rural areas- the ties being perhaps closer with the rural areas (Haggblade, Hazell and Reardon (2006)). This paper aims to analyze structural change in employment in a 'small town economy' with a focus on the role played by higher agricultural productivity in the surrounding villages.

The focus on agricultural productivity change as a driver of employment specialization and structural change is primarily motivated by a longstanding debate about the role of agricultural productivity in industrialization and structural change. The earliest view in development literature identified a trade-off between poverty reduction through agricultural development and long-run structural change, because higher agricultural productivity is likely to increase the wages faced by the nonfarm sectors (Lewis (1954), Foster and Rosenzweig (2004)). The competing view emphasizes the Engel curve effect in consumer demand reflecting inelastic demand for food, and higher income elasticity of manufacturing goods and services. Since much of the rural population are engaged in agricultural activities, a rise in agricultural productivity can increase rural income and thus have a positive demand effect on non-farm activities, including those located in small towns (Mellor (1976), Ranis and Stewart (1973), Haggblade, Hazell and Reardon (2006)). Recent empirical studies suggest a bigger role of labor market linkages. Foster and Rosenzweig (2004) find a negative relationship between manufacturing employment and agricultural productivity growth providing support to the contention that there is a trade-off between agricultural growth and manufacturing growth. Bustos, Caprettini, Ponticelli (2016) on the other hand find that labor saving technical change in soybean production in Brazil led to industrial growth. In this paper, we provide causal evidence on the impacts of agricultural productivity shock on employment growth and specialization in a more general context where both labor market and demand linkages interact with each other, and may lead to contrasting outcomes across different areas within the same country.

We develop a simple model of a small-town economy that formalizes the dual roles that a town plays in such an economy: it draws labor away from the rural areas to produce goods and services whose demand may depend largely on rural income. There are three types of goods produced in this economy: food and informal good (low quality manufacturing and services) are produced in the villages, and a formal good (high quality manufacturing or services) is produced in the small town.[2] A positive productivity shock to agriculture, however, does not necessarily increase village income; given a labor endowment, the village income increases only when the response of wage (i.e, elasticity of wage with respect to productivity shock) is lower than a threshold.[3] When the elasticity of demand for the town good in the village is low so that most of the town good is sold outside the local economy, the labor market linkage predominates and a higher rural wage due to agricultural productivity increase reduces employment in small towns. In contrast, when demand for goods and services produced in small towns comes mainly from the adjacent rural areas, the demand effect can more than offset the negative wage effect, and lead to higher labor allocation to the production of town good.

We test the predictions of the model using panel data compiled from the population and enterprise censuses from Bangladesh. Our data set covers the period between 2000 and 2010. Between 2000 and 2010, Bangladesh experienced substantial reduction in the incidence of poverty, from 48.9 percent to 31.5 percent. This decade also witnessed substantial expansion in non-farm employment as a result of which its share in total employment increased from 47 percent to 52 percent. The rice yield, which is taken as a measure of agricultural productivity, has grown at an annual rate of 3.6 percent.[4]

To understand the implications of agricultural productivity, we exploit variations in rainfall across upazilas and over time, and implement an approach that focuses on the effects of rainfall shocks in reduced form regressions on the outcome variables (employment in different types of non-farm activities) and also on the measure of agricultural productivity (crop yield). Our approach relies on the fact that rainfall variations can be interpreted as shifts in the production function, because rainfall is a major determinant of crop

[2]The assumption that the town produces only one good is for the sake of simplicity. In the empirical analysis, we consider disaggregation of the town good, some of which are of relatively lower quality with lower income elasticity.

[3]In a more general model with a positive labor supply curve at the household level, a positive shock to agriculture is expected to increase village income in general.

[4]Rice is the predominant crop in Bangladesh.

yield in Bangladesh (Sarkar et. al. (2012)). We also provide an instrumental variables interpretation of our estimates, using rainfall deviations (from long term average) across upazilas and over time as an instrument for crop yield (rice yield). Empirical estimation issues and strategies to deal with them are discussed in detail in Section 3. It is worth noting here that while rainfall shocks have been used for identification in a variety of contexts, agricultural productivity is arguably one of the most natural contexts where rainfall can provide reasonable identifying variations ((Foster and Rosenzweig (2004), Adhvaryu, Chari and Sharma (2013), Bruckner and Ciccone (2011)).

The empirical results establish positive and statistically significant effects of rainfall on rice yield and agricultural wages. The positive effect of rainfall shock on agricultural productivity (as measured by rice yield) is similar across village and small town samples but its effect on wage is larger in the village sample compared with the small town sample. A positive rainfall shock increases employment in the production of informal village good (small scale manufacturing and services) but has no statistically significant effect on the labor allocated to large scale manufacturing employment in the rural sample. A positive productivity shock has large and positive impacts on employment in construction and transport, education, health and other services, and manufacturing employment in larger scale enterprises located in STEs. When interpreted as instrumental variables estimates of the effects of productivity increase, the empirical results suggest that agricultural productivity induces structural transformation within the services sector with employment in skilled services provided by larger firms growing at a much faster pace compared with services provided by smaller firms/individuals.

Our analysis brings to focus a methodological point about the sample used in the empirical analysis. Most of the existing analysis of the effects of agricultural productivity relies on a sample of villages where all of the households are classified as rural. In addition to the "village sample", we also use a small towns sample where a significant proportion of households are urban. The evidence shows that the conclusions about the effects of agricultural productivity on structural change depends on the choice of the sample.

The rest of the paper is organized as follows. Section 2 provides a simple general equilibrium model to highlight the different channels of interactions between farm and non-farm sectors located in rural areas and towns. Section 3 describes the econometric strategy followed by a description of data used in empirical analysis in section 4. Section 5 organized in different sub-sections presents the main empirical results. Section 6 concludes the paper.

2. The Model

We develop a simple general equilibrium model of a small town economy (STE, for short) composed of both rural and urban households. The model is intended to capture the local economy at the upazila level as our empirical analysis is based on a upazila level panel data set. The representative rural household lives in a village, is endowed with A amount of agricultural land, and is engaged in the production of food (f) and a composite village good (S) (low quality manufacturing or services produced by small family enterprises). The representative urban household lives in the small town located in the same upazila adjacent to the village, and is engaged in the production of a composite town good denoted as $T-$ good, using capital and labor. The town has no agricultural land and can borrow at interest factor r for capital investment. The $T-$good represents relatively high quality manufacturing and services produced by large scale formal enterprises. To incorporate the fact that the small town is also connected to the large city, we assume that part of the demand for T-good comes from the metropolitan city. To model this link in the simplest form, the income in the metropolitan city Y^o is determined outside the model and the representative agent spends a constant share φ of her income on the$T-$good. Thus the only mechanism through which the metropolitan demand for $T-$good can be affected by agricultural productivity growth is changes in the price of $T-$good. There are $\bar{L}$ households in the small-town economy, each household supplying 1 unit of labor inelastically, implying that the total labor endowment in the small town economy is $\bar{L}$. Labor is assumed to be freely mobile between the village and the town at zero migration costs.[5] In this model, a more rural upazila can be understood as a small town economy with a large endowment of agricultural land, given the labor endowment.

We assume food to be internationally traded and take it as the numeraire commodity, setting $P_f = 1$. The utility functions for households in the village and small town are:

$$U^v = U^v(C_f, C_s, C_T); \quad U^T = U^T(C_f, C_T)$$

where superscript v refers to village households and T to town households, and C_f is consumption of food, C_s is consumption of composite village good produced and consumed within the village, C_T is the consumption of the town good. An important feature of this formulation is that it allows the village households to consume high quality goods and skilled services produced by formal firms in the town, but the low quality village good S is not consumed in the town. To provide an example, a health service available within the village (C_s) could be a traditional healer whereas skilled service in the town could be a doctor trained in formal medical college. To model the Engel curve effect in a simple way, we assume that there is a subsistence requirement for food in the village and the utility function is of Stone-Geary form in food:

$$U^v = \upsilon_f \ln\left(C_f^v - \gamma_f\right) + \upsilon_s ln\left(C_s^v\right) + \upsilon_T ln\left(C_T^v\right), \sum \upsilon_i = 1, \text{and } i = f, s, T \tag{1}$$

[5]The zero migration costs assumption is not necessary for the results that follow. However, this is a good approximation in our context, because we are considering short-distance migration to the small town within a given upazilla.

where $\gamma_f > 0$ is the subsistence or minimum level of consumption of food. For simplicity, utility function in town is assumed to take the log linear form (log linearized Cobb-Douglas) with τ_k as the share of good/service i in town consumption ($\sum_k \tau_k = 1; k = f, T$):

$$U^T = \tau_f ln\left(C_f^T\right) + \tau_T ln\left(C_T^T\right) \tag{2}$$

We assume that $\upsilon_f < Min\left(\upsilon_s, \upsilon_T\right)$ and $\tau_f < \tau_T$. This captures the idea that as income increases, consumers spend a larger share of the additional income on non-food items. We remain agnostic about the relative magnitudes of υ_s and υ_T, because they might differ across areas depending on the level of household income. For example, in a more urbanized (and high income) upazila, we would expect that the share of non-subsistence budget devoted to the better quality $T-$good is the largest. The budget constraint for the households can be stated as:

$$Y^v = C_f + P_s C_s + P_T C_T; \quad Y^T = C_f + P_T C_T$$

where P_s and P_T are prices of village and town goods respectively, and $P_f = 1$ parametrically given from outside the local economy. Y^v and Y^T are total household incomes in village and town respectively. Given the assumptions about preference in equations (1) and (2) above, the demand functions in each location can be expressed as:

$$\text{Village:} \quad C_f = \begin{cases} Y^v & ifY^v \leq \gamma_f \\ \gamma_f + \upsilon_f\left[Y^v - \gamma_f\right] & ifY^v > \gamma_f \end{cases} ; C_i = \begin{cases} 0 & , ifY^v \leq \gamma_f \\ \dfrac{\upsilon_i\left[Y^v - \gamma_f\right]}{P_i} & , ifY^v > \gamma_f \end{cases}$$

$$\text{Town:} \quad C_k = \frac{\tau_k Y^T}{P_k}, \text{ with } k = f, T$$

Assuming that $Y^v > \gamma_f$, the income elasticity of demand for different goods in the village can be expressed as:

$$E_{fY} = \frac{\upsilon_f Y^v}{\upsilon_f Y^v + (1 - \upsilon_f)\gamma_f} < 1; E_{iY} = \frac{Y^v}{Y^v - \gamma_f} > 1, \forall i = s, T$$

For the rural households, demand for food is income inelastic, and demand for village and town goods are income elastic. The larger is the subsistence requirement (γ_f), the higher is the income elasticity of village good S and town good T in the demand function of the village households.

(2.1) Employment and Income Determination in the Village

Households in the village produce food using land and labor under CRS technology. The optimization in food production is as follows:

$$Max_{L_f}\Pi_f = \theta\left(A^{\alpha}L_f^{1-\alpha}\right) - wL_f$$

where $\theta \geq 1$ represents total factor productivity in food production, A is the endowment of land, l_f is the labor allocated to food production and w is the wage rate. A larger land endowment as represented by a higher value of A can be interpreted as a more rural (agricultural) local economy, given the labor endowment $\bar{L}$. A higher agricultural productivity is captured by an increase in θ. We assume that the locally consumed village good (S) is produced under CRS technology using only labor:

$$Max_{L_s}\Pi_s = P_s\left(\phi L_s\right) - wL_s$$

where ϕ is the technology in the production of village good (and service). This specification of the production function for the S good is appealing both in terms of simplicity and realism in the context of a developing country such as Bangladesh where small scale family enterprises in villages use little capital or land.[6] Given a wage rate w, the demand for labor in agriculture and village good can be derived as:

$$L_f^{*} = \theta^{\frac{1}{\alpha}}A\left[\frac{(1-\alpha)}{w}\right]^{\frac{1}{\alpha}},\ L_s = \frac{\upsilon_s}{w}\left[Y^{v} - \gamma_f\right] \tag{3}$$

The equilibrium price of the village non-farm good is pinned down by the wage rate: $P_s = \dfrac{w}{\phi}$. Denoting the return to land by μ, the total income from agriculture ($Y_f = Q_f = wL_f + \mu A$) can be solved using the marginal conditions for optimization as $Y_f = \frac{wL_f}{(1-\alpha)}$. The total household income in the village (denoted as Y^{v}) thus becomes:

$$Y^{v} == Y_f + Y_s = \frac{wL_f}{(1-\alpha)} + wL_s = \Delta_1 wL_f - \frac{\upsilon_s\gamma_f}{(1-\upsilon_s)} \tag{4}$$

where $\Delta_1 = \frac{1}{(1-\alpha)(1-\upsilon_s)}$. Thus village income net of subsistence requirement and the labor allocated to the village non-farm production can be written as below:

$$Y^{v} - \gamma_f = \Delta_1\left[wL_f - (1-\alpha)\gamma_f\right] \tag{5}$$

$$L_s^{*} = \frac{\Delta_1\upsilon_s}{w}\left[wL_f - (1-\alpha)\gamma_f\right] \tag{6}$$

[6] the main implications of the model will hold if we use more general CRS production function using other factors (e.g. capital) as well.

(2.2) Employment and Income Determination in the Town

The demand for town good comes from three sources: village (C_T^v), town itself (C_T^T) and outside areas (e.g. metropolitan city or other countries) (C_T^O).[7] The demand generated by the metropolitan city is $C_T^o = \dfrac{\varphi Y^o}{P_T(1+d)}$ where d is the distance (transport cost) to the metropolitan city from the small town, and Y^0 is the exogenously given income in the metropolitan city. When all of the demand for town good comes from outside the local economy so that there is no demand linkage with the village ($\upsilon_T = 0$), the only linkage between the town and the village within an upazila is due to the labor market linkage. On the other hand, if ($\varphi = 0$) implying that ($C_T^o = 0$), then the demand linkage between the town and the village will be at the maximum.

The town good C_T is produced under CRS technology using labor and capital:

$$Q_T = K^\beta L_T^{1-\beta}$$

We assume that urban segment of the economy is populated by a single representative agent who invests $K > 0$ amounts of capital in the production of town good at an interest factor r which is determined outside the model. The optimization of the representative agent in the town is as follows:

$$Max_{K,L_T}\Pi_T = P_T K^\beta L_T^{1-\beta} - wL_T - rK$$

It is easy to check that the equilibrium price of the town good is a function of w and r , $P_T^* = \left(\dfrac{w}{1-\beta}\right)^{1-\beta}\left(\dfrac{r}{\beta}\right)^\beta$. Since the town borrows the capital from outside, its income equals the labor income, i.e., $Y^T = wL_T = (1-\beta)\, P_T Q_T(w,r)$ where $Q_T(w,r)$ is the optimal output chosen in the town facing the wage rate and interest factor.[8] The demand for labor in town can be described as:

$$\begin{aligned} L_T^* &= \frac{\Delta_3}{w}[\upsilon_T(Y^v - \gamma_f) + \frac{\Delta_3 \varphi Y^o}{w(1+d)}] \\ &= \frac{\Delta_3\Delta_1\upsilon_T(wL_f - (1-\alpha)\gamma_f)}{w} + \frac{\Delta_3\varphi Y^o}{w(1+d)} \end{aligned} \tag{7}$$

where $\Delta_3 = \frac{1}{(1-\tau_T)}$.

[7]For simplicity, C_T^O is assumed to be nominal expenditure on town good by consumers residing outside the village and town economies described here.

[8]The outside here means that it is outside of the relevant metropolitan city. This keeps the model simple without losing any relevant insight. An alternative formulation is where the capital invested in small town comes from the metropolitan city, and metropolitan city income in that case responds to agricultural productivity growth when the two income is influenced.

2.3 Labor Market Equilibrium

We assume that labor is perfectly mobile and migration cost is equal to zero, so that equilibrium wage (w) are the same regardless of location. The labor market equilibrium condition can be written as:

$$\overline{L} = L_f^* + L_s^* + L_T^* = L_f^* + \Delta_1 \left[\frac{\upsilon_s + \upsilon_T \Delta_3}{w}\right] \left\{wL_f^* - (1-\alpha)\gamma_f\right\} + \frac{\Delta_3 \varphi Y^o}{w\,(1+d)} \tag{8}$$

2.4 The Effects on Equilibrium Wage and Village Income

We first analyze the effects of higher agricultural productivity as captured by a higher θ. Proposition (1) below summarizes the results on equilibrium wage w^* and village income Y^v.

PROPOSITION 1

(1.1) *In the small town economy described above, a higher agricultural productivity (i.e., a higher θ) increases wage, i.e., $\frac{\partial w}{\partial \theta} > 0$.*

(1.2) *A higher agricultural productivity increases (reduces) the village income when elasticity of wage w with respect to θ (i.e., $E_{w\theta}$) is less (more) than $(1-\alpha)^{-1}$.*

(1.3) *The magnitude of the effects of an increase in agricultural productivity on wage depends on land endowment. A set of sufficient conditions for the effects of productivity on wage to rise with a larger land endowment are: (a) that the elasticity of wage with respect to θ is low enough at the initial equilibrium to satisfy $E_{w\theta} < \left\{\alpha\,(1-\alpha)^{-1}\right\}$, and (b) that the initial land/labor ratio is higher than a threshold.*

Proof: Omitted. Please see the (online) appendix.

Discussion

Parts (1.1) and (1.2) show that although we would expect the wage rate to respond positively to a an increase in agricultural productivity, there is no guarantee that it will result in higher village income. To understand the uncertainty regarding the effects on village income, first note that the aggregate village income $\left(Y^v = Y^f + Y^S\right)$ can increase with a higher agricultural productivity only when agricultural income increases as a result, because $Y^v = \Delta_1 w L_f^* - \frac{\upsilon_s \gamma_f}{(1-\upsilon_s)}$, and $Y^f = \dfrac{wL_f^*}{1-\alpha}$. The ambiguity in the income effect is the result of the tension that arises from the fact that a higher wage if strong enough may reduce the L_f^* so much that agricultural income falls after a positive productivity shock raising the crop yield. When the elasticity of wage with respect to productivity $E_{w\theta}$ is equal to $(1-\alpha)^{-1}$, the positive effect of a higher wage is precisely offset by the reduction in labor employed in the food production to keep Y^f unchanged. Thus when $E_{w\theta} < (1-\alpha)^{-1}$, the labor demand does not fall enough to wipe out the positive wage effect, leading to a higher agricultural income, and hence to a higher total village income. The focus on the elasticity of wage with respect to productivity change is partly motivated by the fact that in the empirical analysis, we provide an estimate of the elasticity of wage rate with respect to agricultural productivity (rice yield), and the theoretical results provide us a way to check if we can expect a positive demand effect from the observed wage response in the absence of reliable income data in the village. The result regarding the heterogeneous effects on wage rate (part (1.3) of proposition 1) guides our empirical work in that we split the sample into two sub-samples where the upazilas with low or no urbanization are put into a group to represent the purely village sample (large A), and a second sample consists of the upazila's with relatively substantial urbanization.

2.5 The Effects on Intersectoral Labor Allocation

We can utilize the labor demand functions along with the labor market equilibrium condition to investigate the impact of agricultural productivity shock on labor allocation among different subsectors. Proposition (2) below collects the results on the response of labor allocation to three different economic activities in the small town economy.

PROPOSITION 2:

(2.1) *It is not possible to have structural change in employment that reallocates labor from agriculture to the S-goods sector in a village when there is no subsistence requirement for food (i.e., $\gamma_f = 0$), and hence the demand for food is not inelastic. However, if $\gamma_f = 0$ but $\varphi > 0$, a higher agricultural productivity results in reverse structural change by lowering labor allocation to the town good, i.e., $\frac{\partial L_T^*}{\partial \theta} < 0$. With $\gamma_f > 0$, the strength of the reallocation of labor in response to higher agricultural productivity to non-farm sectors is a negative function of the magnitude ofυ_f.*

(2.2) *An increase in agricultural productivity (i.e., a higher θ) leads to structural change in employment in the small town economy described above by reducing the labor allocated to agriculture, when the elasticity of wage with respect to θ is greater than 1, i.e., $E_{w\theta} > 1$. A necessary condition for $E_{w\theta} > 1$ is that the food production technology is such that the elasticity of agricultural output with respect to land is greater than 0.50, i.e., $\alpha > 0.50$.*

(2.3) *Assume that $E_{w\theta} > 1$. Then a higher agricultural productivity increases the employment in the $S-$goods sector in the village, if $E_{w\theta}$ is less than a threshold $E_{w\theta}^S > 1$. Assuming that $E_{w\theta} \in \left(1, E_{w\theta}^S\right)$, a higher agricultural productivity increases employment in the S-good sector more when the value of υ_s is larger.*

(2.4) *Assume that $E_{w\theta} > 1$,and the subsistence requirement is higher than a positive threshold$\gamma_f > \widetilde{\gamma}_f > 0$. Then there exists a cutoff elasticity value $E_{w\theta}^T$ such that$1 < E_{w\theta}^T < E_{w\theta}^S$. When $E_{w\theta} \in \left(1, E_{w\theta}^T\right)$, an increase in agricultural productivity increases labor allocated to town good production.*

Proof: Omitted. Please see the appendix.

Discussion

To see that it is not possible to have structural change in employment that reduces employment in agriculture when $\gamma_f = 0$, consider the labor demand functions in equations (3) and (4). With $\gamma_f = 0$, we have $\frac{L_f^*}{L_S^*} = \Delta_1 \upsilon_s$ which is not affected by agricultural productivity shock θ directly or indirectly through equilibrium wage w^*. So without $\gamma_f > 0$, it is not possible for agricultural productivity shock to affect labor allocation between food and S-good production in an upazila. However, allocation of labor between agriculture (food) and the town good can still be affected. Using equation (7), setting $\gamma_f = 0$, we can rewrite the labor allocation between food and T-goods sectors as:

$$\frac{L_T^*}{L_f^*} = \Delta_3 \Delta_1 \upsilon_T + \frac{\Delta_3 \varphi Y^o}{w^* L_f^*} \tag{9}$$

From equation (9), it is clear that labor allocation between food and the town good is affected by θ even when $\gamma_f = 0$. An intuitive explanation of this effect is that a higher wage caused by a positive productivity shock increase the price of the town good and given Y^o reduces the demand for town good in the metropolitan area. This leads to labor reallocation from town good to food production, resulting in reverse structural change. We have

$$\frac{\partial P_T^*}{\partial \theta} = (1-\beta)\left(\frac{w}{1-\beta}\right)^{-\beta}\left(\frac{r}{\beta}\right)^{\beta}\frac{\partial w^*}{\partial \theta} > 0$$

It is obvious that when both $\gamma_f = \varphi = 0$, then the allocation of labor across three sectors (f, S, T) is not altered by a productivity shock in agriculture.

An important point that comes across from propositions (2.3) and (2.4) is that when part of the demand for the T-good comes from metropolitan city, the effects of agricultural productivity on employment growth in this sector will be limited at best. In contrast, for the goods which are produced exclusively for local consumption (S-goods), it is more likely that the demand effect generated by productivity growth help unleash significant employment growth.

The theoretical analysis brings into focus the role played by the values of $E_{w\theta}$, α, γ_f, and φ. In the empirical analysis, we estimate $E_{w\theta}$, and available evidence provides us a plausible value for α. It is important to appreciate that land (A) in our model denotes all non-labor inputs including land, and thus the value of α is likely to be significantly larger than 0.50, a plausible value is 0.70.[9] If $\alpha = 0.70$, then $(1-\alpha)^{-1} = 3.333$ and $\alpha(1-\alpha)^{-1} = 2.333$.

[9] In green revolution areas, A includes seed, fertilizer etc. in addition to land. The share-cropper usually gets one third of the output when the landlord bears the costs for seed and fertilizer, thus putting $\alpha = 0.6666$.

3. Empirical Strategy

To estimate the effects of agricultural productivity growth on non-farm employment, we use a panel data model:

$$O_{ijt} = \rho_j + \rho_t + \pi\theta_{jt} + \Pi Z_{jt} + \varepsilon_{ijt} \tag{10}$$

where i indexes the outcome variables (e.g. employment, wage etc), and j upazila. O_{ijt} is the outcome variable i in period t for upazila j. ρ_j and ρ_t denote upazila and year fixed effects respectively. θ_{jt} is the measure of agricultural productivity, Z_{jt} is a vector of upazila characteristics and ε_{ijt} is the error term. Estimation of the impact of agricultural productivity on non-farm employment however presents challenges. Unobserved upazila characteristics (e.g., proximity to a river) may attract firms into an upazila (due to ease of transport) and also affect agricultural productivity (due to availability of water for irrigation) positively. In cross-section OLS regressions, one might thus attribute this correlation to agricultural productivity growth. We use upazila fixed effects ρ_j remove any time invariant but unobserved regional effects, including geographic and persistent agro-climatic factors such as soil quality. The year fixed effects (ρ_t) control for any macro economic and international shocks (including commodity price shocks) that may have affected both agricultural productivity and outcomes of our interest.[10]

For the estimation of equation (10), the upazila level unmeasured fixed factors are removed by de-meaning all variables in the regression. Such de-meaning however may lead to attenuation bias as it magnifies any measurement error in agricultural productivity variable (rice yield). To remedy this potential source of bias, we implement an instrumental variable approach. Following a large literature (Foster and Rosenzweig (2004), Adhvaryu, Chari and Sharma (2013)), agricultural productivity is measured by rice yield as rice is the predominant subsistence and cash crop in Bangladesh. We use rainfall shock as an instrument for rice yield. Rainfall is found to affect agricultural yields in both developed and developing countries and hence used widely as an instrument for agricultural yields (Foster and Rosenzweig (2004), Adhvaryu, Chari and Sharma (2013), Bruckner(2012)). To be precise, we use deviation of current rainfall from its long term average as an instrument. The long term average rainfall is defined as the average rainfall over a 30 year period from 1960 to 1990.

In the empirical analysis, we follow a two step procedure: first, we run a reduced form regression of an outcome variable (for example, formal non-farm employment in T-good production) on the instrument, and second, a reduced form regression of the productivity measure (yield per acre) on rainfall deviation. This two-step procedure based on reduced form regressions has some important advantages in our application. First, given the focus of our analysis is on the effects of productivity increase in agriculture, one can

[10] The year fixed effects will control for any general equilibrium effect common to all households (e.g. prices) also.

plausibly interpret the variations in rainfall as variations in the parameter θ in the model. Second, with crop yield as the measure of agricultural productivity, and rainfall as an instrument, the reduced form estimates of rainfall on outcome (employment) provide evidence on the *existence* of a causal effect of higher crop yield on the relevant outcome which is not subject to weak instrument bias (Chernozhukov and Hansen(2008)).[11] Third, by imposing exclusion restriction on the rainfall shock, we can derive instrumental variables estimates of the causal effect as the ratio of the two reduced form estimates.[12]

We estimate the following reduced form regressions:

$$O_{ijt} = \rho_j + \rho_t + \pi_1 R_{jt} + \Pi_1 Z_{jt} + \varepsilon_{ijt} \quad (11)$$

$$V_{jt} = \eta_j + \eta_t + \pi_2 R_{jt} + \Pi_2 Z_{jt} + \upsilon_{jt} \quad (12)$$

where R_{jt} is the deviation of annual rainfall from its long term average in upazila j and V_{jt} is the measure of productivity. The deviation is defined as the difference between log of current rainfall from log of its long term average. Thus our empirical model with upazila and year fixed effects provides estimates of the impact of rainfall shock on the growth of outcome variables. A positive coefficient of rainfall ($\pi_2 > 0$) for instance in the yield regression means that an increase in rainfall over its long term average level (a positive rain shock) increases rice yield.

To ensure that rainfall primarily captures variation in agricultural productivity, we include an appropriate set of controls in Z_{jt}. A potential concern in our context is that rainfall may be correlated with growth in non-farm employment for factors unrelated to agricultural productivity, and hence may not be reflecting the impact of agricultural productivity. For example, upazilas located near large urban centers are likely to attract large firms producing manufacturing and services (Fafchamps and Shilpi (2003) and (2005), Emran and Shilpi (2012), Deichmann et al (2008)). When these areas happen to have higher rainfall as well, then we may observe a positive correlation between rainfall and share of non-farm employment in an upazila which has little to do with agricultural productivity. To address this concern, we take two steps. First, all upazila' located in the two metropolitan areas (Dhaka and Chittagong) are excluded from the sample, Second, we provide strong evidence that in our data rice yield is positively affected by rainfall. In addition, we include travel time from the upazila center to the nearest of the two main metropolitan cities (Dhaka and Chittagong) as a control in the regressions. Travel distance to the nearest metropolitan city also serves a second purpose; it controls for heterogeneity in the price of T- good, faced by a

[11] We, however, emphasize that the main results of this paper do not depend on the exclusion restriction on rainfall; what we need is that rainfall affects productivity significantly.

[12] Moreover, the reduced form estimates of the effects of rainfall on the outcome variables such as non-farm employment are of interest on their own; for example, they provide us evidence on the potential benefits of increased irrigation investment on the rural non-farm economy.

metropolitan consumer (denoted as $P_T(1+d)$ in the model). A second concern is that some non-farm activities may be susceptible to rainfall directly. For instance, construction employment may rise with higher rainfall if rainfall leads to flooding and destruction of housing and infrastructure. Flooding and destruction may also lead to a negative correlation between rainfall and non-farm employment growth if it disrupts production activities of firms. We include a dummy for floodplain in the regressions to control for such possible adverse effects. An important advantage of our empirical approach is that we can use upazila fixed effects to purge off the additive effects of all time-invariant confounding variables. Since both travel time and the floodplain dummy are time-invariant, their additive effects are taken care of by upazila fixed effects. We take a conservative approach, and allow for time varying effects of these variables, and include interactions of these variables with the time trend in the empirical model. As additional control for time varying heterogeneity across upazilas, we include proportion of household with electricity as a control variable. To capture changes in labor endowment, we control for upazila population, total active labor force, and proportion of active labor force with secondary or above education (human capital). This makes the empirical model consistent with the theoretical assumption of a fixed labor endowment (i.e., insignificant labor supply response to productivity shock in agriculture), and enables us to focus on structural change in employment through labor reallocation.[13] To account for any agglomeration externalities that may affect firm location, we control for upazila population in 1991 interacted with time trend (initial condition) and the share of urban households in total households in the upazila as an indicator of agglomeration economy. [14] A final issue for the empirical specification is that rainfall is expected to have significant effect on rice yield only if a upazila has significant agricultural production (i.e., A is not too small in our model). Since we exclude upazilas located in two main metropolitan areas from our sample, this is not an issue with our samples. An important insight from the theoretical analysis is that the effects of rainfall on wage is likely to be stronger when the share of agriculture is higher in the upazila economy. Accordingly we carry out empirical analysis for two different samples: a "rural sample" and a "small town sample" which are defined in the data section.

4. Data

To test the hypotheses regarding the effects of agricultural productivity growth on wage and the structure of employment, we combine three different data sources to construct an upazila (subdistrict) level panel data set covering the period 2000 to 2009/2010.

A primary source of employment data in Bangladesh is the population censuses (1990, 2000 and 2010).

[13]In an economy with growing labor force, a second source of structural change is allocation of new labor to the nonfarm activities, which is not the focus on this paper.

[14]Our empirical results are robust is we instead use finer controls of agglomeration economies such as area share in total industry employment in 1991.

The census unit records are publicly available for 10 percent of population in 1990 and 2000, and for 5 percent in 2010.[15] The unit record data contain employment records of all household members.[16] We define total employment level in each activity from these unit records using appropriate weights. The total employment defined from census data includes employment in both large and small firms, with the large firms in manufacturing and services producing the T-good and the small firms producing the $S-$good in our model. The population census contains a aggregated industrial classification of employment (top level). Specifically, 2010 census distinguishes only between agriculture, manufacturing and services activities, and large and small firms cannot be distinguished. We thus use this data to understand the effects of agricultural productivity on all firms (farms) without any distinction between large and small firms.

Data on employment in large scale formal non-farm activities (corresponding to T-good in the model) are drawn from three rounds of economic censuses (2000, 2006 and 2009). The economic census provides a detailed list of all firms engaged in industrial and services activities (at 4-digit level) with number of employees more than 10. These relatively larger firms are mostly registered, and tend to better quality manufacturing and services to meet demand in larger markets. The larger is the firm size, the greater is the possibility that it produces goods and services for a wider geographical area. This data are useful in two ways. First, we use them to estimate the effects of agricultural productivity on large scale manufacturing and services. A comparison of the estimates on all firms (farms) from population census with the estimates for large firms from economic census help us to analyze possible differential effects across firm size. Given that this data are available at a 4-digit level, we rely on then to perform disaggregated analysis of employment (for example, in construction, education, health etc).

The productivity growth in agriculture is measured by growth in crop yields. Rice (paddy) is the predominant crop in Bangladesh, of which three different types (Boro, Aman and Aus) are grown.[17] The official source of agricultural statistics provides yield data at the district level, but the data are at aggregate level with limited coverage.[18] Another source of yield data is the community part of the Household Income and Expenditure Surveys (HIES) (2000, 2005, 2010). We define rice yield per acre as the average of yields of boro, aman and aus rice reported in the village/community part of HIES. The upazila (subdistrict) level rice yield are the average over villages surveyed within an upazila. Since the number of villages within upazila is not large, these upazila level estimates of rice yield may involve significant measurement error. However, it is reassuring that the yield growth from the HIES data show estimates comparable to that

[15] The sample sizes are 10.6, 12.4 and 7.2 million individuals in 1990, 2000 and 2010 censuses respectively.

[16] Total numbers of employment records in census data are 3.1, 3.5 and 2.1 million for 1990, 2000 and 2010 censuses respectively.

[17] High yielding variety of Boro rice now accounts for more than half of rice production (56%). Aman is the next important crop accounting for 44% of rice production. Yields of both of these varieties are much higher than Aus.

[18] These data are reported at old (and much larger) district level – there are about 20 old districts. With newly created districts, there are now 64 districts in Bangladesh. These data are drawn from Statistical Yearbooks.

from the official estimates during the decade of 2000.

The rainfall data are taken from Bandyopadhyay and Skoufias (2012). The original data on rainfall come from the Climate Research Unit (CRU) of the University of East Anglia. The CRU reports estimated monthly rainfall for most of the world at the half degree resolution from 1902 to 2009. The CRU method combines weather station data with other information to arrive at the estimates.[19] To estimate the sub-district (upazila/thana) level rainfall from the CRU data, Bandyopadhyay and Skoufias (2012) uses area weighted averages.[20] Travel times to metropolitan cities were computed using GIS software and road network from mid-1990s. Data on agro-ecological zones are drawn from the Bangladesh Water Board database.

Over the years, a number of larger upazilas were split to form new upazilas, thus increasing the total number of upazilas from 486 in 1990 to 507 in 2000 to 543 in 2010. We use upazila maps to identify the borders of upazilas overtime and matched all upazilas in 2000 and 2010 to 1990 upazilas. The upazila level panel is defined using 1990 upazila boundaries. To define estimation sample, we take out the upazilas that are located in the two main metropolitan cities (Dhaka and Chittagong), leaving us with a sample of 464 upazilas. We divide the upazilas into two sub-samples on the basis of share of urban in total upazila population in 1991. The median share of urban population in upazila population was 11 percent in 1991. Our "rural sample" consists of 232 upazilas which had less than 11 percent of population classified as urban. The STE sample comprises of the other 232 upazilas with urban share higher than 11 percent.

Table 1 provides the summary statistics for all upazilas in our sample over the years. The population censuses indicate strong employment growth in overall non-farm sector.[21] Total employment in non-farm activities grew at an annual rate of 8.6 percent between 2000 and 2010. Total manufacturing employment posted an annual growth of 18.5 percent during this period. Services employment grew by 6.8 percent. Between 2000 and 2009, employment in firms with more than 10 employees has grown at an annual rate of 5.7 percent, according to the economic censuses. Among the large firms, growth in manufacturing employment has been quite robust at 5.1 percent compared with a 2 percent growth in services employment. A comparison of employment composition shows that employment in small firms (10 or fewer employees) accounts for more than three-quarters of total employment in non-farm sector. Interestingly, the share of employment in larger firms in total non-farm employment declined from 0.22 in 2000 to 0.17 in 2010.

[19] Previous versions of the CRU data were homogenized to reduce variability and provide more accurate estimation of mean rain at the cost of variability estimation. The version 3.1 data is not homogenized and thus allows for better variability estimates. The estimates of rainfall near international boundaries are not less reliable as compared with those in the interior of the country, as the CRU estimation utilizes data from all the weather stations in the region.

[20] For example if an Upazila/thana covers two half degree grid cells for which CRU has rainfall estimates, then upzila/thana rainfall is estimated as the average rainfall of the two grid-cells, where the weights are the proportion of the area of the upazila/thana in each grid-cell. For details, please see Bandyopadhyay and Skoufias(2012).

[21] According to census data, share of non-farm employment in total employment increased from 0.475 in 2000 to 0.53 percent in 2010. The total labor force during this period increased by an annual rate of 2.05 percent from 35 million to 42.5 million.

While about 25 percent of all employment is in manufacturing in 2010, the share of manufacturing in total employment of large firms is much higher (43 percent in 2009). This is expected as few services enterprises are large in size. Larger services enterprises appear to be more concentrated in the provision of health (hospitals, clinics etc) and education (schools) (Table 1). A comparison of summary statistics between our rural and STE samples confirms that most larger firms are located in STEs. These firms tend to serve larger markets compared with firms in rural sample which are smaller and serve mainly local markets.

The summary statistics in Table 1 indicate substantial growth in rice yield between 2000 and 2010. Average rice yield per acre has grown by an annual rate of 3.8 percent. This growth rate is consistent with about 3.7 percent growth in agricultural GDP during the same time.[22] There has been substantial expansion of irrigation during the decade as well -from 61 percent in 2000 to 69 percent in 2010. The standard deviation estimate (Table 1) shows that there are considerable variations in rice yields across upazilas. Among other variables, access to electricity by households improved considerably during the decade (6.5 percent annual growth rate).

5. Empirical Results

In this section, the main empirical results are presented sequentially. All outcome variables as well as rainfall are expressed in logarithms. All regressions include upazila and year fixed effects. All standard errors are corrected for correlation in the error term within the upazila.

5.1 Rainfall, Agricultural Productivity, and Agricultural Wage

We begin by presenting evidence on rainfall shock's impact on agricultural productivity. Table 2 reports the results from OLS regressions where log of rice yield is regressed on deviation of rainfall after controlling for upazila and year fixed effects. Column (1) shows the estimate when no other explanatory variable is included in the regression. The specification in column (2) includes the full set of upazila level controls as discussed in empirical strategy section (Section 3). The first panel reports results for the STE sample and second for the rural sample. The evidence from both specifications shows statistically and numerically significant impact of rainfall shock on rice yield in rural and STE samples. The estimated coefficients imply an *increase* in yield growth due to a positive shock in rainfall over it's mean, with the impact marginally larger in the rural sample compared with STEs. This result is consistent with findings from a rich body of evidence accumulated by the agronomists and crop scientists that shows that rainfall is a major determinant of yield growth in rice in Bangladesh in last few decades (see, for example, Sarkar et. al. (2012)).

While positive rainfall shock increases rice yield, does it increase wage rate? We utilize HIES data on agricultural wage to examine the effect of rainfall shock. Note that the sample size for the wage

[22] Crop agriculture accounts for 56 percent of agricultural GDP and rice is the single most important crop in Bangladesh not only as a subsistence but also as a cash crop.

regression shown in column (3) of Table 2 is somewhat smaller due to the fact that HIES – though nationally representative – does not cover all of the upazilas in our upazila level panel data sample used for columns (1) and (2). The results in column (3) show a statistically significant and positive impact of rainfall on agricultural wage in both samples. Interestingly, the wage response is larger in magnitude in the rural sample, consistent with the theoretical prediction that the wage response to productivity shock, under plausible conditions, is a positive function of the endowment of agricultural land (i.e., a higher A) (proposition 1). This evidence is reassuring as it confirms that the central channel through which agricultural productivity works in the theoretical model is in fact operative in the data.

The effects of rainfall on agricultural income can not be estimated directly, as reliable data on income are unavailable. We can, however, estimate the elasticity of wage with respect to productivity (rice yield) and exploit the theoretical insights to understand if the data supports a positive income effect (a higher Y^v in the model). Using the reduced form estimates from Table 2 (columns (1) and (4)), the implied elasticity of wage with respect to productivity are: $E_{w\theta} = 1.47$ in small town sample, and $E_{w\theta} = 1.82$ in the rural sample. Although we do not have a precise estimate of α , the available evidence in the context of Bangladesh suggest that it is likely to belong to the interval $\alpha \in [0.60, 0.70]$ (Hossain and Bayes (2009)). Thus $(1-\alpha)^{-1} \in [2.5, 3.33]$, thus satisfying the condition specified in proposition 1 $[E_{w\theta} < (1-\alpha)^{-1}]$. Even if we assume a conservative estimate of 2.33, the estimates for $E_{w\theta}$ in both the rural and STE samples imply that a positive productivity shock to rice yield would increase rural income, providing a basis for structural change in employment driven by Engel curve effect.

While a positive rainfall shock increases rice yield, for appropriate interpretation of the results, it is useful to understand whether this reflects only the impact of transitory weather shocks on farming. Though rainfall variations across upazilas and over time are expected to affect the yield directly, they are likely to affect long-term productivity differences by influencing investment in irrigation. In a cross-section regression, irrigation investment is negatively correlated with rainfall, as they are substitutes.[23] But over time, in the same upazila, irrigation expansion is positively correlated with rainfall, as irrigation investment starts in the drought prone areas and expands to the areas with more rainfall over time. Since we use a panel data model with upazila fixed effect, the rainfall shocks in our case would thus pick up irrigation expansion over time. The final column reports estimated effect of rainfall variations on the area irrigated in a specification with upazila fixed effects and other controls used in our main regressions. Though coefficient estimates lack statistical precision, they are positive in both samples. The estimated coefficient is large in magnitude in the rural sample. A positive coefficient on the rainfall variable in this regression provides suggestive evidence that irrigation expansion over our sample period has happened increasingly in areas

[23]It is, however, important to appreciate that rainfall affects productivity even with irrigation (see, for example, ??). This is because of the simple fact that the marginal cost of irrigation water is positive, but it is zero for rainfall.

with relatively higher rainfall.[24] We interpret this as evidence that though rainfall variable in our panel regressions captures mostly transitory shock in agriculture, it may also be capturing to some extent the diffusion of modern technology in farming over time. Note also that modern farming technology such as irrigation may also reduce risk by decreasing variability of yield even without increasing yields. The expansion of irrigation in Bangladesh allowed adoption of boro rice whose yields are significantly higher than other rice types (aman and aus).

Another issue in the IV interpretation of rainfall is that it may capture not only agricultural productivity shock but also resulting price changes. In a completely segmented rice market at the upazila level, a rainfall shock would affect the equilibrium rice price through income effect. However the rice market is the most developed and spatially integrated market in Bangladesh (see, for example, Hossain and Verbeke (2010)). A noted before, we control for the distance from an upazila to the metropolitan city markets, which captures spatial price dispersion due to transport costs. The theoretical model assumes that rice price is pinned down by the international market, and the available evidence on rice markets in Bangladesh clearly supports this assumption.

5.2 Rainfall, Agricultural Productivity and Structural Change in Employment

With the evidence that a positive rainfall shock increases agricultural productivity and wage, with likely positive income effect, we now turn an analysis of the effects of rainfall shocks on intersectoral employment. The dependent variables in the employment regressions are all expressed in logarithms. All regressions include full set of regressors and upazila and year fixed effects.

The first three columns of Table 3 report the fixed effects regression results for employment by all firms (using population census data) and the last three for employment by large firms (using data from economic censuses). In order to facilitate comparison between economic census data on large firms and population census data on all firms, employment categories are kept at a fairly aggregate level distinguishing only between manufacturing and services.[25] The top panel reports results for the STE sample and bottom for the rural sample. The number of periods in census panel data is 2 and economic census is 3. This is because 1990 census data are used to define initial characteristics of upazilas and economic census has an additional data point for 2006 which is a non-population census year.

Evidence on All Firms (Irrespective of Size)

The evidence in first three columns on all firms shows an interesting pattern: the estimated effect of a positive rainfall shock is positive and statistically significant on the manufacturing and services sectors,

[24]Historically, irrigation is adopted first in drier regions in Bangladesh resulting in a negative correlation between area irrigated and rainfall in the cross-section data. However, expansion of irrigated areas happened increasingly in high rainfall areas – as confirmed by our panel regression result.

[25]Census data do not provide employment information at disaggregate level for 2010.

while the effect is negative on agricultural employment, although it is not statistically significant at the 10 percent level. This pattern of estimates is observed in both the rural and the STE samples, with the magnitude of the effect larger for manufacturing and smaller for services in the case of rural sample. The negative effect on agriculture, although imprecisely estimated, suggests labor reallocation away from farming. Note that according to the theoretical analysis, given a labor endowment $\bar{L}$, a higher agricultural productivity results in labor reallocation away from agriculture when $E_{w\theta} > 1$. Given that the estimates of $E_{w\theta}$ in rural and STE samples are 1.82 and 1.47 respectively, the theory predicts a more robust negative effect on agricultural employment. One possible explanation is that the controls we use for changes on labor endowment over time are less than perfect, and thus the negative effect on agricultural employment is diluted by growing labor force.

The evidence from population census data suggests that agricultural productivity growth leads to structural change in employment in favor of manufacturing and services sectors, but we do not know if this structural change also entails employment growth in large (formal) enterprises. To understand whether agricultural productivity increase leads to labor reallocation in favor of large scale (formal) firms, we take advantage of the economic census data.

Evidence on Large Manufacturing and Services Firms (Economic Censuses Data)

The estimates for manufacturing employment in large firms are reported in column (5) of Table 3, and the results suggest a statistically significant positive effect of rainfall in the STE sample, but no effect in the rural sample. The fact that there is no significant effect on manufacturing in the rural sample is especially striking when compared to the estimate for all firms in column (1) where the effect is both statistically significant at the 1 percent level and numerically large. Taken together, the estimates in columns (1) and (5) suggest that agricultural productivity growth in predominantly rural upazilas reallocate labor from agriculture to small scale manufacturing firms producing locally consumed low quality $S-$good. Given the fact that the wage response to agricultural productivity growth is larger in magnitude in the rural sample, the results on the rural upazilas are consistent with a scenario where the demand for manufacturing $S-$goods is much stronger than that for manufacturing $T-$goods (i.e., $\upsilon_s > \upsilon_T$), and the weak demand effect is more than offset by a strong wage response to productivity growth in the case of $T-$goods sector. In contrast, in the small town sample, a higher agricultural productivity results in a very strong growth in employment in large scale manufacturing. A comparison of the estimated effects of rainfall shock on all manufacturing firms and the large manufacturing firms in the STE sample shows that the employment growth in large firms is more than four times of that in all firms (i.e., large and small firms combined together). This implies that employment growth in small firms in STE sample is weak at best. The contrasting effects on large scale manufacturing in rural and STE samples suggest that when the wage response is high enough, it may discourage large firms in locating production in an upazila, consistent with the findings of Rosenzweig and Foster (2004) in the context of India. The negative wage effect can dominate the choices of large manufacturing firms when the $T-$good is effectively a tradable good, but the evidence that in the STE sample employment response in $T-$good (manufacturing) sector is strong rejects the assumption of a tradable $T-$ good.

For services employment in large firms, the estimated coefficient is positive and statistically significant in both the rural and STE samples, but the magnitude of the effect in the STE sample is almost twice that in the rural sample. Thus the effects of agricultural productivity growth seems to be especially potent in those upazilas where the small towns are located. In the rural sample, the estimate for large scale (formal) services is in sharp contrast to that for large scale manufacturing, when a comparison is made with the corresponding estimates for all firms in columns (1) and (2) using population census data. The estimate for employment in large scale services firms in the rural sample is much larger in magnitude (1.50) compared to the estimate for all firms in the services sector in column (2), while the relative magnitudes are reversed in the case of manufacturing. The evidence that the growth in large scale firms in services sector is favorably affected by higher agricultural productivity irrespective of whether there is a small town in the upazila. This probably reflects the fact that formal health and education services are effectively nontradables and also enjoy more income elastic demand. We explore the effects on large scale health and education services in greater depth below.

Our results are partly consistent with findings from Foster and Rosenzweig (2004) for India. Using village level data, Foster and Rosenzweig (2004) find that agricultural productivity growth has negative effect on number of factory workers and positive effect on employment in services. Our evidence that there is no significant effect of agricultural productivity growth on large manufacturing employment in the rural sample, but employment in large scale services increase substantially is consistent their findings. However, using the STE sample, we find that agricultural productivity growth can have strong positive effect on large scale manufacturing when the villages are located in an upazila with a small town. Thus the conclusions depend critically on the sample used. In a related contribution, using district and state level data from India, Adhvaryu, Chari and Sharma (2013) on the other hand find factory employment to be affected negatively by negative productivity (rainfall) shock which is consistent with our evidence from the STE sample. The results in Table 3 thus highlight the need for making a distinction between large and small firms, and the importance of focusing on geographical areas beyond the villages. Indeed ignoring the STEs would lead to a gross underestimation of the positive effects of agricultural productivity shock on structural change in employment.

5.3 The Effects on Employment in Large firms: Disaggregated Analysis

The results discussed above imply that there are important differences in the way agricultural productivity shock affects different types of economic activities located in different areas. In this section, we explore whether these differences are also observed at a more disaggregated sectoral levels of employment of larger firms for which we have data from the economic censuses. Within the manufacturing sector, we make a distinction between food processing and beverages, and other manufacturing. Among services activities, we distinguish between trade, education, health and other services. We also examine employment in transport, construction, and utility as a separate category. The FE regression results are reported in Table 4. As before, all regressions include a full set of controls along with upazila and time fixed effects.

Results in columns 1 and 2 in Table 4 indicate significant and positive effects of rainfall shocks on both food precessing and other types of manufacturing employment in STEs. The effects on all different types of services are positive and statistically significant in the STE sample. In terms of magnitudes, the largest coefficient estimate is found for transport, construction and utilities, followed by education, other manufacturing, other services and health. The smallest impact is observed for the trading services.[26] The estimates from the rural sample in general show a much weaker impact; only in two out of seven types of activities listed in Table 4, the estimated effect is statistically significant at the 10 percent level. The two exceptions are education and transport and construction, but even in these cases the magnitudes of the effects are much smaller in the rural sample when compared to the corresponding estimates for the STE sample.

An important finding from the estimates in Tables 3 and 4 is that an increased agricultural productivity and the resulting higher rural income leads to employment transformation within the services sector in both rural and STE samples: households appear to substitute away from traditional services provided by smaller enterprises, and into services provided by larger and more skilled enterprises, especially in education. Similar transformative effects are found for large scale manufacturing located in STEs. The effects on manufacturing in the rural areas are very different; a positive agricultural productivity shock results in a robust growth of small scale manufacturing employment with no impacts on employment of relatively larger scale enterprises.

6. Conclusions

This paper provides a theoretical and empirical analysis of the role of agricultural productivity in non-farm employment growth, and structural transformation in the labor market, using a broader framework that goes beyond rural-urban dualism, and focuses on the rural towns and smaller cities which we term as small town economy (STE). We develop a simple model that formalizes the demand and labor market

[26] The result for trading is possibly due to the fact that very few trading enterprises are large in size.

linkages between the STEs and the surrounding villages. A positive productivity shock to agriculture, however, does not necessarily increase village income; given a labor endowment, the village income increases only when the response of wage (i.e, elasticity of wage with respect to productivity shock) is lower than a threshold.[27] When the elasticity of demand for the town good in the village is low so that most of the town good is sold outside the local economy, the labor market linkage predominates and a higher rural wage due to agricultural productivity increase reduces employment in small towns. In contrast, when demand for goods and services produced in small towns comes mainly from the adjacent rural areas, the demand effect can more than offset the negative wage effect, and lead to higher labor allocation to the production of town good. Another key insight from the model is that when a significant part of village income is spent on goods and services in STEs, ignoring STEs will lead to serious underestimation of employment reallocation effects of agricultural productivity shocks.

Following a large literature on the importance of rainfall shocks in agricultural productivity variations in Bangladesh, we exploit rainfall shocks (relative to 30 year average level) across upazilas and over time to understand the effects of productivity increase on employment growth and diversification. We use a two step empirical approach that focuses on the reduced form regressions of rainfall on the measure of productivity (rice yield per acre) and on the set of outcome variables noted above. The evidence from the reduced form regressions shows that a positive rainfall shock increases employment in all different types of non-farm activities in STEs, but increases only services activities and small scale manufacturing in rural areas. The largest impacts are found for construction and transport, education, health and other services, and manufacturing employment in larger scale enterprises located in STEs and for educational services provided by larger enterprises in rural areas. When interpreted as instrumental variables estimates of the effects of productivity increase, the empirical results suggest that agricultural productivity induces structural transformation within the services sector with employment in skilled services provided by larger firms growing at a much faster pace compared with services provided by smaller firms/individuals. We find much larger positive impacts on non-farm employment growth and transformation in STEs. In rural areas, it increases employment mostly in small scale manufacturing and skilled educational services. The estimates confirm the transformative effect of agricultural productivity increase on nonfarm activities in STEs. These results suggest that policies promoting agriculture would be beneficial to employment growth and transformation in the STEs in Bangladesh.

[27] In a more general model with a positive labor supply curve at the household level, a positive shock to agriculture is expected to increase village income in general.

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Appendix

PROOF OF PROPOSITION 1

(1.1) The labor market equilibrium in equation (8) in the text can simplified as:

$$w\overline{L} = \Delta_5 w^{1-\frac{1}{\alpha}} \theta^{\frac{1}{\alpha}} - \Delta_4 \Delta_1 (1-\alpha) \gamma_f + \Delta_3 \left(\frac{\varphi Y^o}{1+d} \right) \tag{13}$$

where $\Delta_4 = \upsilon_T \Delta_3 + \upsilon_s$ and $\Delta_5 = A(1-\alpha)^{\frac{1}{\alpha}}(1 + \Delta_4 \Delta_1)$. The effect of agricultural productivity shock on wage cane be derived from equation (13) as:

$$\frac{\partial w}{\partial \theta} = \frac{\alpha \Delta_5 \theta^{\frac{1-\alpha}{\alpha}} w}{\alpha w^{\frac{1}{\alpha}} \overline{L} + (1-\alpha) \Delta_5 \theta^{\frac{1}{\alpha}}} > 0 \tag{14}$$

(1.2) We show that the stated restrictions on land/labor ratio and $E_{w\theta}$ are sufficient for $\dfrac{\partial^2 w}{\partial \theta \partial A} > 0$.

Using equation (14), we get:

$$\frac{\partial^2 w}{\partial \theta \partial A} = \frac{w}{D\theta} \left[(\theta (1-\alpha))^{\frac{1}{\alpha}} (1 + \Delta_4 \Delta_1) \{ \alpha - E_{w\theta} (1-\alpha) \} + E_{wA} \left\{ \alpha (\theta (1-\alpha))^{\frac{1}{\alpha}} (1 + \Delta_4 \Delta_1) - E_{w\theta} \frac{\bar{L}}{A} \right\} \right] \tag{15}$$

where D is the denominator in the RHS of equation (14), and E_{wA} is the elasticity of wage with respect to land endowment A. Now, $\{\alpha - E_{w\theta}(1-\alpha)\} > 0$ if $E_{w\theta} < \alpha (1-\alpha)^{-1}$, and the first term in [.] in the RHS of equation (15) is positive. It is easy to check from labor market equilibrium condition (13) that $E_{wA} > 0$. A sufficient condition for the second term in the RHS of equation (15) to be positive when we set $E_{w\theta} = \alpha (1-\alpha)^{-1}$ is that the labor/land ratio is small enough to satisfy the following condition:

$$\frac{\bar{L}}{A} < (1-\alpha)^{\frac{1+\alpha}{\alpha}} \theta^{\frac{1}{\alpha}} (1 + \Delta_4 \Delta 1) \tag{16}$$

So when inequality (16) is satisfied, it is over-sufficient for the RHS of equation (15) to be positive that $E_{w\theta} < \alpha (1-\alpha)^{-1}$.

(1.3) From equation (4) in the text, the total village income is given by:

$$Y^v = \Delta_1 w L_f^* - \frac{\upsilon_s \gamma_f}{(1-\upsilon_s)}$$

Thus a necessary and sufficient condition for Y^v to increase with a higher $\theta$is that $\dfrac{\partial \left(w L_f^* \right)}{\partial \theta} > 0$.

Using the solution for L_f^* from equation (3) in the text, we have the following:

$$\frac{\partial\left(wL_f^*\right)}{\partial\theta}=\frac{[A\theta(1-\alpha)]^{\frac{1}{\alpha}}}{\alpha\theta}w^{\frac{\alpha-1}{\alpha}}\left\{1-(1-\alpha)E_{w\theta}\right\} \tag{17}$$

From equation (17), $\dfrac{\partial\left(wL_f^*\right)}{\partial\theta}>0$ iff $E_{w\theta}<(1-\alpha)^{-1}$.

PROOF OF PROPOSITION 2

(2.1) From equation (3) in the text, we have:

$$\frac{\partial L_f^*}{\partial\theta}=\frac{A[\theta(1-\alpha)]^{\frac{1}{\alpha}}}{\alpha\theta w^{\frac{1}{\alpha}}}\left\{1-E_{w\theta}\right\} \tag{18}$$

From equation (18), it is obvious that $\dfrac{\partial L_f^*}{\partial\theta}<0$ iff $E_{w\theta}>1$.

(2.2) See P. 10 in the text.

(2.3) Using equation (6) in the text, we have:

$$\frac{\partial L_S^*}{\partial\theta}=\frac{\Delta_1\upsilon_s(1-\alpha)}{\theta w}\left[\gamma_f E_{w\theta}+\frac{A\theta^{\frac{1}{\alpha}}(1-\alpha)^{\frac{1-\alpha}{\alpha}}}{\alpha w^{\frac{1-\alpha}{\alpha}}}(1-E_{w\theta})\right] \tag{19}$$

It is obvious from equation (19) that $\dfrac{\partial L_S^*}{\partial\theta}>0$ when $E_{w\theta}=1$. By continuity, there exists a threshold value $E_{w\theta}^S>1$ such that $\dfrac{\partial L_S^*}{\partial\theta}>0$ remains true.

(2.4) Using equation (7) in the text, we get:

$$\frac{\partial L_T^*}{\partial\theta}=\frac{\Delta_3\Delta_1\upsilon_T(1-\alpha)}{\theta w}\left[\frac{A\theta^{\frac{1}{\alpha}}(1-\alpha)^{\frac{1-\alpha}{\alpha}}}{\alpha w^{\frac{1-\alpha}{\alpha}}}(1-E_{w\theta})\right]+\frac{\Delta_3E_{w\theta}}{w\theta}\left[\Delta_1(1-\alpha)\upsilon_T\gamma_f-\frac{\varphi Y^o}{(1+d)}\right] \tag{20}$$

A comparison of equations (19) and (20) makes it clear that as long as $\varphi>0$, the effect of agricultural productivity growth on employment growth in the town goods sector is likely to be limited compared to that in the S-goods sector. If the subsistence requirement γ_f is large enough to satisfy $\gamma_f>\widetilde{\gamma}_f\equiv\dfrac{\varphi Y^o}{\Delta_1(1-\alpha)\upsilon_T(1+d)}$, then the last term in equation (20) is positive and there exists a threshold value $E_{w\theta}^T>1$ such the RHS of equation (2) is positive. The stronger is the consumer preference for town good in the village (i.e., higher value of υ_T), and the farther away is the metropolitan city (i.e., a higher d) , the larger is the value of $E_{w\theta}^T$, and the more likely it is that agricultural productivity has a positive effect on the employment in T-goods sector.

Table 1: Summary Statistics: Sub-district level Employment, Yield and other indicators (Full Sample)

	Mean	SD	Mean	SD	Mean	SD
Economic Census	**2000**		**2006**		**2009**	
Employment (Firm size>=10)	3128	4161	4256	6537	5158	9487
Manufacturing	1419	2925	2117	5806	2225	6256
Services	1062	1142	1319	1044	1267	991
of which						
Trade	64	178	47	127	40	110
Education	692	672	978	684	951	658
Health	151	208	169	196	162	183
Other (construction, transport, utility etc.)	1701	2052	2132	2010	2926	5343
Population Census	**2000**				**2010**	
Employment (Total)	14054	4161			32214	31322
Manufacturing	1458	10871			7985	12043
Services	12595	2559			24229	22137
Proportion urban	0.13	0.13			0.14	0.11
Population	213274	108269			276587	153595
Proportion with Secondary or higher Education	0.11	0.04			0.13	0.04
Proportion of households with electricity	0.25	0.23	0.36	0.25	0.46	0.27
Household Income and Expenditure Survey	**2000**		**2005**		**2010**	
Rice Yield (mt/acre)	0.94	0.11	1.01	0.13	1.36	0.48
% of land irrigated	61	30	60	33	69	26
Real Per Capita Expenditure	749	200	848	206	1098	266
Real Daily Wage	74	29	76	39	94	31
Annual Rainfall (mm)	1444	487	1653	410	1472	379

Table 2: Rainfall Shocks and Agricultural Yields

	Log (Rice Yield/acre)		Log(agricultural wage)	% of Area Irrigated
	(1)	(2)	(4)	(5)
Small Cities and Towns Sample				
Rainfall Deviation	0.387***	0.448***	0.567**	14.53
	(7.316)	(8.801)	(2.459)	(0.731)
Observations	696	696	458	355
Number of Upazila	232	232	208	180
Rural Sample				
Rainfall Deviation	0.449***	0.498***	0.821***	27.94
	(8.472)	(9.845)	(2.792)	(1.154)
Observations	696	696	436	386
Number of Upazila	232	232	205	195
Year & Upazila Fixed Effects	Yes	Yes	Yes	Yes
Area Characteristics	No	Yes	Yes	Yes

Note: Rainfall Deviation is defined as the difference between log(current rainfall) and log(30 year average rainfall). The regressions in even numbered columns include a number of controls (log of travel time to Capital and/or Port cities interacted with time trend, flood prone dummy interacted with time trend, proportion of household with electricity, log of 1991 population interacted with trend, log of total active labor force, and proportion of labor force with above secondary education, share of urban households. All regressions include year and upazila fixed effects. Standard errors are clustered at upazila level.

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Rainfall Shocks, Agricultural Productivity and Non-farm Employment

	Log (Employment)						
	All Firms				Large Firms		
	Manufac-turing	Services	Total Non-Farm	Log(Agri. Employm.)	Manufac-turing	Services	Total Non-farm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Small Towns Sample							
Rainfall Deviation	0.656**	0.310***	0.385***	-0.126	2.680***	2.875***	3.113***
	(2.298)	(3.168)	(4.979)	(-1.064)	(2.812)	(3.080)	(3.098)
Observations	464	464	464	464	696	696	696
Number of Upazilas	232	232	232	232	232	232	232
Rural Sample							
Rainfall Deviation	1.373***	0.246**	0.337***	-0.0444	0.309	1.501**	1.064
	(4.087)	(2.138)	(3.135)	(-0.868)	(0.386)	(2.016)	(1.449)
Observations	464	464	464	464	696	696	696
Number of Upazilas	232	232	232	232	232	232	232
Year & Upazila Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Rainfall Deviation is defined as the difference between log(current rainfall) and log(30 year average rainfall). The regressions include a number of controls (log of travel time to Capital and/or Port cities interacted with time trend, flood prone dummy interacted with time trend, proportion of household with electricity, log of 1991 population interacted with trend, log of total active labor force, and proportion of labor force with above secondary education, share of urban households. All regressions include year and upazila fixed effects. Standard errors are clustered at upazila level.

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Rainfall Shocks, Agricultural Productivity and Employment in large firms

	Log (employment in manufacturing)			Log(employment in services)			
	Food & Beverages	Other Manfact.	Transport Const. & other	Trade	Education	Health	Other Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Small Cities and Towns Sample							
Rainfall Deviation	1.769**	2.306**	2.699***	1.215*	2.436***	2.071***	2.189***
	(2.151)	(2.486)	(3.043)	(1.691)	(3.150)	(3.005)	(3.048)
Observations	696	696	696	696	696	696	696
Number of Upazilas	232	232	232	232	232	232	232
Rural Sample							
Rainfall Deviation	-0.249	-0.108	1.382*	0.189	1.430**	0.758	0.590
	(-0.362)	(-0.133)	(1.970)	(0.394)	(2.307)	(1.224)	(0.944)
Observations	696	696	696	696	696	696	696
Number of Upazilas	232	232	232	232	232	232	232
Year & Upazila FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Rainfall Deviation is defined as the difference between log (current rainfall) and log(30 year average rainfall). The regressions include a number of controls (log of travel time to Capital and/or Port cities interacted with time trend, flood prone dummy interacted with time trend, proportion of household with electricity, log of 1991 population interacted with trend, log of total active labor force, and proportion of labor force with above secondary education, share of urban households. All regressions include year and upazila fixed effects. Standard errors are clustered at upazila level.

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1