Transport Costs, Comparative Advantage, and Agricultural Development: Evidence from Jamuna Bridge in Bangladesh

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Transport Costs, Comparative Advantage, and Agricultural Development: Evidence from Jamuna Bridge in Bangladesh

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Abstract

This paper studies the effects of a large reduction in transport costs on agricultural development in a developing country with a focus on the interactions among comparative advantage and transport costs of a location, and transport intensity and value of a commodity. We extend the von Thunen model of land allocation to incorporate costly technology adoption and comparative advantage based on land productivity. The theoretical analysis predicts spatial non-linearity in cropland allocation, and produces deviation of observed cropping pattern from the efficient crop choices. A reduction in transport costs leads to adoption of productivity-enhancing inputs in the newly-connected region, and increases the share of land devoted to the high-value transport-intensive crop, with the strongest effect in the areas that are not too near or too far from the center and also have a higher land productivity in that crop.

The empirical context of our analysis is the Jamuna bridge in Bangladesh, which opened in 1998, and reduced the transport costs from the poor hinterland in the north-west to the capital city Dhaka by more than 50 percent. Using sub-district level panel data, we implement doubly robust estimators in a difference-in-difference design where the comparison areas come from a region which is supposed to be connected to the capital city by the proposed, but yet to be built, Padma bridge. We find that the construction of Jamuna bridge led to increased adoption of technology (fertilizer, irrigation, green-ness and cropping intensity) and reallocation of land from low-value and non-perishable crop rice to high-value crops, pulses (non-perishable) and vegetables (perishable). The evidence indicates spatial non-linearity in the effects on cropping intensity and on the reallocation of land in areas with comparative advantage in vegetables production. For cropping intensity, the magnitude of the effect is large in the intermediate distance (130-150 km) from the bridge. In areas with relatively higher vegetables productivity, land allocated to rice declined, and in particular, land was reallocated from HYV rice to vegetables in the intermediate distance (110-150km). This improved productive efficiency by aligning the cropping pattern more closely with comparative advantage. The bridge thus led to agricultural development through technology adoption, higher cropping intensity, and by reducing the spatial mismatch between land suitability and crop choice.

Keywords: Land Reallocation, Technology Adoption, Cropping Intensity, Agriculture, Bridge

JEL Classification: R40; O18; O13; O16

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1 Introduction

The implications of segmented and imperfect rural markets for resource allocation and technological change in agriculture have occupied a prominent position in both theoretical and empirical literature in development economics from 1970s onward (see, among others, Bardhan (1984), Braverman et al. (1993), Basu (1997)). High trade costs arising from the absence of transport and communications infrastructure are among the most important factors behind spatial segmentation of markets and may result in isolated village economies that are effectively cut-off from the urban growth centers. This paper uses a quasi-experimental study of a major bridge construction in Bangladesh, the Jamuna bridge, to analyze the effects of a large reduction in trade costs on the spatial pattern of agricultural specialization and technology adoption in a lagging region of a developing economy. As noted by Donaldson (2015), there are two important advantages in focusing on agriculture when estimating the effects of trade costs: (*i*) the main factor of production, land, is immobile, (*ii*) reliable measures of natural productivity of land are available (GAEZ, FAO).[2]

The 4.8 kilometer long Jamuna bridge opened in 1998, and connected about 26 million people residing in the underdeveloped and poor region in the Northwest Bangladesh to the growth centers in the East including the capital city Dhaka and the port city Chittagong. The bridge reduced the freight costs by more than 50 percent and travel time from areas in the North-west to Dhaka city by 3-4 hours. Such a large reduction in transport costs provides an excellent opportunity to examine the effects on spatial organization of agricultural activities which may not be detectable with marginal infrastructure interventions such as improvements in existing roads, construction of rural feeder roads, or small bridges over canals in a village.

The theoretical and empirical analysis of this paper focuses on two major issues. First,

[2]Duranton and Venables (2018) note that the reallocation of resources in response to a decline in trade costs will be according to absolute advantage in manufacturing and services sector where the main inputs (labor and capital) are spatially mobile across regions of a country. This implies that to understand the role played by comparative advantage derived from initial endowment, agriculture is the most suitable sector.

the interaction between transport costs and natural land productivity in determining the spatial pattern of land allocation across crops and technologies (modern vs. traditional) is analyzed. We extend the standard von Thunen model of spatial specialization of crops to incorporate land productivity heterogeneity and costly technology adoption. An important prediction from the extended von Thunen model is that the pattern of crop choices and technology adoption across villages may exhibit nonlinearity with respect to distance from the urban center (spatial non-monotonicity). The positive effect of bridge on the share of land devoted to high-value transport intensive crop (e.g. vegetables) is felt most prominently in areas that are not too near or far from markets and also have higher relative land productivity in that crop.

Second, a major caveat emphasized in the recent literature is that the estimated effects of transport infrastructure in the target region may primarily be due to reallocation (reorganization), without any significant efficiency and growth effects (a spatial zero-sum reallocation) (Redding and Turner (2014), Donaldson (2015)). Our analysis focuses on two factors central to efficiency and growth in agriculture: comparative advantage based on crop suitability of land in a village, and technology adoption through investment in irrigation and fertilizer. Reallocation improves productivity when land is allocated to crops according to comparative advantage rather than transport cost differences. The interdependence between technology choice and crop choice can render some of the widely-used measures of reallocation and productivity change misleading. For example, a reduction in the share of land allocated to the modern variety of rice (HYV) in response to a reduction in trade costs may not imply adverse effects on technology adoption.[3] A third source of productivity improvements, largely neglected in the recent literature on the effects of trade costs, is multiple cropping, made possible through irrigation in dry seasons. The changes in cropping intensity may be especially important in land-scarce countries where the traditional extensive margin of agriculture in the standard von Thunen model cannot adjust

[3] The share of High Yielding Variety (HYV) of rice in total cropped land is used by many as a measure of technological change in agriculture in Asian countries where rice is the major crop. Our theoretical model shows that the expansion of area under high-value transport intensive crops such as vegetables can come at the expense of less transport intensive crop produced under modern technology such as HYV rice.

to a reduction in transport costs.

For empirical analysis, we use a subdistrict (upazila) level panel data set, and develop a difference-in-difference strategy where the comparison areas come from a region which were supposed to be connected to the growth centers in the center (Dhaka city) by the proposed, but not yet constructed, Padma bridge.[4] The identification is grounded on the following observation: the fact that Jamuna bridge was built in 1998, while the proposed Padma bridge is yet to be built, reflects idiosyncratic political factors (birth places of presidents and prime ministers) and thus can be treated as quasi-experimental. We take two additional steps to address potential biases in the DID estimates for the Jamuna treatment areas. First, we include upazila and year fixed effects in all of the regressions. Second, we implement doubly robust estimators that combine two alternative reweighting schemes with regression adjustments as suggested by Kline (2011), Busso et al. (2013) and Moretti and Kline (2014).

The empirical analysis uses four different indicators of technology adoption: proportion of land using chemical fertilizer, proportion of households owning irrigation equipment, cropping intensity, and green-ness depicted by Normalized Differences Vegetation Index (NDVI) during dry months. The analysis of cropland allocation focuses on four crops covering a range of transport costs and prices: High Yielding Variety (HYV) of rice, total rice crop, pulses, and vegetables. Rice is the main crop in Bangladesh; approximately 75 percent of land is allocated to rice (BBS, 2014). Rice (and paddy) is not perishable and can be transported from remote areas, but high-value vegetables are perishable and need quick transport to the urban market. Pulses are also high-value crop, but similar to rice in terms of transport intensity. Since we have data on whether the land in a village is more suitable for rice or vegetables, a comparison of these two crops allows us to analyze the trade-off between comparative advantage and trade costs.[5]

[4] Most of the studies on the effects of trade costs in the context of developing countries we are aware of rely on household level data. As pointed out by Donaldson (2015), among others, estimating the effects at such a disaggregate spatial level is subject to potentially serious biases from spillover (the SUTVA assumption is violated). We focus on a much larger spatial unit, upazila. There were 490 upazila's in Bangladesh in 1991, and most of the upazilas had population between 150,000 to 350,000.

[5] Unfortunately, the crop-specific land productivity data are not available for pulses. Land productiv-

The empirical evidence shows that, on average, subdistricts in the region connected by Jamuna bridge use chemical fertilizer in more land, have higher irrigation equipment ownership and higher cropping intensity, and show greater green-ness (NDVI), especially in the dry months. The results for the cropland allocation indicate a decline in the share of rice land, particularly HYV rice, and an increase in the share of pulses and a modest increase in the share of vegetables in the treatment region compared with the comparison region. The average effects, however, conceal interesting spatial nonlinearity in many cases, driven, in part, by land productivity heterogeneity. While the effects on fertilizer use decline monotonically with an increase in the distance from the bridge, the effects on cropping intensity display a non-linear (concave) spatial pattern. The areas that are 130 km-150 km away from the bridge experience the highest increase in cropping intensity compared with the areas near to or farther away from the bridge. The pattern of reallocation of cropland in areas with relatively higher vegetables productivity: land moved away from rice, particularly from HYV rice, to vegetables in the intermediate distance (110-150km) and into rice particularly in HYV rice in areas farther than 150km. This result suggests that construction of the bridge allowed cropping pattern in areas located in intermediate distance from bridge to align more closely to their natural advantages. This reallocation is associated with productivity gain even if we ignore the technology adoption since it allows vegetables to be grown in land better suited for vegetables production.

We contribute to the literature on the effects of better market access on agriculture in two ways.[6] First, we provide evidence on how a large reduction in trade costs improve effi-

ity for crop production is determined by million years of interactions of natural forces such as rainfall, temperature, wind, river, volcanic and glacial activities along with other terrain characteristics. Data on indicators of land productivity combining all these different factors have also become available recently.

[6] Among recent papers, Jacoby (2000) and Shrestha (2016) find positive impact of better access to markets on agricultural land value in Nepal. Several studies also find higher propensities for households to use modern inputs (fertilizer, irrigation, high yielding variety of seeds) and sell in the markets (Shamdasani (2016) for India, and Shrestha (2016) for Nepal, Ali et al (2016) for African countries, Kyeyamwa et al. (2008) for Uganda, Omamo (1998) for Kenya) and agricultural yields (Ali et al. (2016)), Dorosh et al. (2012) for sub-Saharan Africa. The positive impacts of better access to market is confirmed in the case of developed countries as well (see Donaldson and Hornbeck(2016), and Atack and Margo (2011), Haines and Margo (2006), Chandra and Thompson (2010)). See also Costinot and Donaldson (2016) and Costinot, Donalson and Smith (2016) for broader impacts of trade costs on agriculture.

ciency in resource allocation in a poor agricultural region by reducing the spatial mismatch between land productivity and crop choice because of heterogeneity in transport intensity and unit value of different crops. A lower trade cost allows better matching of crops with suitable land, consistent with comparative advantage. Although there is substantial evidence in the existing literature that better market access due to lower transport costs lead to crop diversification, especially in favor of the noncereal crops, it is not clear how to interpret this finding without evidence on the role played by land productivity heterogeneity.[7] If land in the treatment areas is less suitable for non-cereal production than that in rest of the country, then increased diversification into non-cereal crop may not improve over-all productive efficiency even though it increases a farmer's income in the treatment areas. Second, we provide evidence on spatial nonlinearity where the areas in the treatment areas located in the intermediate distance from the bridge experience the strongest effects on cropping intensity and reallocation of land with comparative advantage in vegetables. This spatial nonlinearity has two important implications: (i) the standard practice of using areas close to a bridge (or other transport infrastructure) as the treatment catchment is likely to underestimate the effects of bridge construction on reallocation of land, and (ii) large transport infrastructures such as a bridge may result in spatial inequality within the treatment region, even though the average effect is positive.

The rest of the paper is organized as follows. The next section sets up an extended von Thunen model of cropland allocation and technology production and derives testable predictions about the effects of a reduction in the cost of crossing the river. Section (3) discusses the background of the Jamuna bridge. We develop the empirical strategy in the next section, and discuss the data sources and construction of the variables in section (5). Sections (6 and 7) is devoted to empirical results. The paper ends with a summary of the findings and their implications for the literature.

[7]Shamdasani (2016) provides evidence that a better access to markets increases the land devoted non-cereal crops in India, and Emran and Shilpi (2012) find that market access leads to crop diversification in Nepal.

2 Theoretical Model

The Basic Set-Up

We extend the canonical von Thunen model of crop land allocation to incorporate technology adoption and land productivity heterogeneity. The possibility of investment in technology can introduce non-linearity in the cropping pattern with respect to the distance from urban markets. The standard von Thunen model focuses on the transport cost variation across areas, but assumes away heterogeneity in land productivity. This assumption, however, excludes any interaction of transport cost with natural advantage in determining the cropping pattern. Heterogeneity in land productivity is introduced in the model to allow for natural (and comparative) advantage to vary across areas. The productivity and transport cost heterogeneity help to explain deviation of the actual cropping pattern from inherent natural advantage when transport cost is especially high. This simple model provides a flexible framework to investigate the impacts of a *large* transport investment such as a major bridge on technology adoption and cropping pattern.

Geography

We consider the geography where all possible locations are ordered along a line between interval $[H_1, K_1]$ (please see Figure 1). The line is divided into three segments by the presence of two rivers. The first river (RV_H) is located between H_0 and C_H, and the second (RV_K) between C_K and K_0. As shown in Figure 1, the presence of rivers defines three regions: $H = [H_1, H_0]$; $C = [C_H, C_K]$; and $K = [K_0, K_1]$ where C is the central region and the other two are underdeveloped lagging regions. There are continuum of locations in each of the regions. Each location in region H (K) is indexed by h (k), where h (k) also depicts the distance from riverbank $C_H(C_K)$. In the absence of bridges, each river is crossed by using ferry. Two rivers are identical in width and water flow resulting in identical cost of ferry. The crossing of the river using ferry involves a product specific cost $(F_{Hi} = \beta_i F_H = F_{Ki})$ where $F_H(= F_K)$ is the travel time to cross the river and β_i is the marginal cost of crossing the river for product i. To avoid confusions, the notational conventions are: the subscript

i is the crop index ($i = X, Y$)and subscripts h and k are the location index in regions H and K respectively, and superscripts T and M denote traditional and modern technology respectively.

Each location is endowed with one unit of land. Regions H and K are identical to each other with one exception that they are located on the opposite sides of the region C. Region C is a central region consisting mostly of urban population and constitutes the primary market for agricultural goods. Following the standard von Thunen model, we assume that crop prices are determined in the urban markets in the central region C, and are exogenous for farmers in the peripheral regions H and K. Since regions H and K are identical, we can characterize the spatial equilibrium in this economy by focusing on region H. The effect of bridge can be posed as changes in equilibrium outcomes in H in response to building a bridge relative to that in K which remains cut-off without a bridge.

Production Technology and the Crop System

Each region can produce two crops: X and Y. Both crops can be produced using a traditional and a modern technology. While under traditional technology (T), each unit of land in an area h can produce A_{ih} unit of output of crop $i = X, Y$ and $h \in H$. Farmers can invest in an indivisible irrigation equipment per unit of land ($\overline{Z}$) and without loss of generality, we set $\overline{Z} = 1$. The irrigation equipment facilitates the adoption of modern technology (M) that increases land productivity multiplicatively by $\mu_i > 1, i = X, Y$. To purchase the irrigation equipment, farmers in location h need to pay P_{Zh}.

Rivers and Transport Costs

Let P_i be the price of crop i in the urban central region C where $i = X, Y$. We assume that X is perishable and transport intensive but also high-value ($P_X > P_Y$). Shipping crop i within the region is subject to iceberg cost ($1 > \tau_i > 0$) such that a unit of output shipped from distance h becomes $(1 - \tau_i h)$ at the riverbank. Crossing the river involves ferry cost and thus unit price of i at any location h is equal to $P_{ih} = P_i(1 - \beta_i F_h - \tau_i h) = P_i d_{ih})$ where F_h is distance of the river in terms of hours of ferry travel and β_i is product specific unit cost of ferry crossing. Irrigation equipment is imported from the central region where its price is fixed at P_Z. Crossing the river and traveling inside region H adds to cost of acquiring an irrigation equipment, so its price at h is equal to $P_{Zh} = P_Z(1+\beta_z F_h + \tau_z h) = P_Z d_{zh}$ where τ_z is cost of shipping the equipment from riverbank to location h and β_z is the unit cost of river crossing. Denoting revenue of crop i by $r_{ih} = P_i A_{ih}, i = X, Y$ the bid rent R_{ih} of crop at a distance $h \in [0, H_1]$ and under different production technologies can be written as follows:

$$
\begin{aligned}
R_{ih}^M &= \mu_i r_{ih} d_{ih} - P_Z d_{Zh} \text{ under modern technology} \\
R_{ih}^T &= r_{ih}\ d_{ih} \text{ under traditional technology}
\end{aligned}
$$

where superscripts M and T refer to modern and traditional technologies respectively, $i = X, Y$. Without land productivity heterogeneity across locations, the revenue of crop i is $r_i = P_i A_i$. The slope of the bid rent curve for i under traditional technology is determined by its price, transport cost and land productivity. The slope is steeper and intercept is larger if productivity (A_i) and price (P_i) are higher. Thus the bid rent curve for a high-value crop such as vegetables exhibits steeper slope when compared to a low-value crop such as rice. Also, the higher price and transport cost of irrigation equipment imply a steeper slope. Profit maximization by the farmers involves two decisions: whether to adopt modern technology and which crop to produce. The optimal decision can be described as:

$$R_h^* = Max\{R_{Xh}^T, R_{Xh}^M, R_{Yh}^T, R_{Yh}^M, 0\}$$

where R_h^* is the equilibrium land rent at the location h. Each location produces the crop with the technology that provides the highest land rent, and the equilibrium land rent thus encompasses the upper envelope of all bid rent functions. Given the assumption that crop X is more transport intensive, the slope of R_{Xh}^j is steeper than that of R_{Yh}^j for $j = M, T$. Farmers in region H will not produce X if $R_{X0}^j \le R_{Y0}^j$ at the riverbank where $h = 0$. To rule out this trivial case, we assume that $R_{X0}^j > R_{Y0}^j$. The extensive margin of cultivation can be defined as

$$H^E = \min\{H^*, H_1\}$$

where H^* is determined by setting $R^*_{YH^*} = 0$, since Y is less transport intensive crop.

(2.1) Equilibrium Allocation of Land and Technology Adoption Without Land Heterogeneity

As a benchmark, proposition 1 below summarizes the equilibrium spatial configuration of technology adoption and cropping pattern in the absence of land productivity heterogeneity across locations implying that $A_{ih} = A_i$, and the revenue $r_{ih} = r_i = P_i A_i$. This helps us to see how technology adoption alone can introduce non-linear pattern of crop land allocation with respect to the distance to markets. We relax this assumption later. Before describing equilibrium configuration of technology adoption and cropping pattern, we introduce some notations to help the exposition. Let i^j denote crop i produced using technology j where $i = X, Y$ and $j = M, T$. Let h^{jm}_{in} be the distance from riverbank such that $R^j_i(h^{jm}_{in}) = R^m_n(h^{jm}_{in})$, $i, n = X, Y$ and $j, m = M, T$.Thus h^{MT}_{XY} defines the intersection of R^M_X and R^T_Y and so on.

Proposition 1: *Under the assumptions that land productivity in each location varies across crops but is the same for a given crop across locations* ($A_{ih} = A_i$) *and that* $R^j_{X0} > R^j_{Y0}$, $j = M, T$, *the spatial equilibrium configuration of technology adoption and crop land allocation depends on the cost of irrigation equipment and the transport costs of crops and irrigation equipment:*

(i) *If the price of irrigation equipment is high and above a threshold* ($P_Z > \hat{P}_Z$), *then the farmers do not adopt modern technology and crop* X^T *is produced in all locations closer to the bridge* $h \in \hat{H}^T_X = [0, \hat{h}^{TT}_{XY}]$ *and crop* Y^T *in relatively remote locations* $h \in \hat{H}^T_Y = [\hat{h}^{TT}_{XY}, H^E]$;

(ii) *If* P_Z *is lower than a threshold,* $P_Z < \bar{P}_Z$, *then all of the farmers in region* H

produce both crops using modern technology, crop X^M is produced in all locations in the interval $\bar{H}_X^M = [0, \bar{h}_{XY}^{MM}]$ located closer to the bridge and crop Y in $h \in \bar{H}_Y^M = (\bar{h}_{XY}^{MM}, H^E]$ located farther from the bridge;

(iii) When the price of the irrigation equipment falls into an intermediate range defined by $\bar{P}_Z < P_Z < \hat{P}_Z$, the pattern of technology adoption and allocation of land to crops with respect to distance from the riverbank (h) depend on the relative transport costs. Farmers in locations $h \in H_i^M = [0, h_i^M]$ use modern technology in producing crop i. Depending on the relative lengths of $h_i^M, i = X, Y$, determined by the differential transport costs, three subregions can be defined in terms of land use. Crop X will be produced using modern technology in the subregion closest to the riverbank and crop Y using traditional technology in the subregion farthest from the riverbank. In the intermediate subregion, either crop Y will be produced using modern technology or crop X using traditional technology or both.

Proof: The cost of irrigation equipment is the lowest at the riverbank ($h = 0$) and increases at the rate of τ_z with an increase in distance from the riverbank (h). Noting that, at the riverbank (i.e., location $h = 0$), $R_{X0}^M > R_{Y0}^M$, $\hat{P}_Z$ in proposition $1(i)$ can be determined by setting $R_{X0}^M(\hat{P}_Z) = R_{X0}^T$. Intuitively, $\hat{P}_Z$ is the price at which the bid rents for crop X at the riverbank are equated across traditional and modern technology. With $P_Z > \hat{P}_Z$, technology adoption is not feasible in any location $h \in H$, and thus both crops are produced with the traditional technology. Because R_{Xh}^T is steeper than R_{Yh}^T, areas closer to the riverbank $h \in \hat{H}_X^T = \hat{H}_X^T = [0, \hat{h}_{XY}^{TT}]$ are planted with X, and areas farther away with crop Y, where $\hat{h}_{XY}^{TT}$ is determined by setting $R_X^T(\hat{h}_{XY}^{TT}) = R_Y^T(\hat{h}_{XY}^{TT})$.

In proposition $1(ii)$, threshold of irrigation cost $\bar{P}_Z$ is determined by equating the bid rents for crop Y at the boundary of extensive margin H^E with and without adoption of technology, i.e., $R_{YH^E}^M(\bar{P}_Z) = R_{YH^E}^T$.The intuition for allocation of land is similar to that for proposition $1(i)$ where $\bar{h}_{XY}^{MM}$ is determined by equating $R_X^M(\bar{h}_{XY}^{MM}) = R_Y^M(\bar{h}_{XY}^{MM})$.

For $\bar{P}_Z < P_Z < \hat{P}_Z$, $R_{ih}^M > R_{ih}^T$ at $h = 0$ and $R_{ih}^M < R_{ih}^T$ at $h = H^E$, $\forall\, i = X, Y$. Farmers producing crop i will use modern technology up to the distance h_i^M such that $R_{ih}^M \geqq R_{ih}^T$ for $h \leqq h_i^M$, and $R_{ih}^M < R_{ih}^T$ for $h > h_i^M$. The border of the zone of modern technology for each crop i (h_i^M) is determined by equating R_{ih}^M and R_{ih}^T.

$$h_i^M = \frac{r_{i0}d_{i0}(\mu_i - 1) - P_Z d_{Z0}}{(\mu_i - 1)\tau_i r_{i0} + \tau_z P_Z} \text{ for } i = X, Y \tag{1}$$

where $d_{i0} = (1 - \beta_i F_h)$ and $d_{Z0} = (1 + \beta_z F_h)$.Under the assumptions that crop X is more transport intensive and also of higher-value, i.e., $\tau_x > \tau_y$ and $R_{X0}^M > R_{Y0}^M$, the slope of bid rent curve for X $(\tau_x r_{x0}\mu_x + \tau_z P_Z)$ is greater than that for Y $(\tau_y r_{y0}\mu_y + \tau_z P_Z)$ when both are produced using the modern technology. The larger is the transport cost (τ_x), the greater is the possibility that $h_X^M < h_Y^M$. Similarly, R_X^T is steeper than R_Y^T. The slopes and intercepts of these four bid rent functions determine the equilibrium cropping pattern. In the appendix, we describe the possible outcomes that may result from different values of transport cost parameters along with prices and land productivity differences of the two crops. The regularity that emerges from these outcomes is that transport intensive X is produced using modern technology near the riverbank and less transport intensive crop Y is produced under traditional technology in the subregion farthest from the riverbank. In the intermediate sub-region, either X is produced under traditional technology, or Y using modern technology or both. When both are produced, their relative location within the sub-region is determined by the underlying slope and intercept parameters.

Technology Adoption and Cropping pattern in Bangladesh

It is clear from proposition 1 that many different outcomes and spatial configurations of technology adoption and cropping pattern are possible depending on the magnitudes of productivity parameters, transport costs, product prices and the cost of technology investment. Before describing the possible impact of constructing a bridge over the river, we highlight some distinctive features of land use in Bangladesh that help to narrow down these possibilities. First, population density in Bangladesh is exceptionally high even in rural areas (800/sq km) and all available agricultural land has been under cultivation for many decades.[8] To account for the land constraint in agriculture, we relax the standard von Thunen assumption that opportunity cost of land is zero at the extensive margin by normalizing transport cost of Y to zero ($\tau_y = 0$). This assumption implies that $H^E = H_1$. Second, the HYV rice is more water and thus irrigation intensive crop than vegetables. We assume that irrigation boosts productivity of Y (rice) more than that of X (vegetables) ($\mu_y > \mu_x$), but because of higher value of vegetables, the bid rent at the riverbank is higher for vegetables, and we have $R^j_{X0} > R^j_{Y0}$, $j = M, T$. R^T_X curve (line) is assumed to be flatter than R^M_Y : $(\tau_x r_{x0} < \tau_z P_Z)$, partly because of indivisibility of irrigation equipment (P_Z). While viewed as a tax, this assumption implies that the transport tax on irrigation is higher than that on crop X. Note that the slope of bid rent curve R^M_{Yh} is $\tau_z P_Z$ whereas for R^T_{Xh}, it is $\tau_x r_{x0}$. As shown in the appendix A, several different cropping patterns may result depending on the slopes and intercepts of the bid rent functions.

We focus on the equilibrium where both crops are produced under both technologies.[9] This equilibrium land allocation is illustrated in Figure 2a. The equilibrium shows interesting and non-linear spatial pattern. The area near the riverbank (closest to the urban markets in C) are planted with the transport intensive crop X $(h \in H^M_X = [0, \bar{h}_1 = h^{MM}_{XY}])$ followed by a subregion that produces Y $(h \in H^M_Y = (\bar{h}_1 = h^{MM}_{XY}, \bar{h}_2 = h^{MT}_{YX}])$, and both crops are produced using the modern technology. Farther away, land use reverts back first to X $(h \in H^T_X = (\bar{h}_2 = h^{MT}_{YX}, \bar{h}_3 = h^{TT}_{XY}])$ and then to Y $(h \in H^T_Y = (\bar{h}_3 = h^{TT}_{XY}, H^E])$, both produced under the traditional technology. It is illustrative to consider the cropping pattern that would have resulted from a traditional von Thunen set up without productivity heterogeneity and technology adoption. The equilibrium outcome would be to produce X in the interval $(0, h^{TT}_{XY})$ and Y in $(h^{TT}_{XY}, H^E]$. The possibility of technology adoption introduces non-linearity in cropping pattern with respect to distance from market (bridge). This non-linearity is often taken as an evidence of reverting back to subsistence (Fafchamps and Shilpi (2003)). The modified von Thunen model presented here provides an alternative

[8] According to 2008 agricultural census, arable land per person is only about 0.0482 hectare.

[9] Both crops are produced using both technologies if $(\tau_x r_{x0} > \tau_z P_Z)$. But cropping pattern in this case is different from what is shown in Figure 2a. In this case, X^M is produced in the interval nearest to riverbank followed by X^T, then Y^M and Y^T.

explanation for this non-linearity which arises because of higher transport cost of indivisible irrigation equipment relative to that of perishable high-value crops. Before introducing land productivity heterogeneity, we consider the possible effects of bridge on technology adoption and cropping pattern in the benchmark model without productivity heterogeneity.

The Impact of the Bridge on Technology Adoption and Cropping Pattern

Suppose a bridge is constructed over river RV_H, but no bridge is built over RV_K. A reduction in the cost of crossing the river (F_H) increases prices of both crops received by the farmers and reduces the price of irrigation equipment paid by the farmers. Proposition 2 summarizes the predictions regarding the impacts of bridge on technology adoption and cropping pattern if bridge led to a reduction in cost of river crossing.

Proposition 2: *A decrease in the ferry cost* (F_H) *leads to the following results:*

(i) *extends the zones within which farmers adopt modern technology,*

(ii) *increases the extensive margin of cultivation if* $H^E < H_1$,

(iii) *increases land allocated to crop* X *if* $H^E = H_1$ and $\beta_x \geqq \beta_y$ *and where* β_x *and* β_y *are unit ferry/river-crossing costs for* X *and* Y *respectively; and*

(iv) *its impacts on cropping pattern in the intermediate subregion is ambiguous. The larger is the decrease in ferry cost, the greater is the extension of zones of modern technology and extensive margins.*

Proof: Proposition $2(i)$ follows directly from equation 1. A reduction in F_H increases h_i^M by increasing the price received by farmers for their crop and by decreasing the price they need to pay for the irrigation equipment. Proposition $2(ii)$ follows from the fact that at the edge of the extensive margin, Y is produced either using modern or traditional technologies. At $H^E < H_1$, $R_Y^j = 0, j = M, T$. As a lower ferry cost increases R_Y^j, it follows that $\frac{\partial H^E}{\partial F_h} < 0$.

For propositions $2(iii)$ and $2(iv)$, we show in the appendix that $\frac{\partial h_{in}^{jm}}{\partial F_h} < 0, i, n = X, Y$ and $j, m = M, T$, if $\beta_x \geqq \beta_y$. A lower ferry cost shifts all of the bid rent curves upward and thus pushes all intervals of crop specialization towards the farthest border of region H (H_1). This unambiguously increases land under X near the riverbank if $H^E = H_1$.The impacts in the intermediate zone depends on the initial configuration of cropping pattern which, as shown in proposition 1, in turn is determined by the cost of technology adoption and intercepts and slopes of bid rent functions. In the aggregate, the share of land allocated to X increases as bridge pushes all the circles of crop specialization toward the farthest areas and because extensive margin of land can not be increased.

(2.2) Implications of Land Productivity Heterogeneity

The model so far assumed land productivity of each crop to be homogeneous across areas. To illustrate how heterogeneity in land productivity across areas can affect technology adoption and cropping pattern, we focus on a simple case where land productivity of Y is homogeneous across areas but that of X varies with distance in the following manner:

$$A_{xh} = (1 + \psi h) A_{x0} \tag{2}$$

where ψ can be positive or negative. A positive ψ indicates increasing land productivity with an increase in the distance from the riverbank and vice versa. The bid rent function for X becomes nonlinear when land productivity changes with respect to the distance from the riverbank. As we show in the appendix, the bid rent function R^M_{Xh} is concave (convex) if $\psi > 0$ $(\psi < 0)$. For $\psi < 0$, the bid rent for crop X produced using either technology declines with the distance on account of a decrease in land productivity in addition to transport cost. In other words, the farmers located farther away from the riverbank face double disadvantages due to the higher transportation costs and a lower land productivity. The pattern of technology adoption and land allocation described in proposition 1 would hold however with band/intervals for crop X becoming shorter. *Heterogeneity in land productivity with respect to the distance to the riverbank either accentuates or offsets the impacts of transport costs on technology adoption and land allocation described in proposition (1).*

For $\psi > 0$, land productivity increases with distance raising bid rents above what it would have been with $\psi = 0$. The productivity increase can offset the decrease in bid rent due to higher transport cost depending on the magnitude of ψ. But the bid rent curves are now concave. For $\psi \leq \frac{1}{1-\beta_x F_h}\left[\tau_x + \frac{\tau_z P_Z}{\mu_X r_{X0}}\right]$, bid rent curve R^M_{Xh} is downward sloping but lie above the straight line bid rent curve for $\psi = 0$ described in proposition 1 (see Figures 2a and 2b). For $\psi \leq \frac{\tau_x}{1-\beta_x F_h} < \frac{1}{1-\beta_x F_h}\left[\tau_x + \frac{\tau_z P_Z}{\mu_X r_{X0}}\right]$, bid rent curve R^T_{Xh} is concave but downward sloping. The pattern of technology adoption and land allocation described in proposition 1 still holds, but the intervals for crop X produced under modern and traditional technologies both expand.[10] With a large enough ψ, it may become feasible to adopt modern technology in the production of X in the intermediate sub-region. The basic insights derived from the parametric land productivity function carry over to the case where land productivity is not distributed monotonically over space according to a formula as in equation (2). With random distribution of land productivity parameter over geographic space, the probability of technology adoption and the amount of land allocated to a crop will increase with an increase in land productivity in the intermediate subregion.

By assumption, $R^M_{X0} > R^M_{Y0}$ at the riverbank ($h = 0$) implying that $P_X \mu_X A_{X0} > P_Y \mu_Y A_{Y0}$. However, this condition may hold even if $A_{X0} < A_{Y0}$ as long as $\frac{P_X}{P_Y} > \frac{\mu_Y A_{Y0}}{\mu_X A_{X0}}$. Thus X^M is produced near the riverbank because of its high value even though the land there may not be the most suitable for its production. On the other hand, at much farther distance from the riverbank, the high transport cost of X may more than offset any advantage from a higher land suitability, resulting in the land being used in less transport intensive crop Y. Proposition 3 below summarizes the key insights when land productivity of a crop can vary across areas.

Proposition 3: *A Moderate land productivity heterogeneity may not affect the technology adoption and land allocation pattern in the nearest and the farthest sub-regions from the central market while its effects are felt more prominently in the subregion located at the*

[10] When ψ is large enough $\left(\psi > \frac{1}{1-\beta_x F_h}\left[\tau_x + \frac{\tau_z P_Z}{\mu_X r_{X0}}\right]\right)$, production of X may become feasible even if $R^M_{X0} < R^M_{Y0}$ at the riverbank.

intermediate distance. In the intermediate sub-region, the higher is the land productivity of a crop relative to that of other crops, the higher is the possibility that it is produced in that location.

Land Productivity heterogeneity in Bangladesh

The impacts of bridge depend on the distribution of land productivity with respect to the distance to the bridge. In Figure 4a, we plot the non-parametric graph of subdistricts top-ranked for vegetables relative to subdistricts top-ranked for rice production with respect to the distance to the bridge site. The relative productivity of vegetables (X) is lower in the subregions located nearest and farthest from the bridge site and higher in the intermediate sub-region. For simplicity, we divide region H into three sub-regions V_1, V_2 and V_3 such that V_1 is located at the riverbank and consists of all areas in distance interval $[0, h_1)$, and V_2 in the interior and covers all areas in distance interval $[h_1, h_2)$. Subregion V_3 is located even farther away at distance h_2 from the riverbank and covers all locations in distance interval $[h_2, H_1]$. To reproduce the relative productivity of X, we normalize land productivity for Y to unity in each location $A_{Yh} = 1$. We assume that land productivity for vegetables X is equal to A_X in V_1 and V_3 but higher in V_2 ($A_{X2} > A_X$). To highlight the source of mismatch between natural advantage and the actual cropping pattern, we assume that ($A_{X2} > A_Y = 1 > A_X$). In Figure 2a, the borders of the three subregions are identified and the bid rent curves for X (labeled $R^J_{x2}, J = M, T$) are shown in brown color.

As shown in Figure 2a, actual land use pattern does not overlap well with natural advantage reflected in land productivity. This mismatch arises partly because of transportation costs for irrigation equipment and partly because of higher value of transport intensive perishable product (X). Without transport cost of equipment, all land in $h \in [h^{MM}_{XY}, H_1]$ should be planted with Y. On the other hand, if there were no cost of transporting X, then all land in region H should be planted with high-value crop X, resulting in a mismatch of natural advantage and actual cropping pattern in V_1 and V_3.

Land Productivity Heterogeneity and the Effects of Bridge

The impacts of bridge on technology adoption and cropping pattern vary with land productivity.

Proposition 4: *A reduction in river crossing cost increases the probability of technology adoption and land use in a crop that is transport intensive and has relatively better land productivity and this effect is most prominent in the intermediate sub-region. The expansion of land under transport intensive crop (X) may come at the expense of less transport intensive crop (Y) produced under modern technology.*

To see the intuition behind this, we start with initial equilibrium where $R_Y^M > R_{X2}^M > R_X^M$ at $h = h_1$, where R_{X2}^M is the bid rent function at land productivity A_{X2}. The minimum reduction in F_h that is required to switch land from crop Y to crop X is then $\Delta F_h \geqq \frac{R_Y^{M0}(h_1) - R_{X2}^{M0}(h_1)}{\beta_x r_{x0} - \beta_y r_{y0}}$. The higher is A_{X2}, the lower is the reduction in ferry cost needed to induce a change in cropping pattern. Note also that this expansion of crop X produced under modern technology in V_2 comes at the cost of a decline in land to crop Y produced under modern technology (Figure 3). Similarly, large enough decrease in F_h can make technology adoption feasible for Y in V_3, shrinking land allocated to both X and Y produced using traditional technology. As a result of bridge, land allocated to modern variety increases at the expense of traditional variety for each crop, the effects of bridge on total land allocated to each crop at the regional level may not change.

3 Costs of Crossing the River and the Jamuna Bridge

Bangladesh, a riverine delta, is sliced into three separate regions by two major rivers in Asia: the Ganges (locally known as Padma) and Brahmaputra (locally known as Jamuna) (see map 1). These two rivers effectively cut-off the north-west and southern regions of the country from the growth centers in the middle where the capital city Dhaka is located. The 4.8 kilometer long Jamuna bridge connected the poor north-west region (about 26 million and 24.5 percent of country's total population in 1991) to the main growth centers

(Dhaka city). The bridge has 4 vehicle traffic lanes, and a railway line. The actual cost of building the bridge was about $985 million. Three donors (World Bank, JICA and Asian Development Bank) each contributed roughly about $200 million, and the rest was borne by the country itself.

The bridge had significant impact on the travel time and transport costs. Before the opening of the bridge, crossing the river by ferries took more than 3 hours, and during heavy traffic periods (e.g. Eid festivities), the average waiting time at the ferry ran as high as 36 hours (Staff Appraisal report, World Bank).[11] River crossing after the opening of the bridge in June 1998 takes less than an hour (including waiting time). According to government estimates, the bridge cut the average travel time by 4 hours during the normal traffic time, and reduced the freight costs by a half. Travel time by truck between Bogra town in the north-west region and the capital city Dhaka was reduced from 20 hours to 6 hours.[12] The bridge thus removed a critical bottleneck in the transport connection and led to a very substantial reduction in transport time and costs. Such a large and discontinuous reduction in transport costs provides an excellent opportunity to estimate the effects of trade costs on spatial pattern agricultural development.

To identify the effects of the bridge, we exploit the fact that the southern part of the country is also separated from the growth centers in the capital city Dhaka and port city Chittagong by Padma river. While bridges were proposed to be built on both Padma and Jamuna rivers to connect the southern and north-western regions of the country respectively, the bridge over Jamuna river was built first due to idiosyncratic political reasons (birth places of presidents and prime ministers). 17 years of the two decades between 1977 and 1999, Bangladesh was governed by leaders (Ziaur Rahman, Hossain M. Ershad and Khaleda Zia) who hailed from the north-west region, and the Jamuna bridge got priority during these 17 years. The construction of the bridge required large investment for which donor funding was necessary. The fact that the north-west region suffered disproportionate

[11] The estimate is for 1993.

[12] It took much longer for trucks to cross the river by ferry because buses carrying people had priority in getting access to the ferry boats.

fatality during the 1974 famine made it easier to secure donor funding for Jamuna bridge first. The construction of the proposed Padma bridge started only in December, 2015 under the current prime minister whose ancestral home is located in the sourthern region. We use the sub-districts (upazilas) in the southern region as controls for the treatment areas in north-west.

4 Empirical Strategy

To estimate the effects of the Jamuna bridge, we compare the subdistricts in the treatment area with the subdistricts in the appropriately defined comparison area with similar pre-bridge characteristics. We use the following fixed effect difference-in-difference (FE-DID) specification:

$$Y_{ijt} - Y_{ijt-1} = \alpha + \beta \left(T * Yr \right) + \gamma_1 Z_{ijt_0} + \gamma_2 Z_{ijt} + \delta T + \mu Yr + \varepsilon_{ijt} \tag{3}$$

where Y_{ijt} is the outcome variable j in subdistrict i and period t. T is a dummy which takes a value of unity if a subdistrict is located in the service area of Jamuna bridge and zero if it is located in the comparison area. Yr is a dummy that takes the value of unity if the year is after 1998 and zero otherwise. Z_{ijt_0} is a matrix of pre-bridge characteristics and Z_{ijt} is a matrix of contemporaneous and exogenous characteristics (e.g. rainfall). We implement the location fixed effects by first differencing of the dependent variable which wipes out the location specific and time-invariant factors, whereas α captures the common shocks. In this formulation, the estimate of β is the treatment effect of the bridge.

The vector of pre-bridge covariates includes log of population density in 1991, an index of suitability of land for crop production, dummies for whether the land quality in a subdistrict is top-ranked for rice or vegetables. Since our focus is on agricultural development, the variation in rainfall across subdistricts may influence the estimates of treatment effects. To guard against this possibility, we include contemporaneous rainfall as an additional comparison. To correct for possibly spatial correlations, all regressions cluster standard errors at the regional level ('divisions' in local term).[13]

In addition to the fixed effect DID (FE-DID) estimates using OLS for equation (3), we undertake two weighting schemes using the pre-bridge characteristics to improve the comparability of treatment and comparison areas. The first approach uses propensity scores from a logit model of the probability of being included in the treatment area using the pre-bridge characteristics. The predicted probabilities are used to define weight for each observation (subdistrict) in the comparison subset. The logit regression include pre-bridge characteristics such as log (population in 1991), the ranking of upazilas in terms of suitability of land for vegetables production and for rice production, and the distance to bridge (the Jamuna bridge for the treatment and the proposed Padma bridge for comparison) as controls. For vegetation index, distance to the capital city Dhaka is also included in the controls. Note that the DID regressions directly control for the pre-bridge characteristics, and thus the approach is similar to the doubly-robust estimators proposed by Robins et al. (1994) and Wooldridge (2007). We call this approach LWRA (logit weighted and regression adjusted) estimator. The second estimator developed by Kline (2011) and Moretti and Kline (2014) uses weights generated from the Oaxaca-Blinder approach as suggested by Kline (2011). The variables used for the Oaxaca-Blinder weights are the same as the ones used in computing the logit probability weights. The Oaxaca-Blinder estimates of the effects of bridge are also doubly robust, as discussed by Kline (2011).

5 Data

To estimate the effects of Jamuna bridge on the pattern of agricultural specialization and technology adoption, we rely on subdistrict (upazila) level panel data. Several data sources, including agricultural and population censuses and different GIS databases, are utilized to create the dependent and explanatory variables in our analysis. The agricultural censuses are available for two years (1998 and 2008). Agricultural specialization is measured by the

[13] The country is divided into 7 regions/divisions, each of treatment and control areas comprises of two divisions.

share of total cropped land allocated to rice, pulse and vegetables.[14] Rice is the staple crop and less perishable whereas vegetables are high-value but perishable and transport intensive. Pulse is also high-value, but less transport intensive, similar to rice. Cropping intensity depicts multiple use of land for crop production and thus captures agricultural intensification, especially through irrigation during the dry season. Though agricultural land is approximately fixed in Bangladesh, multiple use of the same land as reflected in higher cropping intensity can in practice extend the availability of land similar to an expansion of the extensive margin in the standard von Thunen model. From the census data, two indicators of technology adoption are considered: the share of land where fertilizer is applied and the average ownership of shallow tube-wells, the main equipment used in irrigation, in an area. The data for crop land allocation and technology adoption are drawn from two agricultural censuses (1998 and 2008). The data for 2008 come from the sample survey conducted as a part of the 2008 agricultural census. For 1998, the data set consists of about 30 percent of the unit records from agricultural census. To make data comparable, we deflate all of the variables by total cropped land in the relevant upazila, with the exception of irrigation equipment. Irrigation equipment is measured by proportion of households owning a shallow tube-well in the upazila. Shallow tube-well is the most common equipment used for irrigation in rural Bangladesh.

We supplement the census data by using remote sensing data on normalized difference vegetation index (NDVI) which depicts green-ness of an area/pixel. Using satellite data on strong plant reflectance, The normalized difference vegetation index (NDVI) is defined using sattellite data on strong plant reflectance (see appendix B for more detail). To minimize the gaps in the early satellite data, we restrict our analysis to the period covering 1996-2014 and define quarterly averages from bi-weekly data.[15] The first quarter corresponds to the driest months in the year whereas third quarter covers the monsoon time. While NDVI data have been used to examine changes in forest covers, its use in detecting changes in

[14] Total cropped land is equal to total agricultural land in use multiplied by cropping intensity where cropping intensity measures the number of times same piece of land is used in cultivation.

[15] The NDVI data are available for a sufficiently long period of time (bi-weekly data from mid 1980s to 2014 but not for every year before 1996).

agricultural practices in the context of Bangladesh is aided by couple of factors. The forest cover is very limited in the country, concentrated mainly in three areas: Sundarban in the south, Hill tract districts in Chittagong and the tea gardens in Sylhet division. The rest of the land outside of urban settlements are utilized in agriculture. The land constraint for agriculture is evident in the average farm size which is less than an acre. For the empirical analysis, we restrict our sample to the areas not covered by forest/tea gardens. Second, the leaf canopy on cultivated land changes depending on the utilization of land as well as irrigation, particularly in the dry months (first and last quarters). Thus changes in NDVI can capture changes in technology adoption and agricultural intensification. In the empirical analysis, we consider annual average vegetation index along with its average during two relatively dry seasons: first and fourth quarters of the year.

To create a consistent upazila level panel from the censuses and the remote sensing data, we use upazila maps to identify the borders of upazilas overtime. The upazila level panel is then defined using 1990 upazila boundaries. All censuses and surveys use the same master codes and names for the upazilas and thus matching of the upazilas that did not change boundaries is quite straightforward. Most of the upazilas in rural areas did not change overtime. The matching for those upazlias that were split and/or recombined was done by superimposing digital maps from different years. We use area weights to link the newly created upazilas to 1990's upazilas. Total number of upazilas in our data is 122 in the treatment region (Jamuna bridge service area) and 105 in the comparison region (Padma hinterland).

Among other variables, population data are drawn from census. The original data on rainfall are 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 2014. The CRU method combines weather station data with other relevant information to arrive at the estimates. To estimate the sub-district (upazila/thana) level rainfall from the CRU data, we use area weighted averages. The crow-fly distance between the geographical center of a subdistrict to the Dhaka city is estimated using GIS software.

Data on agro-ecological zones are drawn from the Bangladesh Water Board database which was prepared as background work for FAO's broader GAEZ database.[16] The advantage of this data set is that in addition to providing information on agro-ecological zones, it also ranks land in terms its suitability to production of certain crops. Ranking is provided in a scale of 1 to 5 with 1 being best. This ranking is available for rice and vegetables but not for pulses.

6 Evidence on the Plausibility of the Research Design

(6.1) Comparability of Treatment and comparison Areas

The treatment sample consists of 122 upazilas, located in the North West (henceforth NW) region that was connected by the Jamuna bridge to the central region where the capital city Dhaka is located. The upazlias in the south that remained cut-off from Dhaka city due to the delay in constructing a bridge over Padma river serves as our comparison/comparison. After dropping 4 upazilas that constitute the protected natural forest in Sundarban, our comparison sample consists of 105 upazilas. To see whether the south provides a good counterfactual region for the treatment region (NW), we provide summary statistics during the pre-bridge period in Table 1. Column 1 reports the means for the treatment areas in the NW and columns 2-4 report unweighted and weighted means for the comparison areas in the south, and the last three columns provide the respective p-values of a test of the null hypothesis that the difference between the treatment and comparison upazilas is zero. As explained in the econometric strategy section above, the weights are derived from Logit and Oaxaca-Blinder regressions.

The top panel in Table 1 reports the evidence on land productivity measured by the average rank of land in terms of its suitability in crop production. This suitability index can be taken as a measure of natural advantage of land. A higher average for the rank

[16] These detailed data sets were put together by researchers and scientists at Bangladesh Agricultural Research Council in collaboration FAO researchers under a project by the Water Board and formed the basis for Global Agro-Ecological Zone data on Bangladesh compiled by FAO.

indicates less suitability and less land productivity for the crop in question. The evidence suggests an absence of statistically or numerically significant differences in land productivity between the treatment and the comparison regions (the smallest p-value=0.17). The second panel reports the means of a number of pre-bridge characteristics of treatment and comparison areas, and the two regions appear quite similar in terms of total population and its density, and rainfall and its variability. In terms of the level of NDVI, the comparison areas are on average greener, and the difference between the comparison and treatment areas are statistically significant in the driest months during the first quarter of the year (p-value=0.03 for the unweighted means difference). In the case of annual change in NDVI, the difference in means is numerically small and is statistically significant only in the first quarter of the year. There are some statistically significant differences in the cropping pattern: both the land under high yielding variety (HYV) of rice and vegetables are larger in treatment areas, whereas that under pulses is higher in the comparison areas. However, there is no significant difference in the proportion of land under chemical fertilizer and of household owning irrigation equipment. When considered along with the evidence of no significant difference in land productivity discussed above, this evidence on productivity enhancing inputs suggests strongly that the treatment and comparison areas were similar in the pre-bridge period in terms of agricultural potential and technological development. For most variables, the differences in the weighted averages are smaller than in the unweighted averages, with the exception of some of NDVI variables.

(6.2) Doubly Robust Approach: Evidence from Placebo Tests During the Pre-treatment Period

The evidence from Table 1 shows that the treatment and comparison areas balanced in terms of some variables, while they differ significantly for other variables such as land allocated to high-yielding variety of rice and vegetables. For some of the variables, these differences are not smoothed out by weighting (logit or Oaxaca-Blinder). The recent literature suggests that a doubly robust approach that combines weighting with regression adjustments is likely to be better at achieving pre-treatment balance and providing credible estimates of treatment effects. To see if our treatment and comparison subdistricts are well balanced in terms of pre-bridge characteristics when we use the doubly robust approach, we estimate the effects of a placebo bridge on our dependent variables using the pre-bridge data. We estimate the effects of the placebo treatment on changes in vegetation indices for dry seasons and annual average during pre-bridge period. These false experiments test whether the outcome variables are statistically different between treatment and comparison areas once we implement both weighting and regression adjustments. Because tests are done with data prior to the opening of the bridge, these falsification tests should be able to indicate if the doubly robust approach is successful in dealing with any selection bias between the treatment and comparison subdistricts.

Table 2 reports the results from these doubly robust placebo regressions. Columns 1 and 2 in Table 2 report the differences between the treatment and comparison subdistricts and p-values when logit weighting is buttressed with direct regression adjustments using the same set of pre-bridge characteristics, and columns 3 and 4 report the results for the Oaxaca-Blinder (OB) regressions. The vector of controls include the log of population density in 1991, suitability of land for crop production, log of average and standard deviation of rainfall in 1991, and whether an upazila is top-ranked for rice and vegetables production. In contrast to the evidence in Table 1, the estimates in Table 2 indicate *the absence of statistically significant differences between treatment and comparison regions for all of the variables*. Overall, we find no significant differences in the *levels* of outcome variables between the treatment and comparison areas during the pre-bridge periods. For the outcomes such as vegetation indices for which we have multiple years of observations before the opening of the bridge, we find no significant differences in *trends* either. We interpret this evidence as supportive of the research design based on fixed effect DID and doubly robust estimators.

7 Evidence on the Effects of Jamuna Bridge on Agricultural Development

(7.1) The Average Effects of Jamuna Bridge on Technology adoption, Land use intensity and Cropping pattern

The estimated effects of Jamuna bridge on treatment areas in NW compared with the comparison areas in south are reported in Table 3. The FE-DID-OLS estimates conditioned on a small set of pre-bridge characteristics described above are reported in column 1. Columns 2 and 3 report the estimates from logit and OB weighted regressions, using the same set of controls for direct regression adjustments, respectively. A comparison of the estimates across columns indicate some differences among the three sets of estimates, but those differences are numerically small. For most of the regressions, the magnitudes of the estimates are smaller in OB weighted regressions with a few exceptions (e.g. the share of rice land). The weighted estimates have smaller standard errors as well. For the discussion below, we focus on the OB weighted estimates.

The upper panel in Table 3 reports the estimates for technology adoption using six indicators. The estimates suggest positive and statistically significant impacts of Jamuna bridge on all six indicators of technology adoption. While cropping intensity and fertilizer use increased in both the treatment and comparison areas during the post-bridge period, the estimates imply an additional 3 percent increase in the cropping intensity, and a 7 percent increase in the share of land using chemical fertilizer in the treatment upazilas compared with the comparison upazilas. The implied additional increase of ownership of irrigation equipment is much larger (0.157) which compares favorably with its level in the pre-treatment period (0.11). The impressive increase in fertilizer use and irrigation adoption is reflected in the changes in vegetation index NDVI. The estimates suggest that the treatment areas have become greener compared with the comparison areas after the opening of the bridge. The increase in NDVI is much larger during the dry seasons (first and fourth quarters of the year) relative to the average for the year consistent with a substantial increase in irrigation.

The results for cropping pattern are more complex. There is a significant decline in the share of HYV rice as well as in the share of total rice, but an increase in the share of land allocated to pulse. The increase in the share of vegetable while statistically significant is modest numerically. The decrease in the share of land devoted to the low-value and low transport-intensive crop rice is consistent with the canonical von Thunen model where a reduction in the transport cost increases the share of land going into transport intensive high-value vegetable crops. However, a considerable decline in the share of HYV rice on the other hand appears puzzling in the light of robust positive response found in technology adoption after the opening of the bridge. The modified von Thunen model presented in section 2 shows that land productivity heterogeneity can lead to such an outcome (Figure 3) when upward shifts in the bid rent curve due to a reduction in costs of transportation for vegetables are larger than that for rice.

(7.2) Heterogeneous Land Productivity and the Effects of Bridge

A central focus of this study is to understand whether a large reduction in trade costs lead to a better matching of land productivity and crop choices according to comparative advantage. To see if the reduction in transportation cost due to bridge opening helped cropping pattern to align more closely with the natural land productivity, as predicted by the modified von Thunen model in section 2 above, we explore the heterogeneity in the effects of Jamuna bridge with respect to land productivity. The theoretical analysis, however, suggests that the inherent land productivity matters much less if an area is too close to the markets in the central region or too far away. As a first step to examining this heterogeneity, we define relative land productivity for transport intensive high-value crop vegetables. Using the ranking of land in terms of its suitability for production of different crops developed by the agronomists, we define the relative productivity as the ratio of the rankings of rice and vegetables. Recall that land productivity for a crop is ranked in the scale of 1 to 5, with 1 being the best. The relative productivity variable as defined (rank of HYV rice/rank of vegetables) indicates how good the land in a subdistrict is for vegetables production relative to the high-yielding variety of rice production. Figures 4a and 4b plot the non-parametric graphs of this relative productivity indicator and of the actual share of land allocated to vegetables in the NW during the pre-treatment year (1998) against the distance from bridge location respectively. The average vegetable productivity relative to HYV rice is low at the riverbank and remains nearly flat for the distance up to 100 km from the bridge location, and it rises with distance, reaching its peak at around 200 km from the bridge. In contrast, the share of land devoted to vegetables in 1998 increases with distance up to 100 km from the bridge location and starts falling after 110 km. That the peak of vegetables land share is reached half way to its peak of land productivity is indicative of very high transport costs during the pre-bridge period.

According to the modified von Thunen model, the large reduction in transport cost due to the opening of the bridge should help expand the share of land to vegetables in the areas farther from the bridge (beyond 110 km), and particularly in those areas with higher vegetables productivity. To test this formally, we define a dummy D_i^V that takes the value of unity if relative vegetable productivity of a subdistrict is greater than unity and zero otherwise. This dummy represents the subdistricts which have better productivity ranking for vegetables compared with HYV rice. We then define a set of distance dummies using different distance cut-offs. The dummy is labeled 'D^{Far}' because it takes the value of unity if a subdistrict is located farther than the cut-off. For instance, for a distance cut-off of 110 km, the dummy is called 'D_{110}^{Far}' is unity if a subdistrict is farther than 110 km away from the bridge location and zero otherwise. The average distance from bridge in our sample is 110 km.

Each panel in Table 4 reports the results for a distance cut-off. The first row in each panel reports coefficient on the treatment-year interaction, $(T * Yr)$ in equation (3) above, and the second row the coefficient on the quadruple interaction term treatment-year-productivity-distance $\left(T * Yr * D^V * D^{Far}\right)$. The focus is on the coefficient on the quadruple interaction term which shows how cropping pattern and technology adoption in areas that have relatively higher vegetable productivity and are not close to the bridge location responded to bridge opening in a fixed effect DID model.On the other hand, the coefficient of treatment-year $(T * Yr)$ variable indicates the response in areas which are within the distance cut-off from the bridge and have comparative advantage in HYV rice production. In the appendix Table A.1, we also report the coefficients on triple interaction dummies which are insignificant either numerically or statistically or both anr are omitted for the sake of brevity.

(7.2.A) Spatial Heterogeneity in Technology Adoption and Cropping Intensity

The results display some interesting patterns for technology adoption and cropping intensity (please see first three columns on Table 4) . For cropping intensity, the estimated coefficient of treatment-year dummy $(T * Yr)$ is 0.27 for areas within 110 km of the bridge, and it increases to 0.53 when the distance cut-off is extended to 130 km, and declines to 0.43 and 0.35 when the distance cut-offs are extended to 150 km and 170 km respectively. The results suggest non-linear effects of bridge on cropping intensity in the Jamuna treatment region in the NW. Relative to the comparison areas in the South, cropping intensity has increased everywhere in NW, but increased the most in the interval of 130 km-150 km. This non-linear pattern is observed for the coefficients on the quadruple interaction term $\left(T * Yr * D^V * D^{Far}\right)$ as well though none of the coefficients are estimated with statistical precision. The estimated coefficients on $\left(T * Yr * D^V * D^{Far}\right)$ are twice as large in magnitude as the coefficients on treatment-year dummy $(T * Yr)$.

For fertilizer and irrigation, the estimated coefficients of treatment-year $(T * Yr)$ dummy becomes smaller in magnitude with an increase in the distance cut-off for the far dummy. This implies somewhat larger impacts near the bridge than farther away. For irrigation, the statistical precision of the estimates also suffers with an increase in the distance cut-off. None of the coefficients on the quadruple interaction term $\left(T * Yr * D^V * D^{Far}\right)$ is estimated with precision except for fertilizer in the areas father than 170 km from the bridge where it has a positive coefficient. The coefficients of treatment-year dummy $(T * Yr)$ in the NDVI regressions are indistinguishable across different distance cut-offs. The quadruple interaction term $\left(T * Yr * D^{V} * D^{Far}\right)$ has statistically significant coefficients for the distance cut-off of 170 km but the coefficient is rather small in magnitude. The results show that impacts on fertilizer use is higher near bridge whereas on cropping intensity in intermediate distance of 130-150 km. Even with lower increase in fertilizer use in these areas, total land under modern technology may have gone up due to higher cropping intensity. It is reassuring to note that the impacts on NDVI which subsumes intensity of both land and iput use did not vary with respect to distance from bridge.

(7.2.B) Spatial Heterogeneity in Land Reallocation Across Crops

The results shown in Table 4 suggest a significant reduction in the share of land allocated to HYV rice, and an increase in that to pulses, with no significant change in either vegetables or total rice in the areas that are within 110 km of the bridge. However, the areas that enjoy relatively higher vegetable productivity, but are located farther than 110 km saw a significant increase in the share of land to vegetables: the estimate implies a 25 percent increase over its pre-bridge level. The evidence suggests that the increase in share of vegetables land remained limited up to 150 km of the bridge. Overall, the non-linear pattern of effects on the share of land to vegetables is consistent with that of cropping intensity described above. In contrast to vegetables, the results suggest diversification of cropland away from rice for all distance cutoffs and into pulses. But the areas good in vegetables production and farther away from 150 km, the share of land to rice increases, and the increase is much larger for HYV rice. The increase in the share of rice in the areas farther than 170 km is associated with a small decline in the share of pulse.

The results indicate a nonlinear pattern in reallocation of cropland in areas with relatively higher vegetables productivity: land moved away from rice, particularly HYV rice, to vegetables in the intermediate distance (110 km-150 km), and it reverses in the areas farther than 150km, land moves into rice, particularly HYV rice. This reallocation is associated with productivity gain even if we ignore the technology adoption, since it allows vegetables to be grown in land better suited for vegetables production in the intermediate distance from the bridge. The areas in the intermediate distance also have much higher cropping intensity. All areas regardless of distance experienced increased technology adoption in terms of cropping intensity, fertilizer use, irrigation ownership and greenness particularly in dry seasons. The evidence also indicates that the pattern in green-ness aligns well with use of fertilizer and irrigation and cropping intensity, it is unable to detect change in cropping pattern. However, it is technology adoption and increase in cropping intensity made feasible by the bridge that in the end allows actual cropping pattern to align more closely to natural land productivity.

(7.3) Discussion

The empirical results discussed in section (7) above provide evidence of positive effects of the Jamuna bridge on technology adoption, agricultural intensification and the share of land allocated to higher value crops (pulses and vegetables). The evidence suggests that large reduction in trade costs following the opening of the Jamuna bridge led to agricultural development in the newly connected Jamuna hinterland through both technology adoption, and better matching of land to crops according to comparative advantage. It also confirms spatial heterogeneity in the effects of the bridge on cropping pattern as predicted by the extended von Thunen model in section 2 above.

However, there are a few potential issues regarding the empirical estimates that may come to a reader's mind. First, one might wonder whether the empirical estimates of the treatment effects of the bridge and the substantive conclusions are likely to be significantly affected by inter-regional labor mobility. The issue of spatial reallocation (reorganization effect in the terminology of Redding and Turner (2014) effect is of first order importance when population density, labor allocation, and wages (and income) are the focus of an analysis, as is the case in many recent studies. Our focus is on allocation of an immobile resource, land among different crops where the effects of labor mobility is not likely to be of first order consequence (see the discussion in Donaldson and Hornbeck (2016)). A related concern is the price effects of the bridge. The theoretical model assumes prices to be determined in the center, and are not subject to change in response to bridge. While the small country assumption is a plausible one in the context of agricultural products such as rice and pulses in Bangladesh, vegetables prices may be more responsive to local supply conditions. Since both treatment and comparison regions trade with the center, a reduction in vegetables price in the center due to an increase in the supply from the treatment region would affect farmers in both treatment and comparison regions, and are not likely to affect the conclusions in the DID-FE estimation in a significant way. An additional concern is that opening of markets may expose farmers to higher price volatility and encourage them to diversify (Allen and Arkokalis (2017)). Since the price of vegetables tend to be more volatile than that of rice or pulse (BBS (2014)), it can not explain the increase in the share of vegetables in cropland in response to the bridge. Neither spatial displacement nor price volatility can explain the heterogeneous effects of the bridge discussed earlier within the treatment region.

8 Conclusions

This paper utilizes a quasi-natural experiment to study the effects of a large reduction in transport cost (more than 50 percent) due to the construction of a bridge on agricultural specialization and technology adoption, with a focus on spatial heterogeneity. We extend the classical von Thunen model of land allocation to incorporate costly technology adoption and land productivity heterogeneity. Technology adoption introduces non-linearity in crop land allocation with respect to the distance to the urban market. Land productivity heterogeneity along with technology adoption produces deviation of observed cropping patterns from efficient pattern based on comparative advantage due to land productivity. The areas closer to the bridge devote more land to transport intensive high-value crop (vegetables) even if the land productivity for vegetables is relatively lower, whereas in the areas farther away, transport costs outweigh land productivity advantage. The model predicts that the positive effects of bridge on the share of land devoted to high-value transport intensive crop is felt most prominently in areas that are not too near or far from markets and also have higher relative land productivity in that crop.

The empirical analysis is based on a subdistrict level panel data set and exploits a difference-in-difference framework motivated by idiosyncratic political factors; the comparison region comes from the hinterland of the proposed but yet to be built Padma bridge which remains cut-off from the growth centers in the capital city Dhaka and port city Chittagong. The central findings are as follows. The Jamuna bridge contributed to agricultural development in the treatment areas in the poor Nortwest region through technology adoption, and better matching of crops according to land productivity, thus reducing the spatial mismatch between comparative advantage and the actual cropping pattern in an upazila. The results indicate non-linear spatial patterns in the effects, consistent with the predictions from the extended von Thunen model. For cropping intensity, the largest effects are observed in the areas in the intermediate distance (130 km-150 km) from the bridge. The reallocation of cropland in areas with relatively higher vegetables productivity show interesting spatial nonlinearity: land moved away from rice, particularly from HYV rice, to vegetables in the intermediate distance (110-150km), and the pattern changes after 150km where more land is allocated to HYV rice in response to the bridge.

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Figure 1: Geography of the country with two rivers and three regions

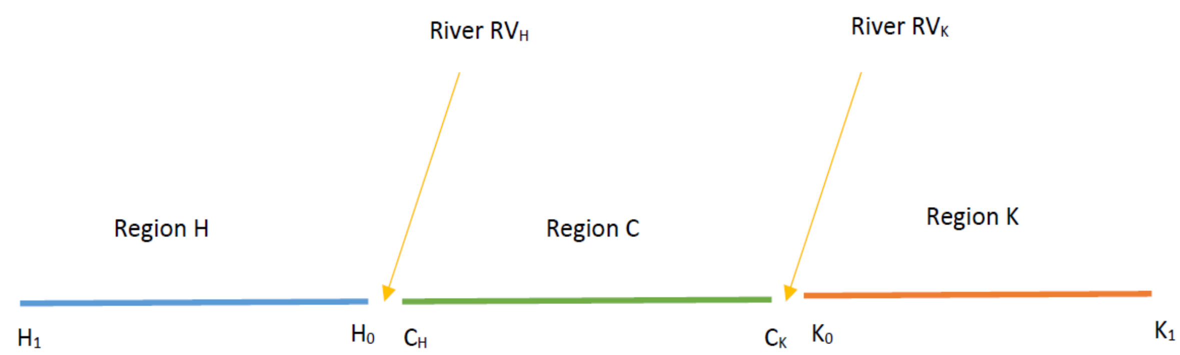
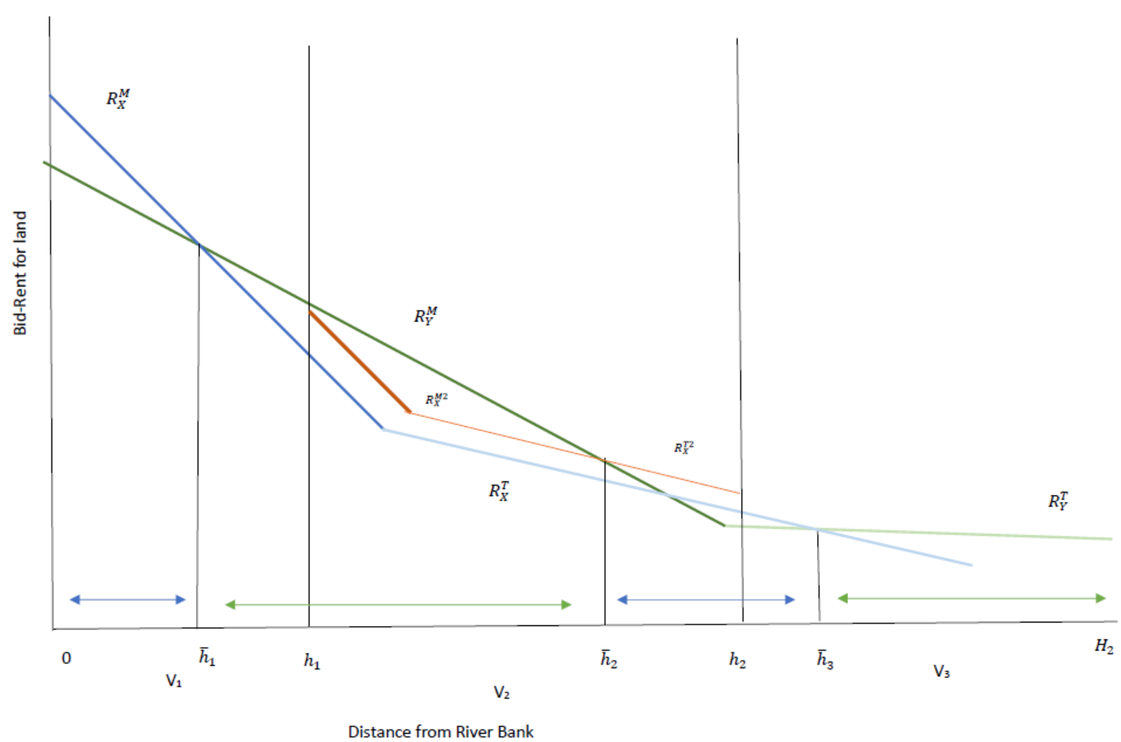
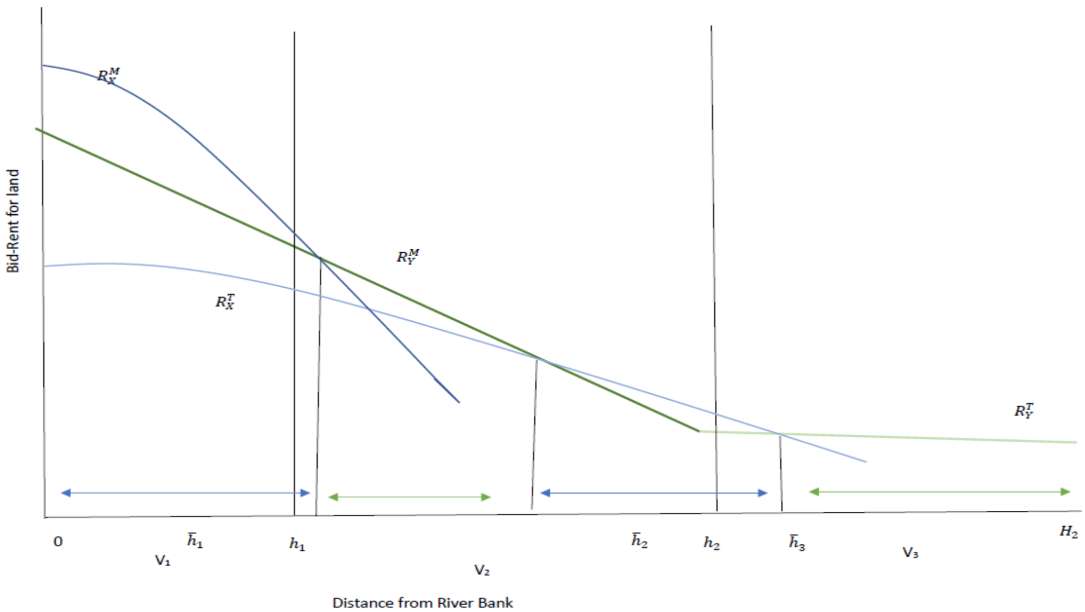


Figure 2a: Technology Adoption and cropping pattern with homogenous land productivity



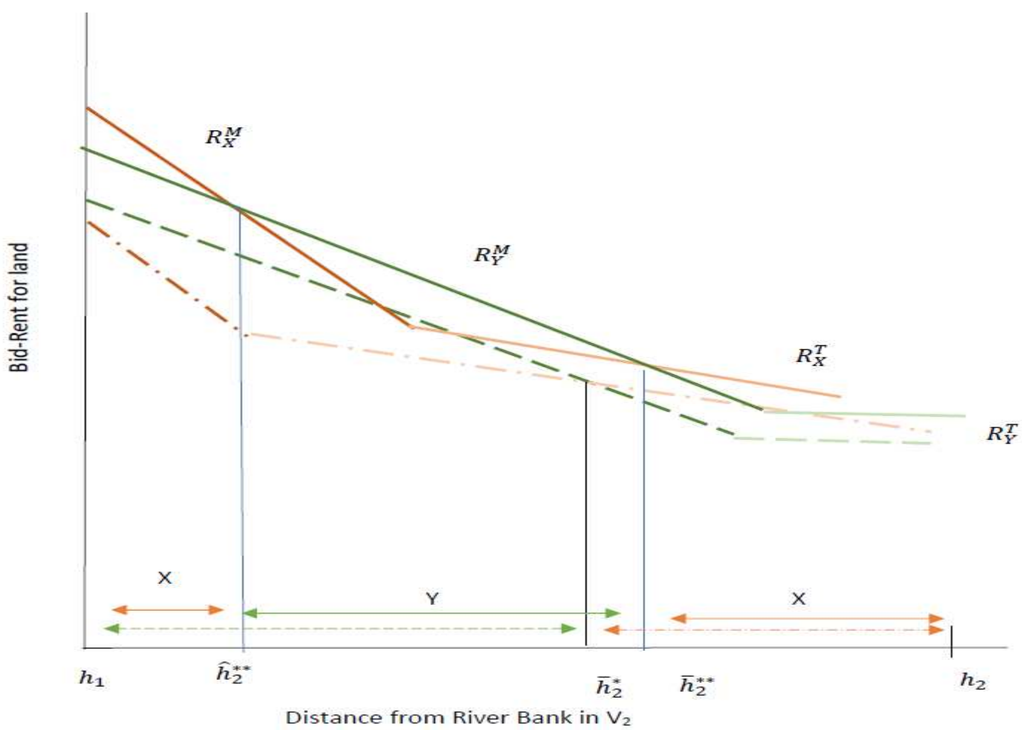
Note: Blue depicts bid rent curve for X and green for Y. Lighter shade for crop produced under traditional technology and darker for crop under modern technology. Arrowed lines of respective color show land under different crops.

Figure 2b: Technology Adoption and cropping pattern with heterogenous land productivity



Note: Blue depicts bid rent curve for X and green for Y. Lighter shade for crop produced under traditional technology and darker for crop under modern technology. Arrowed lines of respective color show land under different crops. Land productivity of X increases with distance from bridge location, while it is constant for Y.

Figure 3: Cropping pattern before and after bridge in village V_2



Note: Brown depicts bid rent curve for X and green for Y. Lighter shade for crop produced under traditional technology and darker for crop under modern technology. Dashed lines depict before bridge and solid after bridge bid-rents and land allocation. Arrowed lines show land under different crops.

Figure 4a: Land productivity for Vegetables relative to HYV rice and Distance from Bridge Location

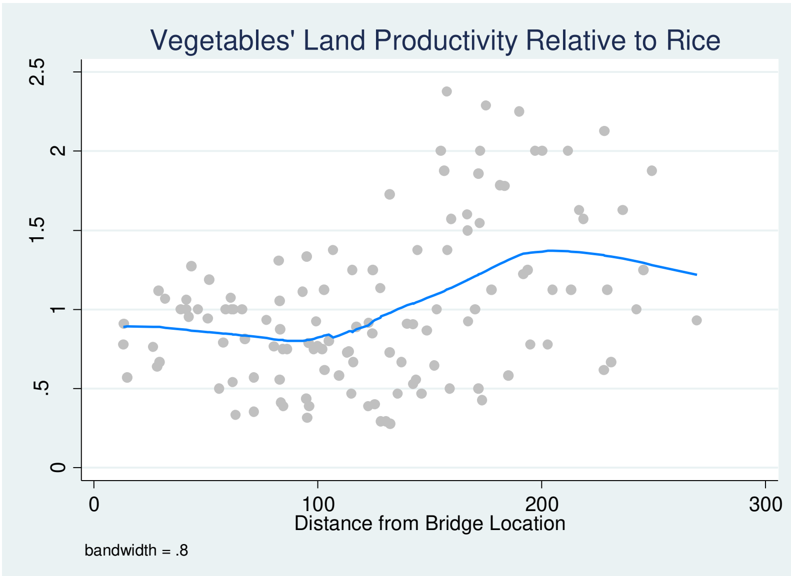


Figure 4b: Vegetables' share of cropland in per-bridge period (1996) and Distance from Bridge Location

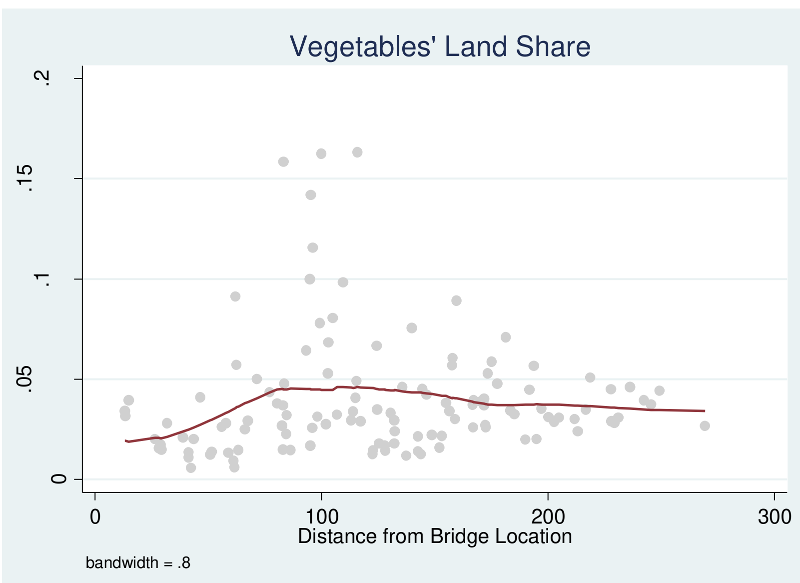


Figure A.1: Location of Jamuna and Proposed Padma Bridges and Treatment and Comparison areas

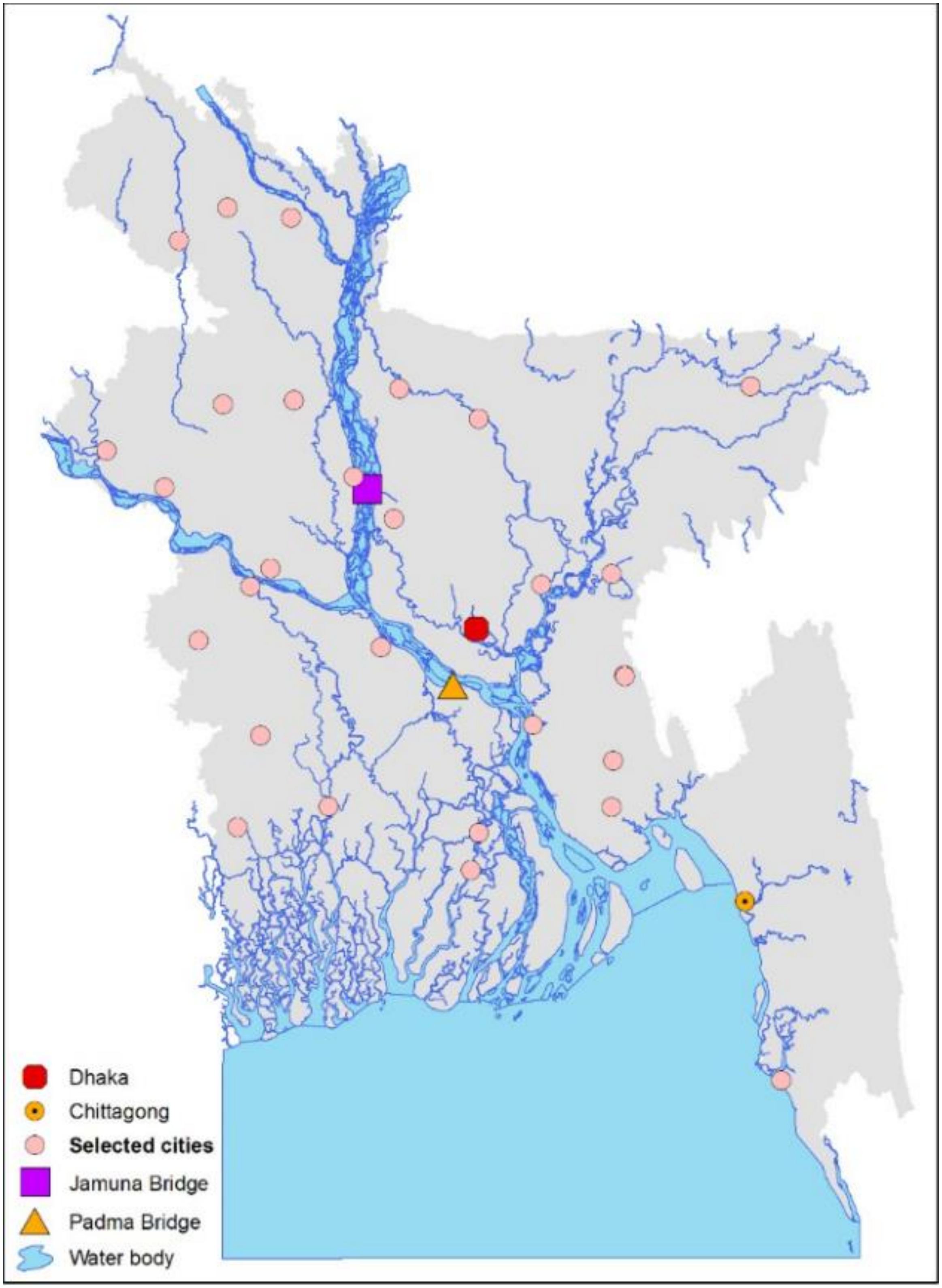


Table 1: Pre-Bridge Sample Means in Treatment and Comparison Areas

	North-West (Jamuna Bridge)	South (Padma Bridge)			P-value of Null Hypothesis of no difference between North-West and South		
		Un-weighted	Logit weighted	OB weighted	Un-weighted	Logit Weighted	OB weighted
Average Rank in terms of							
Suitability of Land for all crops	2.91	3.31	2.86	2.94	0.31	0.87	0.95
Suitability of Land for Rice	2.07	2.25	2.09	2.09	0.28	0.87	0.88
Proportion of Upazilas top ranked for rice	0.86	0.88	0.95	0.95	0.82	0.21	0.17
Suitability of Land for Vegetables	2.65	3.19	2.63	2.75	0.35	0.96	0.85
Proportion of Upazilas top ranked for vegetables	0.92	0.67	0.86	0.82	0.23	0.62	0.48
Population in 1991	210041	203068	214034	212908	0.27	0.61	0.70
Population Density in 1991	767	774	754	757	0.82	0.54	0.60
Average Rainfall	52	53	48	50	0.86	0.68	0.80
Standard Deviation of Rainfall	56	48	43	44	0.47	0.26	0.32
Cropping Pattern							
Share of HYV rice in total cropped land	0.464	0.189	0.259	0.244	**0.01**	**0.03**	**0.02**
Share of rice in total cropped land	0.686	0.675	0.626	0.643	0.85	0.17	0.35
Share of vegetables in total cropped land	0.040	0.022	0.024	0.024	**0.00**	**0.00**	**0.00**
Share of pulses in total cropped land	0.032	0.105	0.099	0.105	**0.04**	**0.04**	**0.04**
Agricultural Technology							
Cropping Intensity	1.778	1.740	1.748	1.739	0.61	0.63	0.56
Share of land under chemical fertilizer	0.536	0.419	0.466	0.419	**0.04**	0.13	0.11
Prop. of households with Shallow tube-well	0.111	0.051	0.082	0.074	**0.072**	0.273	0.198
Change in Normalized Vegetation Index(NDVI)							
Annual Average	-0.013	0.000	0.003	0.003	**0.026**	**0.011**	**0.009**
Average in First quarter (January-March)	-0.014	0.017	0.008	0.011	**0.032**	**0.049**	**0.047**
Average in Fourth Quarter(October-December)	-0.059	-0.022	-0.013	-0.013	**0.031**	**0.010**	**0.008**

Note: The unit of observation is sub-district (upazila). Data on NDVI from satellite data and crop suitability from Bangladesh Agricultural Research Council, and everything else from agricultural and population censuses. Logit weights are inverse probability weights based on logit regression of treatment status on pre-bridge characteristics. Oaxaca-Blinder (OB) weights are estimated using a procedure suggested by Kline (2011). Both logit and OB regressions used the same set of pre-bridge controls.

Table 2: Treatment and Comparison Areas during Pre-bridge period: Effects of a Placebo Bridge

	DID-FE with Regression Adjustments				
	Logit Weight		OB weight		
	Coefficient	P-value	Coefficient	P-value	N
Agricultural Technology adoption (1998)					
Cropping Intensity	-0.038	0.615	-0.065	0.502	229
Share of land under chemical fertilizer	0.020	0.330	0.014	0.519	229
Prop. of households with Shallow tube-wells	0.013	0.395	0.015	0.309	229
Difference in NDVI (1993-1998)					
Annual Average	-0.003	0.606	-0.004	0.485	401
Average in First quarter (January-March)	-0.007	0.374	-0.011	0.155	365
Average in Fourth Quarter(October-December)	-0.020	0.167	-0.022	0.112	397
Agricultural Cropping pattern (1998)					
Share of HYV rice in total cropped land	0.022	0.921	0.035	0.875	229
Share of rice in total cropped land	-0.045	0.820	-0.037	0.856	229
Share of vegetables in total cropped land	-0.002	0.892	-0.001	0.944	229
Share of pulses in total cropped land	0.003	0.923	0.001	0.981	229

Note: The results for each outcome are reported in a row. The odd numbered column provides the difference-in-difference estimate of coefficient of treatment dummy and adjacent even numbered column its robust standard errors. Column 1 provides the simple OLS results for the full sample, columns 3 and 5 inverse probability weighted and Oaxaca-Blinder weighted estimates. Controls in each regression includes log (population in 1991), log (crow-fly distance to bridge location), log (average rainfall in 1998), log (standard deviation of rainfall in 1998), suitability of land for crop production, and dummies indicating top ranking of land for its suitability for rice and vegetables production. For NDVI regressions, rainfall variables are for 1995-1998. Standard errors are clustered at regional (division) level. Legend: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Jamuna Bridge and technology adoption and cropping Pattern in agriculture: DID-FE with regression adjustments

	DID-FE with Regression Adjustments			
	Un-weighted	Logit Weighted	OB Weighted	N
Agricultural Technology adoption				
Cropping Intensity	**0.059****	0.045	0.047	211
	(0.020)	(0.023)	(0.023)	
Share of land under chemical fertilizer	**0.038***	**0.037*****	**0.036*****	211
	(0.017)	(0.006)	(0.006)	
Prop. of households with Shallow tube-wells	0.184	**0.143***	**0.155***	202
	(0.090)	(0.058)	(0.060)	
Normalized Difference Vegetation Index (NDVI): Difference				
Annual Average	**0.019*****	**0.019*****	**0.019*****	2961
	(0.002)	(0.003)	(0.003)	
Average in First quarter (January-March)	**0.038****	**0.026***	**0.030***	2904
	(0.013)	(0.011)	(0.013)	
Average in Fourth Quarter(October-December)	**0.042****	**0.047****	**0.048****	2975
	(0.014)	(0.011)	(0.011)	
Agricultural Cropping pattern				
Share of HYV rice in total cropped land	**-0.107****	**-0.114*****	**-0.113*****	212
	(0.024)	(0.015)	(0.016)	
Share of rice in total cropped land	-0.021	**-0.033****	**-0.030****	208
	(0.021)	(0.008)	(0.008)	
Share of vegetables in total cropped land	0.003	**0.004****	**0.004*****	213
	(0.002)	(0.001)	(0.001)	
Share of pulses in total cropped land	**0.029*****	**0.029*****	**0.028*****	197
	(0.004)	(0.003)	(0.003)	

Note: Each labeled row reports results for the labeled dependent variable and its respective standard errors are in parenthesis in the next row (un-labeled). Column 1 provides the simple DID-FE results, columns 2 and 3 inverse probability weighted and Oxaca-Blinder weighted estimates respectively. Controls in each regression includes log (population in 1991), log (crow-fly distance to bridge location), log (average rainfall in 1998), log (standard deviation of rainfall in 1998), suitability of land for crop production, and dummies indicating top ranking of land for its suitability for rice and vegetables production. For NDVI regressions, rainfall variables are for 1995-1998. Standard errors are clustered at regional (division) level. Legend: *** p<0.01, ** p<0.05, * p<0.1.

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Table 4: Heterogeneity of impacts with respect to distance from the bridge: Results from OB weighted DID-FE with regression adjustments

	Cropping Intensity	Fertilizer use (prop. of land)	Shallow Tubewell Ownership	Normalized Vegetation Index			Share of land under			
				Average	1st Quarter	4th Quarter	HYV Rice	All rice	Vegetables	Pulses
Far:>110km					Panel A					
Treatment	**0.027***	**0.058*****	**0.173***	**0.014***	**0.029***	**0.037*****	**-0.101*****	-0.019	0.000	**0.030*****
	(0.011)	(0.010)	(0.067)	(0.006)	(0.011)	(0.005)	(0.017)	(0.010)	(0.003)	(0.002)
Treat*RVeg*Far110	0.087	-0.000	0.171	-0.001	-0.005	-0.008	0.010	-0.019	**0.011*****	0.002
	(0.091)	(0.024)	(0.098)	(0.003)	(0.003)	(0.006)	(0.020)	(0.016)	(0.002)	(0.004)
Far>130km					Panel B					
Treatment	**0.054****	**0.046*****	0.128	**0.015****	**0.030***	**0.040*****	**-0.117*****	**-0.031****	**0.004****	**0.029*****
	(0.019)	(0.004)	(0.064)	(0.005)	(0.012)	(0.007)	(0.022)	(0.010)	(0.001)	(0.004)
Treat*RVeg*Far130	0.123	0.003	0.238	-0.000	-0.004	-0.003	0.019	-0.007	**0.013****	0.005
	(0.087)	(0.019)	(0.167)	(0.004)	(0.005)	(0.005)	(0.037)	(0.012)	(0.003)	(0.006)
Far>150km					Panel C					
Treatment	**0.043****	**0.048*****	0.109	**0.016****	**0.030***	**0.041*****	**-0.112*****	**-0.025***	**0.003****	**0.027*****
	(0.009)	(0.005)	(0.065)	(0.004)	(0.012)	(0.007)	(0.016)	(0.010)	(0.001)	(0.003)
Treat*RVeg*Far150	**0.114***	0.004	0.129	-0.001	-0.000	-0.007	**0.051***	**0.023*****	0.009	-0.003
	(0.041)	(0.007)	(0.132)	(0.003)	(0.003)	(0.003)	(0.018)	(0.003)	(0.004)	(0.002)
Far>170km					Panel D					
Treatment	**0.035***	**0.044*****	0.099	**0.016****	**0.031***	**0.042*****	**-0.111*****	**-0.023****	0.002	**0.026*****
	(0.016)	(0.007)	(0.072)	(0.004)	(0.013)	(0.007)	(0.014)	(0.007)	(0.001)	(0.003)
Treat*RVeg*Far170	0.054	**0.008****	0.041	**-0.003****	**0.002****	**-0.007****	**0.061*****	**0.018****	0.004	**-0.005****
	(0.038)	(0.003)	(0.050)	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)	(0.002)	(0.001)

Note: "Far_K": is a dummy that takes the value of unity if a subdistrict is located farther than the distance cut-off K (e.g. K=110km in panel A) and zero otherwise. Rveg: is a dummy that takes the value of unity if suitability of vegetables production is greater than that for High Yielding Variety (HYV) rice and zero otherwise. Treat is unity if subdistrict is located in North-West region that is treatment region of Jamuna bridge. Each labeled column reports results for the labeled dependent variable and its respective standard errors are below in parenthesis. Each regression uses the same set of controls are reported in Table 3. Standard errors are clustered at regional (division) level. Legend: *** p<0.01, ** p<0.05, * p<0.1.

Appendix A: Theoretical Model (proofs)

A1. Proof of propostion 1(iii):

We have 4 bid-rent functions and can have 12 different outcomes where one bid rent curve intersects another. For proposition 1(iii), 10 different unique outcomes:

For transport cost of X less than a threshold ($\tau_x < \hat{\tau}_x$ such that $h_X^M(\hat{\tau}_x) = h_Y^M$), crop X is produced in $h \in H_X = [0, h_X^j]$ either using modern technology ($j = M$) or a combination modern and traditional technologies ($j = T$) whereas crop Y is produced using traditional technology in subregion farther away from h_X^j. h_X^j is determined by equating $R_X^j(h_X^j) = R_Y^T(h_X^j), j = M, T$.

For transport cost of X above a threshold ($\tau_x > \hat{\tau}_x$), two broader cases each with 3 alternative outcomes are possible:

Case (a): R_X^T is flatter than R_Y^M : $(\tau_x r_{x0} < \tau_z P_Z + \tau_y \mu_y r_{y0})$: Suppose h_i^* is such that $R_i^M(h = h_i^*) = R_i^T(h = h_i^*)$. Three outcomes can be identified if $h_X^* < h_Y^*$:

(1) If $R_Y^M(h = h_X^*) < R_X^M(h = h_X^*)$, then crop X^M is produced in $h \in H_{Xa1}^M = [0, h_{XX}^{MT}]$ using modern technology and in $h \in H_{Xa1}^T = (h_{XX}^{MT}, h_{XY}^{TT}]$ using traditional technology, and crop Y in $h \in H_{Ya1}^T = (h_{XY}^{TT}, H^E]$ using traditional technolgy

(2) If $R_Y^M(h = h_Y^*) > R_X^T(h = h_Y^*)$, crop X^M is produced in $h \in H_{Xa2}^M = [0, h_{XY}^{MM}]$, and crop Y in $h \in H_{Ya2}^M = (h_{XY}^{MM}, h_{YY}^{MT}]$ using modern technology and in $h \in H_{Ya2}^T = (h_{YY}^{MT}, H^E]$ using traditional technolgy;

(3) If $R_Y^M(h = h_X^*) > R_X^M(h = h_X^*)$ and $R_Y^M(h = h_Y^*) < R_X^T(h = h_Y^*)$, then crop X^M is produced by farmers in $h \in H_{Xa3}^M = [0, h_{XY}^{MM}]$ using modern technology and in $h \in H_{Xa3}^T = (h_{YX}^{MT}, h_{XY}^{TT}]$ using traditional technology, and crop Y in $h \in H_{Ya3}^M = (h_{XY}^{MM}, h_{YX}^{MT}]$ using modern technology and $h \in H_{Ya3}^T = (h_{XY}^{TT}, H^E]$ using traditonal technology.

Two more outcomes if $h_X^* > h_Y^*$, so $R_Y^M(h = h_Y^*) < R_X^M(h = h_Y^*)$

(4) Then either crop X^M is produced in $h \in H_{Xa1}^M = [0, h_{XX}^{MT}]$ using modern technology and in $h \in H_{Xa1}^T = (h_{XX}^{MT}, h_{XY}^{TT}]$ using traditional technology, and crop Y in $h \in H_{Ya1}^T = (h_{XY}^{TT}, H^E]$ using traditional technolgy

(5) or crop X^M is produced in $h \in H_{Xa1}^M = [0, h_{XY}^{MT}]$ using modern technology and rop Y in $h \in H_{Ya1}^T = (h_{XY}^{MT}, H^E]$ using traditional technolgy

Case (b): R_X^T is steeper than R_Y^M : $(\tau_x r_{x0} \geq \tau_z P_Z + \tau_y \mu_y r_{y0})$: Three cases as well for $h_X^* < h_Y^*$:

(1) Produce X^M in $h \in H_{Xb1}^M = [0, h_{XY}^{MM}]$,and Y^M in $h \in H_{Yb1}^M = (h_{XY}^{MM}, h_{YY}^{MT}]$and Y^T in $h \in H_{Yb1}^T = (h_{YY}^{MT}, H^E]$;

(2) Produce X^M in $h \in H_{Xb2}^M = [0, h_{XX}^{MT}]$,and X^T in $h \in H_{Xb2}^T = (h_{XX}^{MT}, h_{XY}^{TT}]$and Y^T in $h \in H_{Yb2}^T = (h_{XY}^{TT}, H^E]$;

(3) Produce X^M in $h \in H_{Xb3}^M = [0, h_{XX}^{MT}]$, X^T in $h \in H_{Xb3}^T = (h_{XX}^{MT}, h_{XY}^{TM}]$ and Y^M in $h \in H_{Yb3}^M =$

$(h_{XY}^{TM}, h_{YY}^{MT}]$and Y^T in $h \in H_{Yb3}^T = (h_{YY}^{MT}, H^E]$

Two more outcomes if $h_X^* > h_Y^*$, so $R_Y^M(h = h_Y^*) < R_X^M(h = h_Y^*)$

(4) Then either crop X^M is produced in $h \in H_{Xa1}^M = [0, h_{XX}^{MT}]$ using modern technology and in $h \in H_{Xa1}^T = (h_{XX}^{MT}, h_{XY}^{TT}]$ using traditional technology, and crop Y in $h \in H_{Ya1}^T = (h_{XY}^{TT}, H^E]$ using traditional technolgy

(5) or crop X^M is produced in $h \in H_{Xa1}^M = [0, h_{XY}^{MT}]$ using modern technology and rop Y in $h \in H_{Ya1}^T = (h_{XY}^{MT}, H^E]$ using traditional technolgy

A2. Land productivity heterogeneity and curvature of bid rent function

Consider bid rent function for X^M :

$$\begin{aligned} R_{Xh}^M &= \mu_X r_{X0} (1 + \psi h) (1 - \beta_x F_h - \tau_x h) - P_Z(1 + \beta_z F_h + \tau_z h) \\ \frac{\partial R_{Xh}^M}{\partial h} &= \mu_X r_{X0}[(1 - \beta_x F_h)\psi - \tau_x (1 + 2\psi h)] - \tau_z P_Z \\ \frac{\partial^2 R_{Xh}^M}{\partial h^2} &= -2\psi \tau_x \mu_X r_{X0} < 0 \text{ if } \psi > 0 \end{aligned}$$

Appendix B (Online): Normalized Difference Vegetation Index (NDVI)

Live green plants absorb solar radiation in the photosynthetically active radiation (PAR) spectral region, which they use as a source of energy in the process of photosynthesis. Leaf cells have also evolved to re-emit solar radiation in the near-infrared spectral region (which carries approximately half of the total incoming solar energy), because the photon energy at wavelengths longer than about 700 nanometers is not large enough to synthesize organic molecules. Live green plants appear relatively dark in the PAR and relatively bright in the near-infrared. By contrast, clouds and snow tend to be rather bright in the red (as well as other visible wavelengths) and quite dark in the near-infrared.

Using satellite data on strong plant reflectance, the normalized difference vegetation index (NDVI) is defined as:

$$NDVI=((NIR-red)/(NIR+red))$$

where red and NIR stand for the spectral reflectance measurements acquired in the red (visible) and near-infrared regions, respectively. These spectral reflectances are themselves ratios of the reflected over the incoming radiation in each spectral band individually, hence they take on values between 0.0 and 1.0. By design, the NDVI varies between -1.0 and +1.0. The NDVI data are available for a sufficiently long period of time (bi-weekly data from mid 1980s to 2014 but not for every year before 1996).

Figure A.1: Location of Jamuna and Proposed Padma Bridges and Treatment and Comparison areas

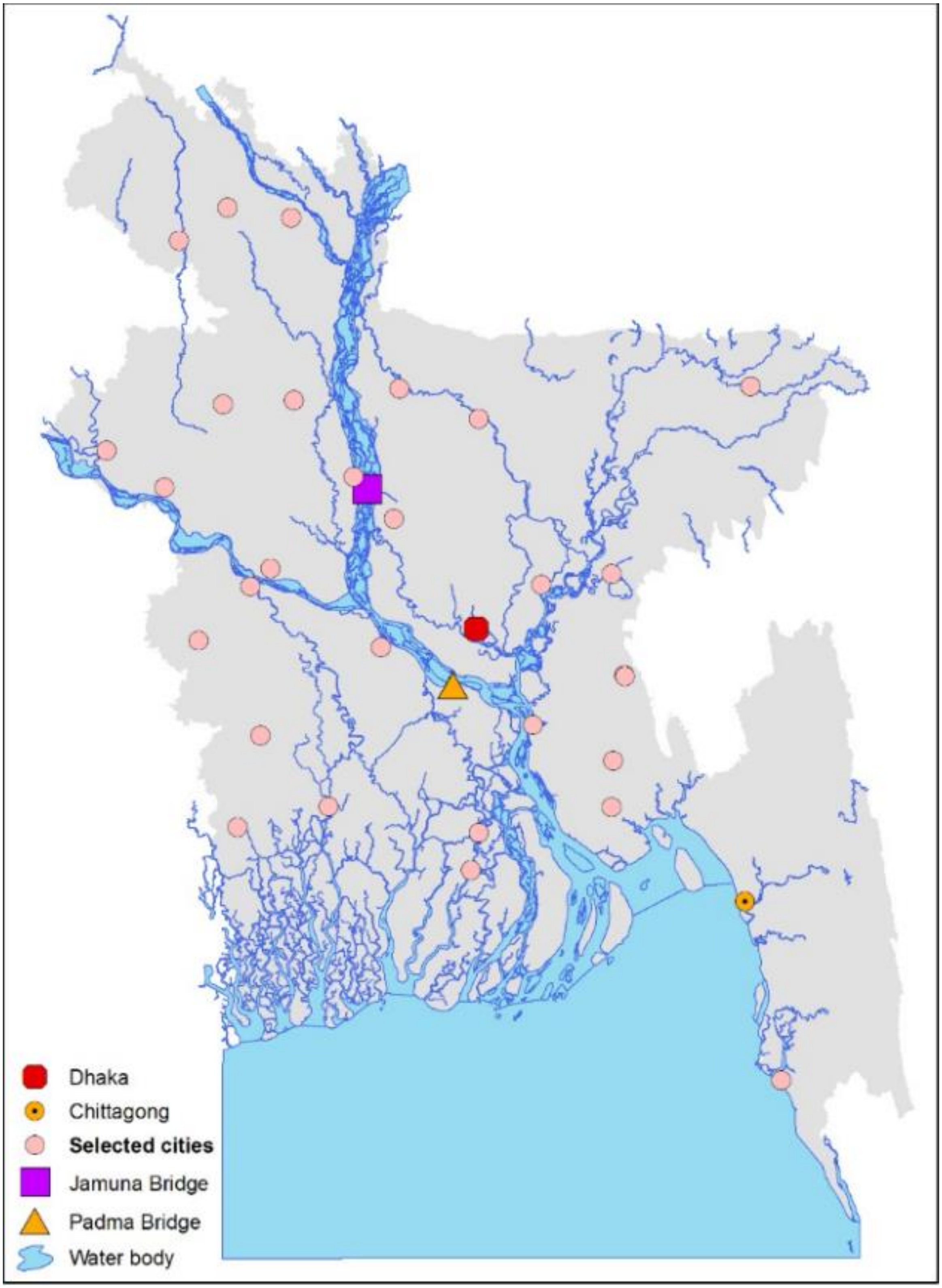

Table A.1: Heterogeneity of impacts with respect to distance from the bridge: Results from OB weighted DID-FE with regression adjustments

	Cropping Intensity	Fertilizer use (prop. of land)	Shallow Tubewell Ownership	Normalized Vegetation Index			Share of land under			
				Average	1st Quarter	4th Quarter	HYV Rice	All rice	Vegetables	Pulses
Far:>110km						Panel A				
Treatment	**0.027***	**0.058*****	**0.173***	**0.014***	**0.029***	**0.037*****	**-0.101*****	-0.019	0.000	**0.030*****
	(0.011)	(0.010)	(0.067)	(0.006)	(0.011)	(0.005)	(0.017)	(0.010)	(0.003)	(0.002)
Treat*RVeg*Far$_{110}$	0.087	-0.000	0.171	-0.001	-0.005	-0.008	0.010	-0.019	**0.011*****	0.002
	(0.091)	(0.024)	(0.098)	(0.003)	(0.003)	(0.006)	(0.020)	(0.016)	(0.002)	(0.004)
Treat*Far$_{110}$	0.038	-0.016	-0.121	**0.009****	0.003	**0.016****	-0.031	-0.014	0.004	-0.008
	(0.037)	(0.030)	(0.093)	(0.003)	(0.005)	(0.005)	(0.028)	(0.014)	(0.008)	(0.005)
Treat*Rveg	-0.039	-0.032	0.015	0.003	0.001	0.012	-0.003	0.008	-0.004	0.003
	(0.101)	(0.023)	(0.030)	(0.002)	(0.001)	(0.006)	(0.009)	(0.019)	(0.003)	(0.002)
Far>130km						Panel B				
Treatment	**0.054****	**0.046*****	0.128	**0.015****	**0.030***	**0.040*****	**-0.117*****	**-0.031****	**0.004****	**0.029*****
	(0.019)	(0.004)	(0.064)	(0.005)	(0.012)	(0.007)	(0.022)	(0.010)	(0.001)	(0.004)
Treat*RVeg*Far$_{130}$	0.123	0.003	0.238	-0.000	-0.004	-0.003	0.019	-0.007	**0.013****	0.005
	(0.087)	(0.019)	(0.167)	(0.004)	(0.005)	(0.005)	(0.037)	(0.012)	(0.003)	(0.006)
Treat*Far$_{130}$	-0.041	-0.012	-0.042	**0.009***	0.002	**0.014****	0.006	0.012	-0.003	-0.012
	(0.063)	(0.045)	(0.055)	(0.003)	(0.007)	(0.004)	(0.022)	(0.016)	(0.008)	(0.010)
Treat*Rveg	-0.054	-0.027	-0.004	0.002	-0.000	**0.008***	-0.002	-0.001	-0.004	0.001
	(0.100)	(0.014)	(0.034)	(0.001)	(0.001)	(0.003)	(0.019)	(0.014)	(0.003)	(0.002)

Continued next page.

Table A.1: Heterogeneity of impacts with respect to distance from the bridge: Results from OB weighted DID-FE with regression Adjustments (continued from earlier page)

	Cropping Intensity	Fertilizer use (prop. of land)	Shallow Tubewell Ownership	Normalized Vegetation Index Average	1st Quarter	4th Quarter	Share of land under HYV Rice	All rice	Vegetables	Pulses
Far>150km					Panel C					
Treatment	**0.043****	**0.048*****	0.109	**0.016****	**0.030***	**0.041*****	**-0.112*****	**-0.025***	**0.003****	**0.027*****
	(0.009)	(0.005)	(0.065)	(0.004)	(0.012)	(0.007)	(0.016)	(0.010)	(0.001)	(0.003)
Treat*RVeg*Far$_{150}$	**0.114***	0.004	0.129	-0.001	-0.000	-0.007	**0.051***	**0.023*****	0.009	-0.003
	(0.041)	(0.007)	(0.132)	(0.003)	(0.003)	(0.003)	(0.018)	(0.003)	(0.004)	(0.002)
Treat*Far$_{150}$	-0.081	**-0.070***	0.085	**0.008****	0.003	**0.017*****	0.045	-0.056	0.002	**-0.023*****
	(0.058)	(0.029)	(0.154)	(0.002)	(0.004)	(0.003)	(0.085)	(0.030)	(0.015)	(0.003)
Treat*Rveg	-0.053	**-0.030****	0.035	0.002	**-0.002*****	**0.008***	-0.016	-0.011	-0.001	0.005
	(0.079)	(0.008)	(0.059)	(0.001)	(0.001)	(0.003)	(0.007)	(0.008)	(0.004)	(0.003)
Far>170km					Panel D					
Treatment	**0.035***	**0.044*****	0.099	**0.016****	**0.031***	**0.042*****	**-0.111*****	**-0.023****	0.002	**0.026*****
	(0.016)	(0.007)	(0.072)	(0.004)	(0.013)	(0.007)	(0.014)	(0.007)	(0.001)	(0.003)
Treat*RVeg*Far$_{170}$	0.054	**0.008****	0.041	**-0.003****	**0.002****	**-0.007****	**0.061*****	**0.018****	0.004	**-0.005****
	(0.038)	(0.003)	(0.050)	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)	(0.002)	(0.001)
Treat*Far$_{170}$	0.080	0.009	0.186	**0.012*****	-0.002	**0.019*****	-0.021	**-0.061***	0.009	-0.001
	(0.069)	(0.010)	(0.171)	(0.002)	(0.003)	(0.004)	(0.011)	(0.023)	(0.005)	(0.005)
Treat*Rveg	-0.011	**-0.032****	0.090	0.003	**-0.002****	**0.009****	**-0.016***	-0.008	0.001	0.006
	(0.056)	(0.011)	(0.066)	(0.002)	(0.001)	(0.003)	(0.006)	(0.009)	(0.004)	(0.003)

Note: "Far$_K$": is a dummy that takes the value of unity if a subdistrict is located farther than the distance cut-off K (e.g. K=110km in panel A) and zero otherwise. Rveg: is a dummy that takes the value of unity if suitability of vegetables production is greater than that for High Yielding Variety (HYV) rice and zero otherwise. Treat is unity if subdistrict is located in North-West region that is treatment region of Jamuna bridge. Each labeled column reports results for the labeled dependent variable and its respective standard errors are below in parenthesis. Each regression uses the same set of controls are reported in Table 3. Standard errors are clustered at regional (division) level. Legend: *** p<0.01, ** p<0.05, * p<0.1.