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Too Small to Be Beautiful?

The Farm Size and Productivity Relationship in Bangladesh

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Abstract

This paper examines the agricultural productivity–farm size relationship in the context of Bangladesh. Features of Bangladesh's agriculture help overcome several limitations in testing the inverse farm size–productivity relationship in other developing country settings. A stochastic production frontier model is applied using data from three rounds of a household panel survey to estimate simultaneously the production frontier and the technical inefficiency functions. The "correlated random effects" approach is used to control for unobserved heterogeneous household effects. Methodologically, the results suggest that the stochastic production frontier models that ignore the inefficiency function are likely mis-specified, and may result in misleading conclusions on the farm size–productivity relationship. Empirically, the findings confirm that the farm size and productivity relationship is negative, but with the inverse relationship diminishing over time. Total factor productivity growth, driven by technical change, is found to have been robust across the sample. Across farm size groups, the relatively larger farmers experienced faster technical change, which helped them to catch up and narrow the productivity gap with the smaller farmers.

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The Farm Size and Productivity Relationship in Bangladesh[1]

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1. Introduction

One of the enduring debates in the development and agricultural economics literature is the inverse relationship (IR) between farm size and agricultural productivity.[2] The IR continues to draw the attention of policy makers and researchers concerned with the unrelenting fall in farm sizes in much of the developing world, persistent poverty (largely concentrated in rural areas and associated with agriculture as the primary livelihood), and insufficient progress in structural transformation (see, e.g., Collier 2008, Collier and Dercon 2014). This paper seeks to contribute to this debate with empirical insights from Bangladesh.

Bangladesh provides a particularly interesting setting – it is one of the most densely populated and cultivated countries in the world, with farm sizes among the smallest in the world. Yet, Bangladesh's agricultural performance has been remarkable since the mid-1990s, with impressive productivity growth (appropriately defined as total factor productivity or TFP). This seemingly paradoxical coexistence of very small – and declining – farm sizes and consistent high productivity growth is itself thought provoking in the larger IR debate. Nevertheless, this casual observation raises conceptual, measurement and methodology issues, leaving open the question on whether the IR holds in the setting of very small farms that characterize rural Bangladesh.

Several unique features of Bangladesh's agriculture make an investigation of the IR particularly interesting and important. A combination of active factor markets, the availability of a household-level panel data set on agricultural production, and application of recent advances in estimation methods (specifically employing the stochastic production frontier approach to jointly estimate the production frontier and technical inefficiency for unbiased and consistent estimates) allows overcoming several of the limitations (conceptual and empirical) identified in the literature on testing the IR.

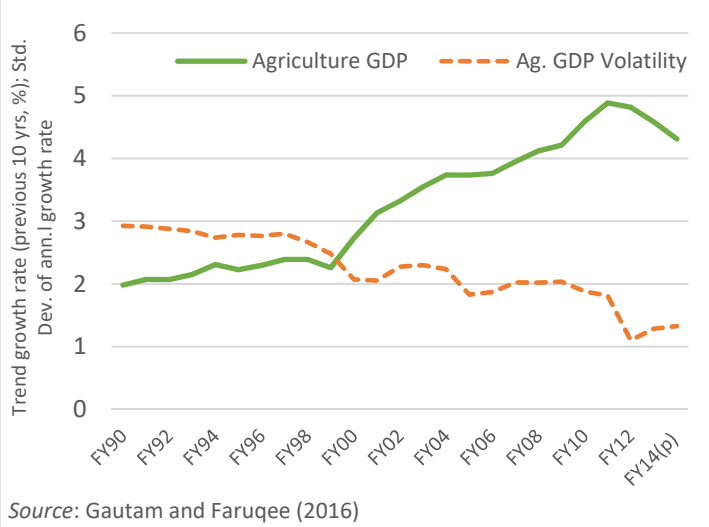
[2] The contemporary debates on the relationship between farm size and productivity date back to a 1962 note by Sen seeking to interpret three broad findings on Indian agriculture emerging from the Studies in the Economics of Farm Management conducted by India's Ministry of Food and Agriculture. One of these findings was that "by and large, productivity per acre decreases by farm size" (Sen 1962). The general interest in the relationship between farm size and productivity, however, dates further back to the late 1800s and early 1900s, in the context of the debates at the time on how to deal with "peasant" farming, specifically in Russia (Thorner, Kerblay and Smith, 1966).

This paper has five sections. Following this introduction, the empirical context and setting for evaluating the IR is presented in section 2. The methodology and data used for the empirical analysis are described in section 3, followed by the results and discussion in section 4. The paper ends with the conclusions and policy recommendations emerging from this study in section 5.

2. The empirical setting in the context of the IR debate

Bangladesh has made commendable progress over the past 40 years, overcoming dire predictions in the early 1970s of widespread starvation to attain its goal of self-sufficiency in rice, its main staple (Hossain and Bayes 2009). Underlying this achievement has been impressive agricultural growth, particularly since the mid-1990s, despite a persistent macro-policy bias against agriculture and high vulnerability to exogenous weather shocks that afflict Bangladesh with regularity – primarily floods and hurricanes (Figure 1).[3] A combination of policy reforms, technological progress, investments in infrastructure and human capital, and the enterprise of rural Bangladeshi households have been credited with driving the trend growth rate (i.e., growth rate over rolling 10 year periods) steadily higher for the past two decades, reaching about 5% in recent years (Gautam and Faruqee 2016).[4]

Figure 1: Agricultural Growth Rate and Volatility 1990-



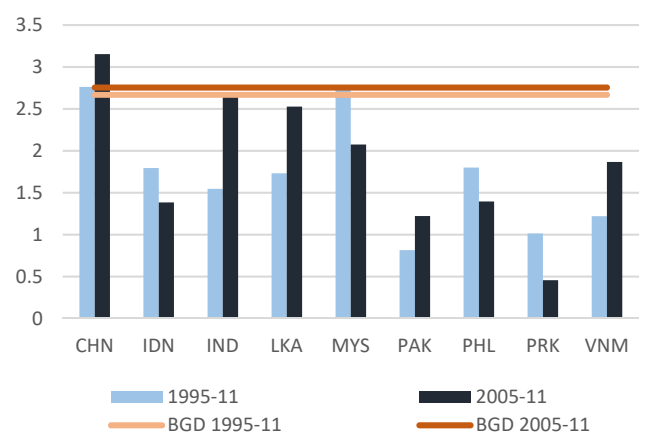
Source: Gautam and Faruqee (2016)

[3] Macro-policy bias is estimated as the Relative Rate of Assistance to agriculture from the global database on agricultural incentive distortions (see Anderson and Nelgen, 2012).

[4] Agriculture has been identified as the main driver of poverty reduction since 2000 (World Bank 2013). Agricultural growth has also unleashed broader and unprecedented changes in the rural economy through its linkages with the rural non-fam economy; every 10 takas of agricultural income is estimated to stimulate an additional 6 takas in rural non-farm incomes (Khandker and Samad 2016).

Available evidence indicates that Bangladesh's enviable agricultural growth has been driven primarily by TFP growth, underpinned by a combination of technical progress and efficiency gains triggered by policy reforms in the 1980s and early 1990s. Using International Food Policy Research Institute (IFPRI) estimates, Gautam and Faruqee (2016) note that agricultural TFP in Bangladesh grew at an average annual rate of about 2.7 percent between 1995 and 2011.[5] During this period, Bangladesh was among the better performers in the world, comparable to China and better than the star performers in East Asia (Figure 2).[6]

Figure 2: Agriculture Total Factor Productivity Growth: Bangladesh and Selected Countries, 1995-2011



Source: Gautam and Faruqee 2016

What is remarkable about this productivity driven growth is that it has been achieved on farms that are best described as very small, especially when compared to those in other countries such as the United States. And these farms have continued to decline in size. Table 1 shows the average farm sizes in Bangladesh for 2000 and 2008, in terms of both area owned and area operated or cultivated, calculated from the rich panel survey used in this study. It is against this dynamic backdrop that this paper investigates the farm size and productivity relationship in Bangladesh's agriculture.

The literature investigating the IR hypothesis is large, with a substantial body of evidence in support of the hypothesis, but also studies that do not find empirical support for it. The traditional approach to examining the IR was to compare yields (output per unit of land) and farm size. This partial or unconditional land productivity measure was supplanted by conditional productivity, an approach that controls for other factors using a production function (see Barrett et al. 2010; Gaurav and Mishra, 2015; and Yamauchi, 2016). While conceptually superior to a partial productivity

[5] See Nin-Pratt (2015) for details on IFPRI's estimation of agricultural TFP by country.
[6] The most recent estimate from the International Agricultural Productivity database shows TFP growth in Bangladesh between 2001-2013 to have been 2.7% per year, which is in the top 20% of performers among the 173 countries in the database [data from USDA (2017); see Fuglie (2015) on the methodology used].

measure, a standard production function specification ignores the relationship between farm size and technical efficiency, which may or may not be in the same direction on the production frontier (Kagin et al., 201h6). More worrisome is the potential bias in parameter estimates by ignoring unobserved farm heterogeneity or other variables correlated with technical efficiency, which may lead to an erroneous conclusion on the IR.

Few studies have examined the relationship between technical efficiency and farm size. These studies have either used the Data Envelopment Analysis or DEA (Townsend et al., 1998; Sharma et al., 1999) or a two-step estimation procedure (with the stochastic frontier and technical efficiency functions estimated sequentially) (Rahman, 2003; Salim and Hossain, 2006; Alam et al., 2014; Henderson, 2015). The results from these studies on the inverse relationship remain mixed, but the approaches used have been criticized on methodological grounds (see O'Donnell, 2014, on a critique of DEA, and Wang and Schmidt, 2002, on the problems with the two-step estimation). There is only one study, to our knowledge, that simultaneously estimates the relationship of farm size with both productivity and technical efficiency (Kagin et al., 2016).[7]

Nevertheless, a number of plausible arguments for and against the IR have been suggested by researchers using different measures of productivity and across a range of empirical settings.[8] The most common among these are factor market imperfections (land and labor); land quality; lack of adoption or constraints to the adoption of improved technology – including credit and risk (production, yield and price); farmer heterogeneity or management skills; and indivisibility of certain inputs (e.g., capital equipment).

Given the potential importance of these factors in explaining the IR, some salient features of Bangladesh's agriculture (in addition to land size) are summarized in Table 1. The data set is described in more detail below, as are the specific variables used in the analysis. The purpose of

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[7] Rahman and Rahman (2008) estimate the frontier and inefficiency functions of an SPF simultaneously using a sample of rice farmers in one district of Bangladesh. They include land fragmentation among the variables influencing inefficiency but do not study how the inefficiency is influenced by farm size. Moreover, their data are from a single cross-section without controlling for soil quality or land characteristics.

[8] See, e.g., Alvarez and Arias, 2004; Assunçao and Ghatak, 2003; Assunçao and Braido, 2007; Barbier, 1984; Bardhan, 1973; Barrett, 1996; Barrett et al., 2010; Benjamin, 1995; Benjamin and Brandt, 2002; Bhalla & Roy, 1988; Carter, 1984; Carletto et al., 2013; Chayanov, 1966; Deolalikar, 1981; Desiere and Jolliffe, 2017; Dyer, 1991; Eastwood et al., 2010; Eswaran and Kotwal, 1986; Feder, 1985; Foster and Rosenzweig, 2010; Gaurav and Mishra, 2015; Hayami and Otsuka, 1993; Heltberg, 1998; Lamb, 2003; Sen, 1966; Sen, 1981; Srinivasan 1973.

the discussion here is to focus on the empirical context and highlight features of Bangladesh's rural economy that help address some of the confounding factors that have dogged a 'clean' explanation of the IR in other developing settings.

Table 1: Characteristics of Bangladesh agriculture

	2000	2004	2008
Household characteristics			
Households with farm income (%)	79.9	80.8	87.2
Households with non-farm income (%)	83.1	89.1	77.4
HHs with both farm and non-farm income (%)	62.9	69.9	64.5
Family size	5.40	5.23	4.94
Number of earners	1.56	1.63	1.58
Number of agricultural workers	0.89	0.93	0.84
Number of non-agricultural workers	0.67	0.69	0.73
Female heads of household (%)	5.89	6.94	13.53
Land			
Total owned land (ha)	0.53	0.48	0.47
Total cultivated land (ha)	0.42	0.38	0.32
Per capita cultivated land (ha)	0.07	0.07	0.06
Per agric. worker cultivated land (ha)	0.42	0.37	0.35
Proportion of irrigated land	0.66	0.77	0.80
Inputs and mechanization			
Percent of cultivator HHs using fertilizer	96.8	96.4	97.7
Percent of cult. HHs using high-yield varieties	83.9	86.6	84.5
Percent of cultivator HHs mechanized	66.2	82.3	88.7
Percent of HHs with electricity	46.1	61.3	82.5
Agricultural capital/agric. worker (2008 BDT)	8,158	8,434	11,758
Non-agric. capital/non-agric. worker (2008 BDT)	15,523	11,514	12,939

Source: Authors' calculation using the 62-village panel survey.
Note: The averages for each characteristic are calculated across all rural households in the survey (i.e., farm and non-farm households). BDT=Bangladesh Taka

One striking feature of Bangladesh's agriculture is the widespread use of technology as embodied in modern inputs – almost all households use fertilizer, a vast majority have adopted high yielding varieties, and have increasingly mechanized over time. Mechanization is not necessarily with owned machinery (though, on average, farm capital has gone up). Most households hire mechanization services, the market for which has grown rapidly, allowing even the poor to cost-effectively rent in services that were once presumed out of their reach (due to capital constraints or simply the small scale of farming preventing large investments in lumpy technology). These indicators are important, as one of the counter-arguments for the IR is that it may hold in

smallholder agriculture, in a largely non-mechanized or traditional setting, but the relationship breaks down for larger farms that are able to afford or adopt better (mechanized) production techniques (e.g., Deolalikar, 1981, Foster and Rosenzweig, 2010). Clearly, the ground rules on the adoption of modern technology have shifted, at least in the context of Bangladesh's agriculture – in no small measure an outcome of the liberalized policy framework adopted in the 1980s and early 1990s that allowed imports of small machinery.

Another important feature is the widespread participation of agricultural households in non-farm work, mostly wage labor, a trend that is on the rise. There is an active labor market, which is by all accounts very competitive and well-functioning, with a substantial degree of non-farm self- and wage-employment (Hossain and Bayes, 2009). This suggests that another major explanation offered in the literature, that labor market failures may result in excess family labor on farms available for more intensive use in agriculture, may not be a major concern for Bangladesh (e.g, Sen, 1966; Bardhan, 1973; Barrett et al., 2010; Henderson, 2015). With regard to management skills, or unobserved ability, an important feature of the data is their panel nature, which allows to methodologically control for time-invariant household specific factors (e.g, Assunçao and Ghatak, 2003; Assunçao and Braido, 2007).

Finally, land quality is often used to explain the IR hypothesis (Benjamin, 1995; Bhalla and Roy, 1988; Lamb, 2003), with differences in land quality arising from variations in soil quality or topography. A common but significant shortcoming of many data sets used to study the IR is the failure to account for soil and land quality differences across households, a potential source of omitted variable bias. An important feature of the data in hand, in addition to their panel structure, is that they contain data on soil type and elevation, two key factors in explaining land quality in Bangladesh. These variables provide additional important controls on production conditions, accounting for possible time variance in land quality through land rentals/leasing, and sales/purchases (which are increasingly observed in Bangladesh and would violate the assumption of time invariance in land quality even with data from a balanced panel), permitting a more robust specification of the production function to obtain unbiased estimates of the critical coefficients.

3. Methodology and Data

Traditionally, and popularly, the terms productivity and yield have often been used interchangeably, but yield is only a partial productivity measure for land. The problem with using yield is that without accounting for inputs other than land, increased yields may represent no increase in productivity *per se* if the increased output is entirely due to increased use of non-land inputs (individually or in combination). The main interest from an economic perspective is how effectively all inputs (or factors of production) are being used to produce the observed output.

3.1 Methodological Approach

The empirical analysis uses the Stochastic Production Frontier (SPF) approach to estimate a household level production function. The SPF allows direct and simultaneous estimation of two distinct components of overall productivity at the farm level: the productivity of the production process itself (evaluated at the best-practice frontier) and the technical inefficiency in production (evaluated as the productivity of individual households/farms relative to that frontier). An ordinary production function (not applying SFA) would conflate the two, and without explicitly accounting for the inefficiency component, is likely to give biased and inconsistent parameter estimates of the production function (similar to the omitted variable bias) (see, Wang and Schmidt, 2002; Kumbhakar and Lovell, 2000).

The simultaneous parametric approach also allows a deeper analysis of the farm-size productivity relationship, as each component may potentially reveal different relationships. For example, those producers defining the best-practice production frontier may exhibit lower/higher levels of output associated with the scale of farming (as indicated by the decreasing/increasing returns to scale or scale elasticity).[9] But there may also be a declining/rising trend in inefficiency with farm size –

[9] Economies of scale and economies of size are often used inter-changeably in practice, but while the two are closely related, in production theory they are distinct concepts (Chambers, 1988, Sheng et al 2014). The two are equivalent if and only if the production technique is homothetic (that is, input proportions do not vary with output). Returns to scale show how output changes if all inputs are changed by the same proportion. Returns to size show how, in addition to the returns to scale effect, output changes due to input substitution. If all inputs change proportionally with size, the returns to size are equivalent to returns to scale. For Bangladesh, given the small scale of farming (with an average of the largest farm size quartile only 1.62 Ha.), it is reasonable to assume input proportions do not vary much by scale. A preliminary look at the data confirms this intuition: using data on rice plots (the predominant crop in Bangladesh),

whereby the larger farmers may be operating closer to (or farther from) the frontier. The direction these components takes is an empirical issue, with each offering potentially important insights for policy.

Estimation of the returns to scale associated with the production frontier, the relationship between technical efficiency and farm size, and the magnitude of technical change provide evidence of the relationship between farm size and productivity in Bangladesh's agriculture. In addition, the parameterization of the inefficiency function allows for directly testing additional policy variables that may be important in explaining technical efficiency – providing further insights to guide policy making.

The stochastic production function is specified as follows:

$$\ln\left(\frac{Y_{it}}{A_{it}}\right) = \alpha_0 + \beta_a \ln(A_{it}) + \beta_x \ln\left(\frac{X_{it}}{A_{it}}\right) + \beta_c C_{it} + \theta_t Year + V_{it} - U_{it}(Z_{it}, P_{it}), \qquad (1)$$

where $\left(\frac{Y_{it}}{A_{it}}\right)$ is the value of output per hectare for farm i in period t, Y_{it} is the total value of output and A_{it} is the farm size measured in hectares. The term $\left(\frac{X_{it}}{A_{it}}\right)$ denotes the (set of) inputs used per hectare. The inputs included in the estimation are fertilizer, hired labor, and an aggregate of other cash outlays (e.g. machine hiring cost, cost for draft animals, pesticide costs etc.) as other costs, all on a per hectare basis. To account for irrigation, the proportion of operated land under irrigation is included. As the data do not have the total amount of family labor used (either in quantity or value terms), the stock (number) of adult family workers, on a per hectare basis, is included as a proxy.[10] Finally, fixed farm capital is included as the value of all agricultural capital (all farm related machinery and equipment owned by the household) per hectare. All values are inflated to 2008 prices using the CPI index from the Bangladesh Bureau of Statistics.

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we find that neither the cost per unit of output, nor input proportions (fertilizer to labor, labor to other costs, and fertilizer to other costs) varies with the scale of operation/farm size (from regressions of each ratio on farm size, with and without household and time fixed effects). With this in mind, in the rest of this paper we use the terms scale and size interchangeably.

[10] To verify the use of adult family workers as a reasonable proxy for family labor used on farms, separate regressions for rice plots were estimated for each of the two main growing seasons (*Boro* and *Aman*). As the dominant crop in Bangladesh, rice was of special interest to the survey team. More detailed information was collected on the main rice plot for each season, including on the actual family labor time spent on each plot. The results using the two options for family labor were very similar. Importantly, findings on the main relationships of interest to this study – those related to farm size – were found to be qualitatively the same using either variable.

A significant shortcoming in many data sets is the lack of information on the production conditions, and specifically soil and other land characteristics. Panel data are often used to overcome such effects. The situation in the study areas, however, is a dynamic one with significant rental/share cropping activity and other demographic changes taking place. As such, the quality of operated land may vary over time within the same household, which may not be accounted for with household fixed effects. To control for these, the share of operated area by soil type and elevation (aggregated across plots to arrive at shares of each type of land at the farm level) are added to the specification to control for physical production conditions. In addition, rainfall and agro-ecological zone indicators are added to further account for exogenous environmental factors that may influence production. These conditioning variables are included in Eq. (1) as C_{it}.

The inefficiency component of the stochastic production frontier is parameterized and estimated simultaneously in a single step to obtain consistent and unbiased estimates. This function, represented by $U_{it(.,.)}$ in (1), measures the unobserved technical inefficiency for each household; that is, the production level achieved by each farm household relative to the production level of households operating at the best-practice production frontier. Farm specific estimates of technical efficiency are calculated using the expression exp(-$U_{it}(.)$). U_{it} is assumed to be independently distributed as $N(\delta Z_{it}, \sigma_u^2)$ but truncated at zero. The main variable of interest for this paper, farm size, is included in log form. Its estimated coefficient and sign provide a direct test of its relationship with inefficiency in production.

Two other sets of factors are considered that may explain inter-farm variability in technical efficiency. One set relates to the household's managerial capacity or technical skills, captured using household demographic characteristics. The other is a set of variables that are reflective of public policies. The specification can thus be represented as:

$$U_{it} = \delta_0 + \delta_a A_{it} + \delta_z Z_{it} + \delta_p P_{it} + u_{it}. \qquad (2)$$

Among the demographic variables, Z_{it}, we include gender and schooling of head of the farm household. An important consideration raised in the literature relates to labor market imperfections. To see how labor market participation may influence inefficiency, a dummy variable is included to indicate if any member of the household participated in non-agricultural

work.[11] A negative coefficient (lower inefficiency) could be interpreted as indicating that non-farm work relieves surplus (or inefficient use of) labor on the farm, suggestive of an imperfectly working labor market. On the other hand, a positive coefficient (higher inefficiency) would suggest that supplying off-farm labor reduces the intensity of family labor on the farm, reducing effective labor quality, and/or reducing the supervision quality of hired labor. This would support the argument that intensive use of family labor might be associated with higher productivity of small farms.

Policies play a critical role in the overall enabling environment with likely strong influence on the efficient use of inputs. Policy variables available for this study are as follows. Distance from the capital city, Dhaka, is used to capture the impact of connectivity (alternatively remoteness). An important factor for production efficiency is access to public services, including agricultural extension and other public services provided by the government. These services are located at the Thana (lowest level administrative office), so the distance of the farm from the Thana headquarters is included to proxy access to these services.

The western part of the country had long lagged the rest of the country, being cut off from the major urban centers in the east, Dhaka and Chittagong, by a major river. This access constraint was removed in 1998 with the building of the Yamuna Bridge. All rounds of the survey were conducted after the building of the bridge, but it is important to test whether the farmers in the west continue to lag or if they have been able to catch up by exploiting the new market opportunities (as reflected in their productive efficiency). A dummy variable for households living in the west is added to the specification to test for this.

Finally, as in many developing countries, inefficient or poorly functioning land markets can be a major constraint in allowing land to move to the most productive users. We include variables related to land fragmentation (measured as the Simpson Index of distinct physical plots of land operated by households) and the tenancy status of the farm (sharecropped land and land leased on a fixed rent basis) to see how they influence technical inefficiency, and whether they point to any concerns about the current operation of land markets.

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[11] An alternative measure of the share of non-agricultural workers in total workers in the household was also tried, with very similar results to those reported here.

The remaining terms in Eq. (1) are Year, which is included to capture technical change, and V_{it}, which represents random errors. As is standard, this error is assumed to be normally independently and identically distribution with an expected value of zero and variance $\sigma^2_{v,it}$.

The estimation of the SPF follows Battese and Coelli (1995) to simultaneously estimate the stochastic frontier and the inefficiency functions. As noted, the sequential or two-step estimation of these equations may produce biased and inconsistent estimates of the production function (and hence the estimate of production efficiency) if the variables in the inefficiency functions are correlated with the inputs in the production function (Wang and Schmidt, 2002; Kumbhakar and Lovell, 2000).

In light of the relatively short time-series dimension in the data, and to avoid the incidental parameter bias associated with maximum likelihood stochastic frontier estimation in such cases, one could control for unobservable household characteristics by estimating a random effects model. Such a model would be appropriate if the random effects are uncorrelated with the inputs (X's), which is unlikely as the use of inputs is often a function of the unobserved household specific effects. To overcome this challenge, two strategies are adopted. First, a list of variables capturing soil quality of the farm, altitude of the parcels, rainfall, and overall agro-ecological indicators are included in the empirical specification of Eq. (1) as conditioning variables. Second, the "correlated random effects" approach (CRE) is used to control for household fixed effects.[12] The CRE approach was originally proposed in Mundlak (1978), extended by Chamberlain (1980, 1982), and has attracted growing attention in the applications of stochastic production frontiers (Wooldridge, 2005, 2009, 2013; Abdulai and Tietje, 2007; Yang et al., 2015). We also adopt the CRE approach to control for the unobserved heterogeneous household effects as determinants of technical inefficiency. It is important to note, however, that while the statistical significance of the mean variables for CRE is an important indicator of the existence of time-invariant unobservable household effects, the magnitudes of these variables lack meaningful interpretation (Wooldridge, 2002; Yang et al., 2015).

[12] In the CRE approach, time-averages of explanatory variables are added in the estimation model to control for time-invariant heterogeneity in the model.

3.2 The Farm-household Data

We draw on three longitudinal survey rounds of a nation-wide sample of Bangladeshi rural households spanning 2000–2008. These surveys followed an earlier survey in 1988 undertaken by the Bangladesh Institute of Development Studies (BIDS) to study changes in rural poverty and livelihoods in response to technological progress, food-price hikes, and other factors. The baseline survey covered 1,240 rural households from 62 villages in 57 of the country's 64 districts (Hossain et al., 1994). The households were revisited in 2000, 2004, and 2008 by the International Rice Research Institute (IRRI) to study the impact of rice research on poverty reduction (Hossain et al., 2006). The principal investigator of the initial (baseline) survey, Mahabub Hossain, undertook repeat surveys in 2000, 2004 and 2008 for additional analyses.

The baseline survey used multistage random sampling, with the sample size adjusted in each round to make it representative of the rural population for that year. In the first stage, 64 unions were selected randomly. In the second stage, one village from each union was selected that best represented the unions in terms of population density, land distribution, and literacy. Two villages were later excluded due to difficulties in administering the survey in their remote location. A census was conducted in the selected villages to stratify households according to landownership, land tenure, and literacy, and a random sample of 20 households was selected from each village, so that each stratum was represented by its probability distribution.

In addition to the original households and their offshoots, the 2000, 2004, and 2008 surveys included additional households from the same villages to address the sample attrition problem. Sample sizes for the repeat surveys were 1,880 in 2000, 1,930 in 2004, and 2,010 in 2008. From these, a total of 720 intact households have complete information on the variables of interest, providing a total of 2,160 observations for this analysis. The household identifier in the farm production module of the 1988 survey is missing which means that the 1988 round cannot be included in this analysis. Exclusion of the 1988 survey, however, does not hurt this study; the 2000, 2004, and 2008 surveys permit an understanding of the drivers of productivity over almost a decade after 2000, a period that was notably dynamic and relevant for this study.

Data collection for the surveys involved a semi-structured questionnaire to collect information on demographic details, land use, costs of cultivation, livelihoods, farm and nonfarm activities, commodity prices, ownership of non-land assets, income, expenditures, and employment. The data

set is particularly well suited for understanding the dynamics of farm productivity, with detailed information on production inputs, outputs, and costs, allowing for better measurement of the key variables needed for the analysis. For example, for every crop grown by a household, the survey data provide price, quantity, and other details on land preparation, application of seed, fertilizer use, irrigation, weeding, pesticides, crop damage, and labor used in harvesting and threshing. The data set also describes how different types of labor were used for cropping activities and marketing of outputs. The data set also provides extensive details about farms' characteristics, such as soil type, elevation, irrigation sources, and tenurial arrangements.

4. Results and Discussion

The descriptive statistics for the panel of farm households used in this analysis are given in Annex Table A.1. In the three rounds of data analyzed, 2004 stands out as a relatively bad production year because of flooding in large parts of the country. The impact of floods, which typically affect the rainy season crop, appears to have been significant – evident not only in lower output per hectare but also lower intensity in the use of inputs in 2004 relative to the other years. The years 2000 and 2008 were normal, with data showing strong improvement in performance over the eight years. Output rose significantly faster than inputs between 2000 and 2008, suggesting strong growth in productivity.

Other important points to note include the widespread use of irrigation, which is expected to positively impact yields and provide stability with better water management. The practice of leasing in land (either on sharecropping or rental arrangements) is also widespread: the share of households leasing in at least some land to supplement their own land is over 50%. Sharecropping is more popular than other rental arrangements. On average, about one-third of the land cultivated by households is leased in each year, and the practice and shares are consistent for all land classes, including for the landless and functionally landless households. Finally, an important characteristic is the high level of land fragmentation, with a large number of small, distinct, and often widely dispersed plots operated by households. These features of the data are important as they help in interpreting some of the estimation results reported below.

Even though the absolute farm sizes in Bangladesh are small, there is still substantial disparity in farm sizes and a skewed farm size distribution. Table 2 shows that average and median farm sizes

are small and declining over time. The table shows the statistics for the panel households as well as for the full sample, indicating that the panel households are reasonably representative of the full sample.[13] The midpoint farm size, that is the farm size at which half of the total cultivated land is operated by farms larger than the midpoint (and the remaining half by farms below the midpoint), also shows a declining trend, but it is significantly higher than the median, confirming the skewed distribution of farm sizes. The average farm size above the midpoint is over four times the average farm size below the midpoint for each year.

Table 2: Farm Size Indicators in Bangladesh

Farm Size Indicators (Estimation Sample)	**2000**	**2004**	**2008**
Mean Farm Size (Ha)	0.77	0.71	0.66
Median Farm Size (Ha)	0.52	0.50	0.43
Midpoint Farm Size (Ha)*	1.20	1.05	0.95
Average farm size below/above the midpoint size	0.47/2.07	0.45/1.74	0.41/1.67
Farm Size Indicators (All Farm Sample)			
Mean Farm Size (Ha)	0.69	0.61	0.56
Median Farm Size (Ha)	0.44	0.41	0.37
Midpoint Farm Size (Ha)*	1.14	0.94	0.85
Average farm size below/above the midpoint size	0.42/2.00	0.37/1.64	0.34/1.50

Source: Authors' calculation using the 62-village panel survey.
Note: *: Midpoint farm size is the farm size at which half of all land is operated by larger farms and the other half is operated by smaller farms.

Before discussing the findings, one remaining methodological concern is the potential endogeneity of inputs in production. To address this issue, it is important to recognize that agriculture production is best characterized as a sequential decision-making process (agricultural production decisions are inherently sequenced with time playing an important role on when and how decisions are made) (Antle, 1983). The first decision a household makes, at the start of a production season, is how much land to cultivate and its allocation across crops. Once land is allocated, decisions on other (variable) inputs in the production process are subsequently made. As such, given that the interest of this paper is on characterizing the physical production process, and not the behavioral aspects or the dynamics of farm portfolio allocation decisions, the production function is interpreted as a conditional production function – conditional on the acquisition and allocation of

[13] The panel includes non-split households while 'full sample' includes split, non-split, and newly added households.

land at the start of the season. Land decisions, including decisions to acquire, rent or lease in land, are thus exogenous to the physical production function.

That said, variable input decisions may still be endogenous as households respond to evolving production conditions. Were data available on the status of crop output at different stages of growth through the growing season, the sequential nature of production could be accounted for (Antle, 1983). But such data are rarely available. With only the end of season final output available, household response to evolving weather and other production conditions may render inputs endogenous. The severity of this potential endogeneity problem is reduced to some extent in the current study setting considering that the vast majority of the land is irrigated. The ability to control water supply (as main or supplemental irrigation) significantly reduces a major source of production uncertainty, making the process more predictable than under rainfed conditions. A direct result of this, with rapid expansion of groundwater irrigation, has been the much faster growth in the dry (winter) season Boro crop relative to the rainy season Aman and the dry (summer) season Aus.[14] Boro production is, not surprisingly, more stable than Aman and Aus, though with major technological breakthroughs in recent years (with drought and flood tolerant seed varieties) even the latter two have seen rapid growth and more stability.

Second, the weather conditions in Bangladesh are stable with reasonably predictable weather patterns and consistent temperature through the major growing seasons. There is the perennial risk of floods, but these floods are often experienced early in the agricultural year, as a result of monsoons that swell the major rivers flowing into Bangladesh. Floods during the growing period, even in the rainy season, are not common.

Bangladeshi agriculture is dominated by rice, and as noted, with widespread use of fertilizers and modern varieties. Given farmers' long experience in growing standard crops (mainly rice), the production process is reasonably predictable, as are the different decisions through the growing season. Finally, to avoid a more serious potential endogeneity problem, pre-harvest labor is used

[14] Agricultural production in Bangladesh is spread out over three distinct seasons through the year, referred to as Boro, Aman and Aus. Aman is the rainy season crop, harvested in December-January; Boro is the dry winter season crop, harvested in March-May; and Aus is the dry summer crop harvested in July-August.

instead of total labor, as labor used at harvest is surely dependent on the level of output, and hence is endogenous.

To allay concerns about endogeneity, the Hausman test for the joint endogeneity of the three key variable inputs (labor, fertilizer and other costs) was conducted. The instruments used were prices, non-agricultural capital (to capture total productive assets to proxy for wealth, as agricultural capital is already included), rainfall variability measured as the standard deviation of monsoon rainfall over the previous ten year period (to capture aversion to production risk), and household size (as potential substitute for labor), in addition to the exogenous variables included in the SPF specification (infrastructure/access variables, agricultural capital, land quality indicators, household fixed effects, etc.). The test revealed no systematic difference between the instrumented and non-instrumented specification, implying that endogeneity of these inputs is not a concern (the estimated χ^2 statistic is 38.24, with a p-value of 0.1736).

Turning now to the main results, the estimates from the stochastic production frontier and the inefficiency function are given in Annex Tables A.2 and A.3, respectively. Four variants of the model presented in equations (1) and (2) are estimated. The first, or basic, model is an SPF but without parametrizing the inefficiency function in (2). This model provides estimates of household level technical efficiency but cannot tell what factors might be influencing efficiency. The remaining three models are estimated with the inefficiency function parameterized. In all three, farm size is a key variable included to test for the farm size-inefficiency relationship. The second model is without soil quality indicators (i.e., without C_{it} in Eq. (1)) to test if household fixed effects suffice in terms of controlling for the conditioning production environment. The third model is the full specification including the soil quality indicators (i.e. with Eqs. (1) and (2) fully specified). The fourth model is an important extension to test if the scale elasticity changes over time. To do this, equation (1) is modified to include interaction terms between farm size and the year dummy variables to capture changes over time.

The results show that the estimated parameters are stable (both in magnitude and significance) across the four models, with one crucial exception. The scale elasticity of the production frontier for the basic model (as specified, the parameter estimate on farm size is a direct estimate of returns to scale in this model) is statistically insignificant and smaller in magnitude than in the other models. It is consistently significant and with a negative sign suggesting decreasing returns to

scale, or a negative relationship between the scale of farming and yields in the second and third models, and for the first two years of the fourth model. The estimates from the fourth model suggest a notable shift in the observed frontier characterizing the production technology, from decreasing in the previous years to constant returns in 2008. These findings suggest that with the wider and more uniform adoption of technology, there appears to be no technology related advantage or disadvantage associated with farm size in terms of conditional yields. However, since farm size is also included in the inefficiency function in these models, a valid comparison with the basic model of how production varies with the scale of farming requires accounting for the marginal effect of farm size in the inefficiency function.

The estimates of the inefficiency function show a strong and statistically significant positive impact of farm size on inefficiency in all the three models; that is, all models show production efficiency falls with size. This is an important result indicating that large farms are more technically inefficient than small farms.

Next, to establish the farm size-productivity relationship, the marginal effects from both the frontier and inefficiency components of the SPF are combined to obtain the adjusted elasticity of output with respect to farm size. These effects are given in Table 3 for each of the four models. The first row shows the scale elasticity from the SPF (coefficient on farm size) for each model. For the extended model, the scale elasticity is shown for each of the three years (using the coefficients from the direct and interaction terms). The estimated coefficients show a notable shift in the production frontier from decreasing returns in the first two years to constant returns in 2008 (the frontier scale elasticity is insignificantly different from zero).

The second row of Table 3 shows the marginal impact of farm size on E(U) or the marginal impact on mean inefficiency, derived using the approach proposed by Wang (2002).[15] Adding this marginal impact to the scale elasticity from the SPF, reported in the third row, shows how productivity varies with farm size. The results show a consistent and statistically significant inverse relationship between farm size and conditional yields in all models (and for all three years in the extended model) except the basic model.

[15] The marginal effects are readily calculated in Stata (see Belotti et al., 2013).

Table 3: The estimated farm size-productivity relationship

				Extended model		
	Basic	**No Soil Quality**	**Full Model**	**2000**	**2004**	**2008**
Frontier	-0.046	-0.062**	-0.050*	-0.071**	-0.072**	0.023
Efficiency	-	-0.054***	-0.048**	-0.051**	-0.051**	-0.055**
Combined	-0.046	-0.116***	-0.098**	-0.122**	-0.123**	-0.032**

Source: Authors' estimates using the 62-village panel survey.
Note: *, **, and *** indicate statistical significance at 10, 5, and 1 percent level.

Two notable findings emerge from these results. One is that the basic model, by ignoring the inefficiency specification, is likely miss-specified and the farm-size productivity relationship inaccurately estimated. This miss-specification is also indicated by the much higher value of lambda for the basic model (see model statistics at the bottom of Annex Table A.3) than the other models, indicating that the inefficiency variance is significantly higher than the random variation (indicative of miss-specification). The second finding is from the extended model, which suggests that the IR, although still statistically significant, appears to have diminished over time, with the scale elasticity much smaller in 2008 compared to previous years.

The third important set of results from the SPF estimation relates to the growth in TFP and its constituent components. Using the extended model coefficients, in addition to the scale elasticity, the results highlight two important findings: (i) there is no technical change detected between 2000 and 2004 (the coefficient on the 2004 year dummy is essentially zero), but this changes dramatically by 2008, with a large, positive and statistically significant parameter value on the 2008 dummy. As noted earlier, 2004 was a bad year weather-wise, and the year dummy is likely picking up a combination of the negative weather shock and technical change, and likely unable to distinguish between them. The estimate for 2008 on the other hand shows a very large 33% improvement over 2000. (ii) Technical change is positively correlated with farm size (the interaction between year dummy of 2008 and farm size is statistically significant and positive) – meaning that larger farmers benefited relatively more from technical change over this period.

The association of the pace of technical change with farm size is an important finding and warrants careful interpretation. It is tempting to conclude, as is traditionally assumed, that perhaps with better access to technology or fewer constraints to adoption, larger farmers benefit more or earlier. The data, however, present a different story – it is the smaller farmers who appear to have been

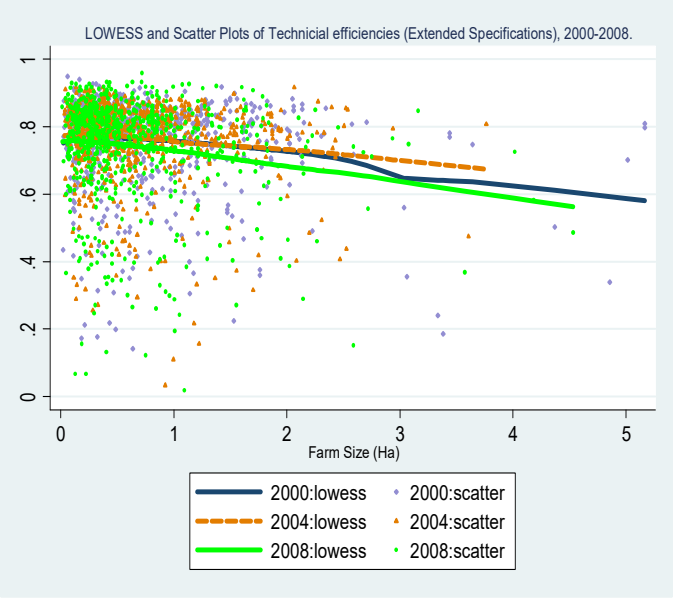
the "first movers" by 2000, with larger farmers catching up in the subsequent years in terms of technology application. As discussed earlier, the use of modern technology is widespread.

Looking beyond the high sample averages of adoption rates, smaller farmers (bottom two quartiles) had a significantly higher share of cultivated area under higher yielding varieties (a key component of modern technology in Bangladesh), a higher intensity of agricultural capital, a higher share of area under irrigation, and slightly higher rates of fertilizer use than the top two quartiles in 2000. By 2008, the larger farmers (top two quartiles) had narrowed these gaps.[16] In other words, starting from a lower base, larger farmers had caught up (albeit to varying degrees) with the smaller farmers in terms of modern technology use. This finding is also consistent with the estimated positive coefficient on the distance to Thana HQ in the inefficiency function, and the average distance to the Thana HQ being higher for larger farms than it is for the smaller ones. The decline in efficiency with distance to the Thana HQ may be due to poor connectivity or insufficient access to public services, crucial extension services, and/or access to newer and better quality seeds, possibly explaining the adoption lag. The latter would be consistent with well documented concerns about the seed sector, suggesting that the constraint to adoption may be more availability of good seeds rather than farmers' willingness to adopt (Naher and Spielman, 2014).

[16] The statistics on the adoption rates by farmer quartiles are not presented due to space limitations, but are available from the authors on request.

In contrast to the rising trend in technical change with farm size, the estimated mean technical efficiency falls with farm size (Figure 3). Notably, technical efficiency losses over the study period appear to have been relatively greater for larger farms. This is more clearly demonstrated in Table 4, which shows mean technical efficiency by farm size quartiles. Technical efficiency first rose marginally in 2004 and then declined in 2008. With no measurable technical change in 2000-2004, technical efficiency improved as the average farmer moved closer to the frontier. But with a shift in the frontier, indicated by the positive technical change by 2008, the distance to the frontier for the average farmer rose, or the average efficiency fell (albeit marginally). A larger decline in the average efficiency for the larger farmers (highest land quartile) reflects the same dynamic; the positive relationship between farm size and technical change suggests that large farmers (as a group) gained relatively more in terms of technical progress, but the average farmer within the largest farm size quartile failed to keep up with the change, operating at a point further from the (new) frontier.[17]

Figure 3: Change in Technical Efficiency by Farm size



Source: Authors estimates from the 62-village panel survey.

[17] A comparison of the estimated technical efficiency from this study with the findings of other studies shows significant differences. These differences may be due to the methodology applied, the scope of analysis (whole farm versus single crop – rice), or time of study. Rahman (2003) found much lower levels of efficiency (ranging from 0.48 to 0.56) with a profit frontier but using a two-step procedure (calculating efficiency scores based on a first step SPF without parameterizing the inefficiency function, and then regressing the efficiency scores in a second step regression to explain the differences in inefficiency). Salim and Hossain (2006) similarly obtained lower estimates of average efficiency (though rising over time from 0.56 in 1977 to 0.60 in 1984 and 0.64 in 1997), again using a two-step procedure. Alam et al. (2014) use the first three rounds (1988, 2000 and 2004) of the same panel survey as used in this study, but use a two-step procedure applied to only rice production, to find a falling level of efficiency from 1988 to 2000 to 2004 (0.85, 0.76 and 0.63, respectively). The study by Rahman and Rahman (2008) is notable as it simultaneously estimates the frontier and inefficiency functions of the SPF. They use data from a single cross-

Table 4: Mean Technical Efficiency by Farm size

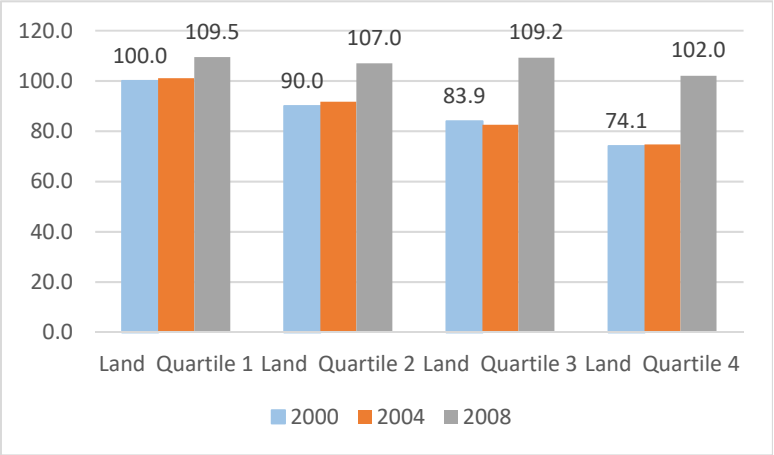
Year	Land Qrtl. 1	Land Qrtl. 2	Land Qrtl. 3	Land Qrtl. 4	Full sample
2000	0.77	0.77	0.76	0.74	0.76
2004	0.78	0.79	0.76	0.74	0.77
2008	0.76	0.75	0.76	0.70	0.74

Source: Authors' estimates using the 62-village panel survey.

Coming next to the growth in productivity, a TFP levels index is derived using the three measures derived from the SPF estimates – scale effects (SE), a technology effect (T) and technical efficiency (TE). The scale effect is derived from the scale elasticity reported in Table 3. The technology effect is estimated using the coefficients on time, indexing the base year at 1 for all farm sizes. The efficiency effect is estimated as average mean technical efficiency. To capture trends over time as well as by farm size, these measures are averaged over farm size quartiles and then indexed to the first farm size quartile in the base year (2000). The estimated TFP index is shown in Figure 4.

The trend of TFP over farm size has shifted from being distinctly negative in 2000 and 2004, to a relatively flatter trend, though the negative trend persists. The implied growth rates of TFP by farm size, and the components of TFP are given in Table 5.

Figure 4: TFP Index by Land quartile and year (Base: LQ1, 2000=100)



Source: Authors' estimates using the 62-village panel survey.

The first finding that emerges from Table 5 is that the primary driver of TFP has been technical change. Annual average TFP growth between 2000 and 2008 is estimated to be high at 2.86%, which is somewhat greater but

sectional survey of rice producers from one southern district of Bangladesh. They find a higher level of efficiency (0.91) for data from 2000. Given the dominance of rice in Bangladesh, a higher level of efficiency in rice production compared to the whole farm estimate of this study is not surprising.

consistent with the TFP growth for Bangladesh (2.41%) from USDA's agricultural productivity database over the same period (USDA, 2017).

Table 5: Estimated TFP growth rates and its components: 2000-2008, in percent, using the extended model

Index	Land Qrtl. 1	Land Qrtl. 2	Land Qrtl. 3	Land Qrtl. 4	Full sample
TFPG	1.14	2.18	3.34	4.08	2.86
TC	2.08	3.00	3.74	4.58	3.20
TEC	0.12	-0.21	-0.09	-0.75	-0.16
SEC	-1.05	-0.58	-0.29	0.27	-0.17

Source: Authors' estimates using the 62-village panel survey.
Note: TFPG is total factor productivity growth, TC is technical change, TEC is change in technical efficiency and SEC is change in scale efficiency.

The second point is that, as noted earlier, the production frontier has moved relatively faster for the larger farmers. Starting from a lower base, technical change has thus helped the larger farmers catch up with the smaller farmers in terms of average productivity. Further, despite the frontier moving faster, it also appears the bulk of the larger farmers are yet to benefit from these technical advances and have fallen further behind in terms of technical efficiency. Finally, it is important to note that with the larger farmers catching up, while the negative trend in TFP remains – that is the inverse farm-size and productivity relationship still holds – it has diminished over time.

The final set of results of interest are the policy variables in the inefficiency function. None of the demographic variables attain statistical significance at any reasonable level, suggesting that the fixed effects model adequately controls for inter-personal variation across farm households. Importantly, the non-farm participation coefficient is not statistically significant, indicating that households that participate in the off-farm work achieved neither higher nor lower levels of inefficiency.

Among other policy variables, households engaged in sharecropping are less inefficient (i.e, more efficient) – a consistent result in all models. Rented land does not show the same result, indicating these households are no better or worse off in terms of technical efficiency than the base category, which is pure owners. The fragmentation index has a highly significant negative coefficient, consistently across farms, indicating it is associated with *less* inefficiency. This result is counter-intuitive from a transaction cost point of view, but makes sense if the households are leasing in lands of better quality than what they own, or of different quality for different (diversification)

purposes.[18] Either way, if the index is treated as a proxy for entrepreneurship, the negative impact on inefficiency (higher impact on technical efficiency) does make sense.

With massive public investments roads over the past two decades, it appears that distance to Dhaka, or physically connectivity to the major urban centers, is no longer a problem. However, connectivity in the sense of access to public services, which are centered at the Thana HQ, remains a significant factor. The positive coefficient implies higher inefficiency. One key service for productivity growth would be access to technical advisory and extension services, and this seems to be the finding emerging from the data. Finally, the insignificance of the east-west dummy shows that living in the west is no longer a disadvantage, undoubtedly a benefit from the connectivity provided by the Jamuna Bridge and large investments by the government in roads.

5. Conclusions and policy implications

Using three rounds of household panel surveys over a period of eight years, this paper looks at the relationship between farm size and agricultural productivity in Bangladesh. The empirical setting is important because features of Bangladesh's agricultural economy help address some of the confounding factors that have dogged a 'clean' explanation of the inverse farm size-productivity relationship in other settings. Technology use and mechanization are widespread (with rental markets helping to overcome the need for lumpy investment in machinery); it has active factor markets (for labor and land leasing); panel data allow controlling for management skills; and several indicators are available to control for soil and land quality across farms.

Methodologically, the findings suggest that SPF models that ignore the inefficiency function are likely mis-specified, implying that the estimated farm size-productivity relationship may be misleading. Empirically, the findings show strong growth in productivity between 2000 and 2008, most of which appears to have been achieved between 2004 and 2008. This may be because productivity change in 2000-2004 cannot be detected as 2004 was a bad agricultural year due to widespread flooding in the country.

[18] Indeed, fragmentation is found to be a highly significant determinant of farm diversification (results not shown for brevity).

The farm size and productivity relationship is estimated to be negative, in terms of both the scale elasticity at the frontier and technical inefficiency, but with the inverse relationship diminishing over time. TFP growth between 2000 and 2008, derived from its constituent components (i.e., scale, technical efficiency and technology effects), is found to be robust across the sample, driven by technical change. By farm size groups, the relatively larger farmers experienced faster technical change. These findings imply two inter-related developments over time. One, the scale characteristic of the effective production frontier changed over time, from decreasing to constant returns. Second, wider adoption of technology helped the relatively larger farmers catch up and narrow the productivity gap with smaller farmers.

As may be expected with a shifting frontier, the bulk of the farmers in the largest farm size quintile have not kept up with the change, resulting in a fall in the average technical efficiency for the quintile. The findings thus confirm that the productivity-farm size relationship remains negative, but the inverse relationship has notably diminished over time.

In terms of policy implications, in addition to continued investment in research and innovation for future technical change, an important priority is the reduction in the prevailing technical inefficiency in production. For this, two areas of focus emerge from the empirical estimates of the inefficiency function. First, investments to improve last mile connectivity, from the Thana HQ to villages, is a top priority. This would provide better access to markets and important public services. Second, well-functioning land markets allow the flow of land from less to more efficient producers. Strengthening the regulatory framework for leasing land, and more broadly promoting efficient functioning of land markets with better land governance and administration is a second area of priority.

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Annex

Table A.1: Descriptive Statistics of variables in production functions and inefficiency functions

	2000		*2004*		*2008*	
Production Variables (output and inputs)	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
Farm size (Ha)	0.77	0.89	0.71	0.78	0.66	0.70
Value of output (BDT per ha) in 2008 prices	62373	40302	59579	33258	90869	72252
Fertilizer costs (BDT per Ha) in 2008 prices	6419	4305	5489	4172	5765	3680
Labor costs (BDT per Ha) in 2008 prices	9780	9945	9663	8821	12221	9889
Share of farm households using hired labor	0.81	0.39	0.82	0.38	0.89	0.31
Other costs (BDT per Ha) in 2008 prices	7718	5534	7471	6239	9382	6470
Agric. capital (BDT per Ha) in 2008 prices	42316	64534	43988	53941	68433	88007
Number of family workers (per Ha)	4.79	6.80	4.66	5.59	5.54	9.86
Share of irrigated land	0.72	0.40	0.79	0.37	0.86	0.33
Production conditions						
Share of sandy land	0.05	0.17	0.05	0.18	0.03	0.16
Share of loam land	0.38	0.42	0.26	0.37	0.14	0.29
Share of sandy loam land	0.30	0.40	0.41	0.43	0.50	0.45
Share of clay loam land	0.26	0.38	0.28	0.40	0.33	0.43
Share of high land	0.39	0.44	0.36	0.42	0.22	0.37
Share of medium land	0.31	0.40	0.31	0.39	0.39	0.44
Share of low land	0.14	0.27	0.16	0.31	0.16	0.32
Share of very low land	0.16	0.33	0.16	0.31	0.23	0.39
Avg. monsoon rainfall (mm) for last 10 years	1528	335	1502	356	1536	344
Inefficiency Variables						
Demographic/Personal Factors						
Female headed HH (%)	0.02	0.12	0.02	0.14	0.04	0.21
Farm HHs with non-agricultural workers (%)	0.35	0.48	0.32	0.47	0.33	0.47
Head's schooling: primary (%)	0.31	0.46	0.22	0.42	0.23	0.42
Head's schooling: secondary (%)	0.33	0.47	0.19	0.40	0.20	0.40
Head's schooling: tertiary (%)	0.09	0.29	0.14	0.34	0.14	0.35
Policy Related Factors						
Sharecropped land (%)	0.37	0.48	0.35	0.48	0.29	0.45
Land rented? (%)	0.23	0.42	0.27	0.44	0.22	0.41
Land fragmentation index (scale: 0-1)	0.59	0.28	0.61	0.27	0.55	0.28
Distance to Dhaka city (in Km)	215	93	214	93	215	93
Distance to Thana headquarter (in Km)	7.21	3.95	7.25	3.97	7.22	3.96
Living in the western region? (%)	0.54	0.50	0.54	0.50	0.54	0.50
Observations	720		720		720	

Source: Authors' estimates using the 62-village panel survey. BDT=Bangladesh Taka.

Table A.2: Parameter estimates of Cobb-Douglas production function (with correlated random effects, CRE)

Dep. Var: Value of output (per Ha., Log)	***Basic model***		***Without Soil Quality***		***Full Specification***		***Extended Model***	
Frontier Production Function								
Log(Farm size,Ha)	-0.046	(0.028)	-0.062**	(0.031)	-0.050*	(0.030)	-0.071**	(0.033)
Log(Fertilizer costs, BDT per Ha)	0.040***	(0.010)	0.039***	(0.010)	0.039***	(0.009)	0.036***	(0.009)
Log(Hired labor costs, BDT per Ha)	0.078***	(0.015)	0.081***	(0.016)	0.074***	(0.015)	0.073***	(0.015)
Log (Other costs, BDT per Ha)	0.125***	(0.020)	0.133***	(0.020)	0.126***	(0.019)	0.124***	(0.019)
Share of Irrigated Land	0.205***	(0.064)	0.277***	(0.064)	0.247***	(0.063)	0.248***	(0.062)
Adult worker in HH/Ha	-0.000	(0.002)	-0.001	(0.002)	-0.000	(0.002)	0.001	(0.002)
Log(Agricultural capital, BDT per Ha)	0.005	(0.004)	0.004	(0.004)	0.005	(0.004)	0.006	(0.004)
Use hired labor(Yes=1)?	-1.057***	(0.203)	-1.090***	(0.207)	-0.995***	(0.201)	-0.977***	(0.201)
Soil quality (share of land; base: sandy)								
Loamy	0.367***	(0.087)			0.360***	(0.087)	0.360***	(0.087)
Sandy loam	0.370***	(0.085)			0.364***	(0.084)	0.363***	(0.084)
Clay loam	0.370***	(0.089)			0.365***	(0.088)	0.363***	(0.088)
Elevation (Share of land; base: very low land)								
Share of high land	0.174***	(0.063)			0.186***	(0.062)	0.188***	(0.062)
Share of medium land	0.083	(0.058)			0.081	(0.056)	0.087	(0.056)
Share of low land	0.055	(0.058)			0.045	(0.057)	0.044	(0.056)
Average rainfall	0.087	(0.107)	0.178	(0.116)	0.348***	(0.117)	0.338***	(0.117)
Agro-ecological zone FE	Yes		Yes		Yes		Yes	
Year (base:2000)								
2004	-0.001	(0.025)	-0.021	(0.025)	0.001	(0.025)	-0.001	(0.031)
2008	0.279***	(0.029)	0.249***	(0.028)	0.257***	(0.029)	0.330***	(0.036)
Land and year interactions								
2004*Farm size							-0.001	(0.027)
2008*Farm size							0.094***	(0.028)

Notes: 1. Standard errors in parentheses, 2. * p<0.10, ** p<0.05, *** p<0.01. BDT=Bangladesh Taka. FE=Fixed Effects.

Table A.2 (Contd.): Parameter estimates of Cobb-Douglas production functions (with correlated random effects (CRE))

Dep. Var: Value of output (per Ha., Log)	***Basic model***		***Without Soil Quality***		***Full Specification***		***Extended Model***	
Mean variables for CRE								
Log (Fertilizer, Ha)	-0.034**	(0.013)	-0.014	(0.013)	-0.028**	(0.013)	-0.027**	(0.013)
Log (Hired labor costs, BDT per Ha)	-0.005	(0.004)	-0.007	(0.005)	-0.006	(0.004)	-0.006	(0.004)
Log (Other costs, BDT per Ha)	0.136***	(0.031)	0.196***	(0.030)	0.120***	(0.031)	0.123***	(0.030)
Farm size (Ha)	0.087**	(0.034)	0.115***	(0.035)	0.113***	(0.034)	0.108***	(0.034)
Share of Irrigated Land	0.196**	(0.079)	-0.014	(0.079)	0.146*	(0.078)	0.148*	(0.078)
Adult worker in HH/Ha	0.003	(0.003)	0.003	(0.003)	0.004	(0.003)	0.004	(0.003)
Log (Agricultural capital, BDT per Ha)	0.009	(0.006)	0.013*	(0.007)	0.007	(0.006)	0.006	(0.006)
Share of loamy land	-0.198	(0.135)			-0.277**	(0.134)	-0.281**	(0.134)
Share of sandy loam land	-0.261**	(0.131)			-0.305**	(0.131)	-0.309**	(0.130)
Share of clay loam land	-0.501***	(0.131)			-0.523***	(0.131)	-0.523***	(0.131)
Share of high land	0.287***	(0.082)			0.311***	(0.081)	0.303***	(0.081)
Share of medium land	0.364***	(0.078)			0.353***	(0.076)	0.339***	(0.076)
Share of low land	0.312***	(0.090)			0.333***	(0.088)	0.328***	(0.088)
Constant	7.503***	(0.801)	6.773***	(0.867)	5.762***	(0.869)	5.810***	(0.864)

Notes: 1. Standard errors in parentheses, 2. * p<0.10, ** p<0.05, *** p<0.01. BDT=Bangladesh Taka. FE=Fixed Effects.

Table A.3: Parameter estimates of inefficiency functions

Dep. Var: Value of output (per Ha., Log)	***Basic model***		***Without Soil Quality***		***Full Specification***		***Extended Model***	
Inefficiency function								
Log(Farm size,Ha))			2.976***	(1.146)	1.164**	(0.526)	1.285**	(0.549)
Female headed HH			2.363	(2.810)	0.953	(1.244)	0.934	(1.273)
Farm HH with non-agricultural worker			-0.726	(1.193)	-0.335	(0.513)	-0.310	(0.516)
HH Head's Education level (base: none)								
Primary			-2.041	(1.481)	-0.833	(0.643)	-0.858	(0.650)
Secondary			-0.301	(1.373)	0.067	(0.582)	0.001	(0.589)
Tertiary			-1.293	(1.771)	-0.508	(0.752)	-0.493	(0.751)
Sharecropped? (yes=1)			-3.721**	(1.699)	-1.378**	(0.692)	-1.369**	(0.694)
Land rented? (yes=1)			-1.771	(1.470)	-0.528	(0.585)	-0.521	(0.587)
Fragmentation index (scale:0-1			-10.18***	(3.428)	-4.061***	(1.532)	-4.219***	(1.570)
Log (distance from Dhaka, KM)			1.960	(1.996)	0.849	(0.877)	0.937	(0.882)
Log (distance from Thana, KM)			6.588***	(2.101)	3.202***	(1.035)	3.146***	(1.024)
East-West Dummy (West=1)			-2.952	(1.890)	0.020	(0.787)	-0.169	(0.790)
Constant	-42.012	(30.766)	-32.150**	(14.038)	-15.169**	(6.250)	-15.305**	(6.341)
sigma_u	3.636		2.338		1.507		1.518	
sigma_v	0.370		0.386		0.367		0.365	
lambda	9.814		6.052		4.102		4.160	
Log likelihood	-1452.340		-1497.337		-1416.213		-1408.892	
chi2	1694.167		1259.024		1553.692		1585.663	
p-value for chi2	0.000		0.000		0.000		0.000	
Average Technical efficiency	**0.751**		**0.752**		**0.756**		**0.755**	
Observations	2160		2160		2160		2160	

Notes: 1. Standard errors in parentheses, 2. * p<0.10, ** p<0.05, *** p<0.01