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Boserupian Pressure and Agricultural Mechanization in Modern Ghana

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ABSTRACT

The adoption of machinery in agricultural production in Africa south of the Sahara has been far behind the level of mechanization found in Asia and Latin America. However, recent survey data have revealed high levels of machinery use in localized areas of cereal production in northern Ghana. A survey conducted by the International Food Policy Research Institute, in partnership with the Savannah Agriculture Research Institute, found that in some areas more than 80 percent of farmers were using machinery for at least one operation. This paper considers the theoretical drivers of agricultural intensification, as outlined by Boserup, Pingali, and Binswanger, and the extent to which they are able to explain the spatial variation in machinery use found in northern Ghana. Population pressure, market access, and agroecological conditions are considered key drivers that cause farmers to find ways to increase productivity and adopt new technologies. Combining survey data with geospatial datasets, the empirical analysis finds that population growth and travel time to the local urban center explain a significant and large proportion of the variation in machinery use by farmers.

Keywords: agricultural intensification, Boserup, mechanization, Africa south of the Sahara

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1. INTRODUCTION

The mechanization of agricultural operations in Africa south of the Sahara has been low, especially among smallholder farmers, who dominate agricultural production (Mrema, Baker, and Kahan 2008). There is also evidence of unutilized arable land in many areas of Africa south of the Sahara where poor infrastructure and low productivity are limiting the returns to cultivation (Jayne, Chamberlin, and Headey 2014). Machinery use has the potential to improve labor productivity, especially as urbanization and structural transformation increase demand for labor outside agriculture and while increasing food demand from net consumers. The low level of mechanization use in the region has been attributed to lack of incentives for farmers to adopt the technology, due to low demand for agricultural output and relatively low agricultural wage (Pingali 2007). However, in some areas, widespread use of agricultural machinery for land preparation, threshing, and harvesting, among farmers of all scales, has been found (Takeshima 2015; Diao et al. 2014). Mechanization can be understood as one of the technologies that enable the intensification of agricultural production. The theories of Boserup (1965), Ruthenberg (1980), Pingali, Bigot, and Binswanger (1987), Pingali (2007), and others have attempted to explain these conditions under which farmers begin to adopt labor-saving technology as part of their profit-maximizing production decision. These hypotheses posit that agroecological conditions, population density, and market demand are the fundamental drivers of agricultural intensification. Intensification in this context is the more intensive farming of land through reduction of fallow periods, increased cropping frequency, and use of fertilizer and other chemical inputs.

There is little evidence of the adoption of agricultural machinery by farmers in Africa south of the Sahara, save for large-scale commercial enterprises for some high-value crops and in certain areas. Therefore, it has been impossible to provide conclusive evidence to support the theories of agricultural mechanization. Pingali, Bigot, and Binswanger (1987) made a convincing case that the failure of state-sponsored mechanization programs in the 1980s was due to the lack of farmer demand for the technology. Without the pressures on the farming system from increased market demand due to nonagriculture-sector growth or population growth, there would be little incentive for farmers to mechanize their operations. However, as will be demonstrated in this paper, farmers of small and medium scale have mechanized some operations in certain areas. Moreover, it is not only a handful of farmers who have adopted the more advanced technology but the majority of farmers within the local farming system who are using agricultural machinery either through ownership or through a service rental market. A unique survey dataset of farmers in northern Ghana provides an opportunity to investigate more thoroughly the correlation between these fundamental drivers of agricultural intensification and machinery use. Survey data of 1,843 farmers from northern districts of Ghana, combined with geospatial datasets, allow analysis of the extent to which these fundamental drivers can explain the spatial variation in machinery use across cereal-producing areas of northern Ghana.

The literature on technology adoption in agriculture is extensive. This paper follows Ruthenberg (1980) in taking a systems approach to the analysis. The analysis is concerned with understanding the fundamental drivers that cause a farming system, that is, most farmers within the local farming system, to become mechanized for some or all operations. In this way, although using household survey data, our concern is not with the individual farmer and plot characteristics or social networks that facilitate technology learning and adoption (Lindner, Fischer, and Pardey 1979; Conley and Udry 2010). Of course, there is interesting analysis there to be done in understanding how mechanization technologies have been imported, adapted, and subsequently adopted by smallholder farmers, but this investigation is left for another paper. The focus will be on the relationship between drivers of agricultural intensification, as proposed by Boserup (1965) and developed by Pingali, Bigot, and Binswanger (1987), and mechanization of local farming systems.

The paper is structured as follows. Section 2 will outline the theoretical framework to explain the drivers of machinery use, drawing from the work of Boserup (1965) and others who have built on her framework. Section 3 describes the data and analytical approach used to investigate the correlations between the theoretical drivers of agricultural intensification and machinery use in Ghana. Section 4 concludes with discussion of the results and highlights further questions for research.

2. THEORETICAL FRAMEWORK: BOSERUP AND BEYOND

Before outlining the theoretical relationship between agricultural machinery use and the fundamental drivers of agricultural intensification, several assumptions are made. First, in the spirit of Ruthenberg (1980), it is assumed that there are certain drivers that will affect all farmers in the local economy or farming system. In addition, there are individual plot and farmer characteristics that will affect the level of input use, productivity, and the capacity to adopt new technologies. This paper will focus on those systemwide drivers, based on the assumption that these drivers are just as important in determining a farmer's use of machinery as individual characteristics such as education, social networks, and land quality. This assumption is supported by quantitative findings that machinery use tends to be concentrated among farmers in the same locality. More work could be done to understand the networks and spillovers that lead to this pattern. This is not to say that individual characteristics are unimportant, but investigating these is left for another paper. A second assumption that is made is that the appropriate technology is available to farmers and that farmers are knowledgeable of the benefits of its use—appropriate technology being that which responds to the bottlenecks and relative production costs for farmers (Stewart 1987). For the context in Ghana, this is a somewhat reasonable assumption given a long history of mechanization use for land preparation and, more recently, for maize shelling (Houssou et al. 2013). There is a steady import of new and used agricultural machinery to Ghana, and its use is spread across cereal-growing areas of northern Ghana (Diao et al. 2014).

Boserup's (1965) famous contribution was to make a theoretical and empirical link between population growth and agricultural intensification. She argued that farming system evolution and technology use under different farming systems are endogenous processes in which population growth is the main determinant, given agroecological conditions. The evolution of the farming system involves a process of land intensification that is associated with higher levels of input use—including labor and fertilizer but also eventually incorporating nonhuman sources of power—whether animal traction or machinery. She argued that mechanization, which is labor saving, would be adopted where there is growing demand for output either because of population growth or because of growth in the nonagriculture sector. She hypothesized that labor-saving technology will be demanded (1) at constant total population growth if labor is moving from agriculture to nonagriculture or (2) with faster population growth and limited food imports, leading to intensification of production. Boserup argues that the growth in demand for agricultural outputs, through population growth or nonagriculture-sector growth, will lead to more intensive crop cultivation, which motivates a technology change from hand-hoe to plowing for land preparation (especially in tropical areas where weed regrowth between seasons is considerable). Pingali, Bigot, and Binswanger (1987) find a positive correlation between the intensification of farming systems, as described by Boserup, and the mechanization of agricultural production. They emphasize that provision of tractors cannot drive agricultural intensification but that the demand drivers required for agricultural intensification—population growth or nonagriculture-sector growth—will need to be in place for African farmers to adopt agricultural machinery.

Agroecological conditions are necessary for mechanized technology to be technically feasible. The topography, soil conditions, and rainfall patterns will limit the range of crops and production techniques that can be used in a particular location. Market demand will determine which crops are cultivated within this range. For example, cocoa trees are perennial and do not require annual plowing, and operations such as cocoa harvesting are less easily mechanized. Cereal crop production is more easily mechanized and in fact will be required in tropical areas where weed regrowth is considerable. Therefore, farmers in grassland areas, which are suitable for cereal production, are more likely to utilize mechanized tillage. Furthermore, the level and variation in rainfall patterns will affect the agricultural productivity and the bottlenecks for farmers. Agricultural production will be more profitable in areas with longer growing seasons or two growing seasons. In northern Ghana, there is only one growing season, whereas the more southerly transition zone benefits from two growing seasons. For land preparation, and other operations, rainfall seasons will determine the time that is available for the operation to be performed. The lower the

number of days of rainfall, the more critical timing will become, and farmers may require machinery to complete their operations in time. Given the technical feasibility of machinery use, the length of the growing period may have a positive effect on machinery use due to higher agricultural potential or a negative effect because the shorter growing time creates demand for time-saving technologies.

The relationship between population growth, agricultural intensification, and machinery use is transmitted through (1) the land-labor ratio and (2) output demand. Farmers will find it more profitable to adopt technology that is biased toward the relatively abundant factor of production (Binswanger and Ruttan 1978; Hayami and Ruttan 1985; Ruttan 1996). Machinery is a labor-saving technology and will therefore more likely be adopted where there is a relative shortage of labor. Higher population growth will be associated with smaller land sizes due to competition over land and relatively lower cost of labor. In addition to the land-labor ratio, rapid population growth will lead to increased demand for agricultural outputs as the number of net consumers increases. Population growth will increase the relative price of agricultural outputs (if there are limited imports) to the cost of inputs, thereby creating the incentives for farmers to invest in technologies that will increase labor and land productivity.

When population growth is constant, growth in the nonagricultural economy will create similar pressure to intensify agricultural production. This is through two avenues: (1) raising the opportunity cost of agricultural labor and (2) increasing demand for agricultural outputs due to urbanization or as industrial inputs. The extent to which a local farming system will be affected by these pressures will rely on market access. Both the distance from farm to market and the quality of infrastructure are found to affect individual farmers' productivity (Stifel and Minten 2008). Growing labor demand from the nonagriculture economy will increase the opportunity cost of agricultural labor and put upward pressure on the agricultural wage. The effect will be greater in areas close to urban markets (Byerlee 1974; de Brauw, Mueller, and Lee 2014). Transport-related transaction costs can cause considerable price differences across locations, affecting the output price received by farmers. The higher the transaction costs, the lower the incentives for farmers to make investments in productivity-enhancing technology. In Madagascar, Stifel and Minten (2008) find evidence of remoteness's affecting farmer input demand for tractors, particularly through increased price variability in areas far from the market, topography, increased difficulty in accessing labor, local population density, and access to credit.

This framework allows the effects of urbanization on the agricultural systems to be disentangled. From Boserup (1965), those farming systems where population density is high or population growth has been rapid are more likely to intensify agricultural production. Where population growth is constant, growth in the nonagricultural sector will increase demand for labor-saving technology, and labor will be pulled out of agriculture. Boserup's theory makes a good attempt to capture the multiple effects of urbanization on the farming system—through population density and through market demand. In areas that are proximate to urban centers and where population density is rising, there will be increasing pressure on land for competing uses and rising land values. Urbanization also can be associated not only with a movement of population from rural to urban areas but with a movement of labor out of agriculture into other economic activities, thereby creating a shortage of labor for agricultural production. Labor migration in Ghana has been due to migration both to cocoa-growing rural areas of the south and to urban centers such as Kumasi and Accra (Otiso and Owusu 2008; Kolavalli et al. n.d.). On the output demand side, however, urbanization will increase demand for agricultural output as the number of net consumers increases. The extent to which farmers are able to benefit from increased urban demand will depend on trade and integration of markets. For Ghana, urbanization has been an important part of its development since the 1980s and can be considered a potential strong driver of agricultural intensification. Most recently, urbanization in the north of Ghana actually fell from 19 percent to 16 percent from 1996 to 2006, whereas urbanization in the south has been rapid. Since 2009, more than 50 percent of the total population has been urbanized (Kolavalli et al. 2012).

A major component of the transaction costs associated with market integration is the quality of the physical infrastructure between the farm and urban center (Renkow, Hallstrom, and Karanja 2004; Stifel and Minten 2008). Therefore, the distance between the farm and the nearest urban market will capture the extent to which farmers are able to benefit from increasing urban demand for agricultural output. Through considering population density and market proximity in the model, both of these dimensions of urbanization are captured. The proportion of urbanized population in the local enumeration area of the district is not considered directly since markets are well integrated in Ghana (Abdulai 2000). Travel time to urban centers is a good measure of the extent to which a farmer is able to access urban markets.

This theoretical framework is represented by the following relationship.

$$\mathrm{P}(y_{ivd} = 1) = \beta_0 + \beta_1 PL_v + \beta_2 PG_d + \beta_3 AEZ_v + \beta_4 M_v + \beta_5 C_i + \varepsilon$$

This equation captures, in a reduced form, the relationship proposed by Boserup (1965) and Pingali, Bigot, and Binswanger (1987) between the drivers of intensification—population density, population growth, agroecological conditions, market access—and mechanization. The left-hand side becomes the probability of individual farmer *i*'s using machinery for land preparation when y_{ivd} is a dummy for an individual farmer's using machinery for land preparation. AEZ_v is a measure of agroecological conditions, which will capture the length and variation of seasonal rainfall. PL_v is the level of population density for a particular village. PG_d is population growth at the district level during the periods 1984, 2000, and 2010. M_v is market access and various measures of market connectivity discussed below. C_i is the set of control variables including land owned (hectare) and whether the farmer has a plan to expand the farm business.

3. DATA AND ANALYSIS

To better understand the use of agricultural machinery in Ghanaian agriculture, the International Food Policy Research Institute, in partnership with the Savannah Agricultural Research Institute, carried out a survey of 1,843 farm households in eight districts of Ghana during October through December 2013. The survey captured large-, medium-, and small-scale farmers. One advantage of this dataset is that the sampling strategy allows us to understand the behavior of tractor users, in contrast to most standard agricultural surveys in Ghana and elsewhere that tend to capture few large-scale farmers and machinery users. The results indicate that mechanization of agriculture is not reserved for a few large-scale commercial farmers but is instead accessed by many small- and medium-scale farmers through an active hiring market (Diao et al. 2014). Furthermore, the survey confirmed that machinery use is not uniform across the northern savannah areas of Ghana but varies by location. The analysis in this paper will consider the spatial variation in machinery use, using this single cross-sectional dataset of eight districts. For such an analysis to be valid, an assumption is made that there is enough similarity across the surveyed areas to assume that those less-mechanized areas would be mechanized had they faced the same exogenous pressures as those that are more mechanized.

The sampling framework that was used for the survey ensures that weighted estimates are representative at the district level. The analytical approach takes advantage of information at the village (or enumeration area) level to match data from geospatial datasets to individual farm households. Through this matching, 1,606 households have been sampled from 205 enumeration areas. Some household observations are dropped from the analysis, as there is no clear match with an enumeration area. No systematic bias was found in the key variables between the matched and unmatched households.

Data limitations mean that the dependent variable can be analyzed only at the level of individual farmers. At the same time, the measures of the independent variables are meaningful only if considered at the level of the farming system. In this case, that means either the village (enumeration area) level or the district level. The analytical approach chosen seeks to exploit the advantages of the data, while I am aware that there are limitations to such an approach. Causality will not be able to be identified. Areas with higher agricultural potential will support population growth and immigration in the long term, and similarly investments in physical infrastructure will be targeted to those areas with higher population and higher agricultural potential. Therefore, while the measures used for agroecology, population, and market access are exogenous to the farmer's decision to adopt machinery, it will not be possible to disentangle the causality of these factors and machinery adoption. The analysis focuses on the correlations between these variables to explain the variation in mechanization across locations.

Descriptive Statistics

Tractor Use and Other Measures of Agricultural Intensification

In addition to capturing a representative sample of all farmers, the survey allowed for estimation of the tractor stock in each district. The highest concentration of tractors is found in the Ejura, Yendi, and Gushiegu districts, each of which has more than 90 tractors. Sissala East also has a high number of tractors (Table 3.1). Interesting to note is the high level of tractor use in most districts, despite a low stock of tractors. A healthy rental market and the movement of tractors with the variation of plowing season explains this across locations (Houssou et al. 2015). Of the tractor owners, 85 percent hired in mechanization services before purchasing their first tractor, and on average, they hired in services for nine years before purchasing the tractor. The most common operation to be mechanized is plowing, followed by maize shelling and transportation of harvest from the field.

Table 3.1 Tractor stock and density by district

Survey district	Total number of tractors	Tractor density ^	Proportion of farmers using machinery for tillage
Ejura Sekye Dumase	165	16.96	0.80
Yendi	124	4.15	0.94
Gushiegu	96	4.12	0.94
Sissala East	52	2.23	0.64
Bawku Municipal	9	2.38	0.13
Kintampo North	9	0.90	0.22
Kasena Nankana E	9	1.49	0.56
Techiman	1	0.08	0.03

Source: Chapoto et al., 2014
Note: ^Number of tractors per 100,00 kilometers square.

As discussed above, use of machinery for agricultural operations should be considered part of the process of agricultural intensification that will involve adoption of other technologies and practices that increase agricultural output. Table 3.2 shows several measures of agricultural intensification for tractor users and nonusers, most of which have a significant difference in means. The definition of a tractor user is a farmer who uses machinery for land preparation on at least part of his or her cultivated land. These farmers may own machinery themselves or borrow/rent machinery services from others. The average farm size for tractor users is greater than that for nonusers in terms of both cultivated land and land owned. However, the average farm size for tractor users is still relatively small at only 3.89 hectares of cultivated land. It is not only large-scale commercial farms that are using machinery.

Table 3.2 Mechanized plowing and other measures of agricultural intensification

Variable	Not tractor users		Tractor users		Number	Significance level^
Cultivated land (ha)	2.768	(0.124)	3.888	(0.126)	1827	***
Land owned (ha)	4.882	(0.387)	7.381	(0.500)	1827	***
Plan to develop farm	0.27	(0.0336)	0.422	(0.0319)	1827	**
Received government or NGO assistance	0.0556	(0.0118)	0.0943	(0.0215)	1827	
Hired-in labor for rice cultivation	0.525	(0.0776)	0.761	(0.0652)	698	*
Hired-in labor for maize cultivation	0.675	(0.0406)	0.702	(0.0332)	1300	
Used herbicide	1.064	(0.0898)	2.766	(0.106)	1817	***
Used inorganic fertilizer	1.169	(0.106)	2.036	(0.103)	1817	***
Used organic fertilizer	0.618	(0.0919)	0.247	(0.0510)	1817	***
Sold maize in 2013	1.369	(0.0394)	1.29	(0.0279)	1611	
Fallow land (ha)	2.357	(0.199)	4.552	(0.560)	938	***
Virgin land (ha)	6.232	(1.971)	7.544	(1.854)	429	
Hired-in machine for plowing	0.0655	(0.0170)	0.831	(0.0197)	1827	***
Hired-in machine for shelling	0.0757	(0.0185)	0.333	(0.0350)	1827	***
Hired-in machine for transport	0.0814	(0.0222)	0.374	(0.0296)	1827	***

Source: Chapoto et al. (2014).
Note: NGO = nongovernmental organization. Linearized standard errors are in brackets. ^ For t statistic for difference in means. *p < .05. **p < .01. ***p < .001.

Most farmers hire in labor, use herbicide and inorganic fertilizer, and sell to the market to some extent. There are slightly higher levels of use for these inputs among tractor users. However, the difference for labor use is not significant between users and non-users of tractors. The variable here is not the quantity of labor used but whether any labor was hired in. As Table 3.2 shows, we would expect there to be higher use of other modern inputs among tractor users. Boserup (1965) proposed that increased use of fertilizer and chemicals would create labor demand for their application and therefore farmers would seek to mechanize other operations. Consistent with Boserup's proposition that farmers will mechanize when chemical use increases, even without population growth, tractor users have higher rates of herbicide use. As the farming system in tropical areas intensifies, the regrowth of weeds between growing seasons becomes a major challenge (Pingali, Bigot, and Binswanger 1987). Both mechanized plowing and chemical herbicide are used to clear the land before planting. Herbicide is a complement to mechanized tillage in Ghana. Fertilizer use is also a sign of agricultural intensification and depletion of soil fertility due to more frequent cultivation of the land.

The story is a little more mixed regarding fallow and virgin land, which reflects the customary land tenure system governing land use and ownership. In the process of intensifying production, we would expect the amount of unused land owned by the farmer to reduce and more land to be brought into annual cultivation. Therefore, more intensive agricultural production is associated with less fallow and virgin land area. The nature of the land tenure system in northern Ghana discourages farmers from keeping virgin land. If land appears to be unused, the threat of that land's being reallocated to another farmer is greater (Goldstein and Udry 2008). Consistent with this, there is no significant difference in the amount of virgin land held by tractor users and nonusers, and less than a quarter of the sample reported having virgin land. On the other hand, approximately half of the sample had fallow land in 2013, and tractor users on average held more fallow land than nontractor users. As a proportion of total land owned, tractor users also held more fallow land. The relationship between land owned and fallow area is unlikely to be linear, as smaller farmers will cultivate a greater proportion of their land. The fact that larger farmers are maintaining a considerable proportion of their land as fallow may indicate that a mixture of short fallow and annual cultivation is being used (Ruthenberg 1980).

The final pattern to note from Table 3.2 is that 83 percent of tractor users hired in machinery services for plowing. This confirms the extensive use of the hiring market by farmers who do not own their own machinery. There is a smaller market for hiring in machinery for shelling and transport, but it is still considerable with more than 30 percent of those using tractors for land preparation also hiring in machinery for these operations.

Population Density and Growth

Total population growth in Ghana was steady from 1960 through 2010 at 2.4–2.7 percent annual growth. Total population density increased from 28.6 to 103.4 persons per square kilometer in 1960 and 2010, respectively (Ghana Statistical Service 2013). However, these national average trends obscure the variation in density and growth rates across the country. The Northern, Brong-Ahafo, and Upper West regions had the lowest population density, less than 60 persons per square kilometer. Between 1970–1984 and 1984–2000, annual population growth in the north of Ghana fell, while growth rose in the many regions in the transition zone and south, that is, the Ashanti and Brong-Ahafo regions (Van der Geest 2011). This trend of slower population growth in the north compared to the rest of the country is explained less by natural population growth and more as a reflection of north-south migration. Van der Geest (2011) suggests that this migration combines the push factor of poor environmental conditions in the north with the pull of fertile land availability in the transition and southern areas. Van der Geest finds some correlation between location of out-migration from the north and environmental factors such as annual rainfall, vegetation index, and yields, indicating the agricultural factors in explaining such north-to-south migration. Some of this migration was to cocoa-growing areas in the south as well as the urban centers of Kumasi and Accra. However, there also has been an expansion in food crop area in the transition zone (author calculations from Ministry of Food and Agriculture statistics), which accounts for

some of the out-migration from the northern areas during 1970–2000. The pattern of migration within Ghana is not simply one of rural to urban. Using the GLSS5 survey, which is from 2005/2006, World Bank (2011) finds that most migration is south-south rather than north-south. The Ashanti region is the second most common destination for migrants, after Greater Accra, although most of those migrants come from within the Ashanti region.

The level of analysis for population data is important conceptually, and the choice of data is limited by meaningful data availability. A variety of measures are considered to ensure a good measure is used for further analysis. First, a geospatial dataset of population density was constructed from LandScan 2012 (HarvestChoice 2015d). This dataset allows the estimation of population density at the level of enumeration area (village). Each household observation is associated with at most one enumeration area.[1] These data are useful in capturing the land-labor ratio at the local level. Other measures of population density and growth have been obtained at the district level using the Population and Housing Census from 1984, 2000, and 2010 (Ghana Statistical Service 2013). The level of population density for the district in 2010 is compared with the population density estimate at the level of enumeration area. In addition, the ratio of rural population to cropland at the district level has been calculated using geospatial datasets for the rural population for 2000 and estimated cropland in 2005 at 1-kilometer gridcells (HarvestChoice 2015a, 2015c). Table 3.3 indicates that the measures of population density at the district level are highly correlated. The measure at the level of enumeration area is significantly correlated with the district-level measures, although understandably the magnitude of correlation is less since they have different numbers of data points. For the purposes of regression analysis, the measure at village level will be used since it provides the most variation (Figure 3.1).

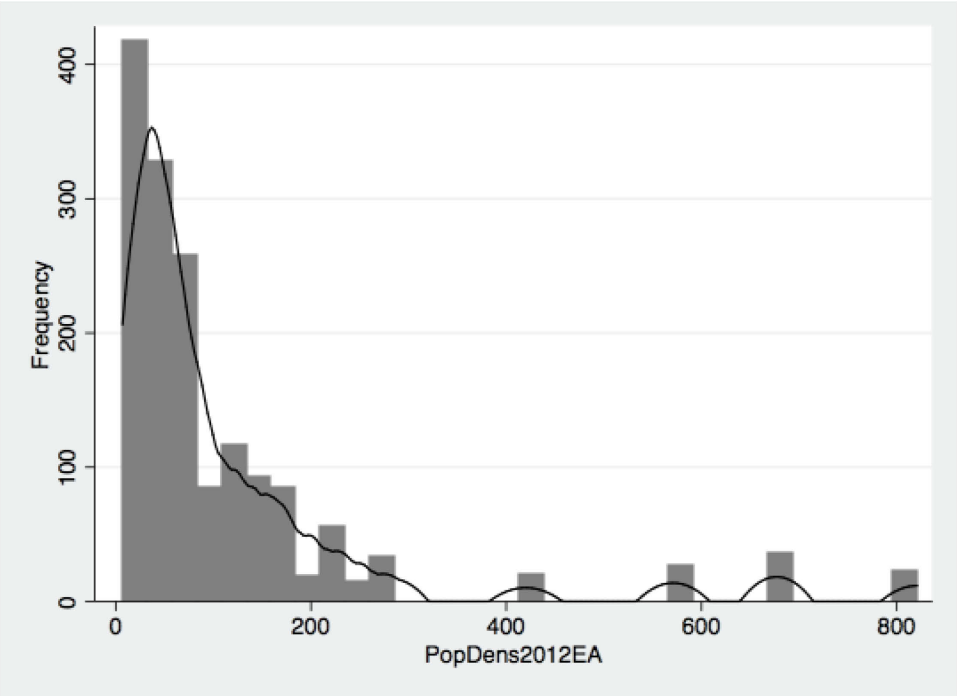
Table 3.3 Correlation matrix for population density

Variable	Village population density	District population density	Rural population to cropland ratio
Village population density (2012)	1	.536	.537
District population density (2010)	.536	1	.944
Rural population to cropland ratio	.537	.944	1

Source: HarvestChoice (2015a, 2015d) and Ghana Statistical Service (2013).

[1] For approximately 200 observations, the survey data are unable to be matched to an enumeration area for the purposes of Geographic Information System data analysis. There appears to be no systematic bias in the unmatched observations.

Figure 3.1 Histogram and density plot for population density (2012, by enumeration area)

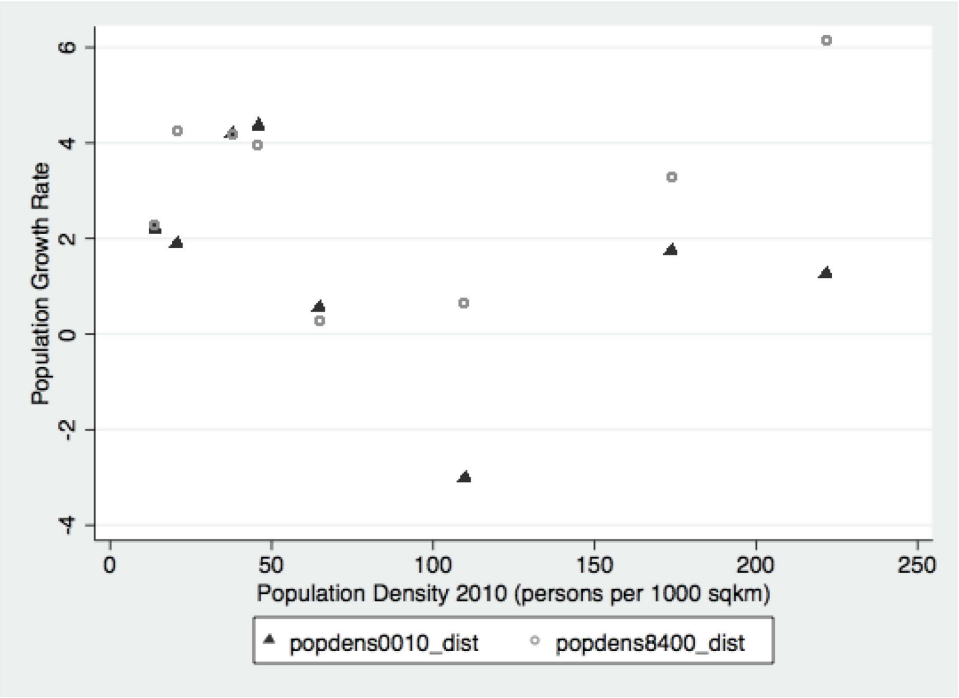


Source: LandScan 2012 (HarvestChoice 2015d).
Note: PopDens2012EA = geospatial dataset of village population density in 2012.

Boserup (1965) emphasizes the importance of the rate of population growth, as opposed to the level of population density, in determining the adoption of new labor-saving technologies by farmers. Therefore, the growth rate of the population at the district level is included in the regression analysis.[2] Figure 3.2 shows the variation in annual average growth (y-axis) during 1984–2000 and 2000–2010 by the level of population in 2010 (x-axis). For those districts with higher levels of population density in 2010, population growth was higher in the early period (1984–1990). Those districts with low population density in 2010 had higher levels of population growth in the more recent period.

[2] The boundaries of some districts changed between the 1984, 2000, and 2010 censuses. As far as possible, meaningful comparisons have been made.

Figure 3.2 Scatter plot of population growth and level



Source: Ghana Statistical Service (2013).
Note: sqkm = square kilometers.

Agroecological Conditions

Broadly speaking, Ghana is split into three agroecological zones—north, transition, and south (HarvestChoice 2015b; Kolavalli et al. 2012). In the north, there is savannah grassland and low rainfall that provides for a single annual growing season. The transition zone benefits from higher annual rainfall with two growing seasons. The land cover is a mix of grassland and forest. In both the savannah and transition zones, cultivation of food crops such as maize, rice, soybean, cassava, and yam dominates. In the south, the forest zone is dominated by cocoa cultivation and also benefits from two rainfall seasons annually. Figure 3.3 maps the surveyed districts in relation to these agroecological zones. No districts were surveyed in the forest zone as the perennial cocoa trees do not require annual tillage and are not easily mechanized.

Figure 3.3 Agroecological zones of Ghana

Source: Harvest Choice (2015b) and Global Administrative Areas (2012).

To more fully capture the variation in rainfall patterns across the surveyed areas, geospatial data on the length of growing period—number of days and the coefficient of variation—were captured at the level of enumeration area. The data on the length of the growing period were derived from the International Institute for Applied Systems Analysis and Food and Agriculture Organization of the United Nations dataset from 2010, provided by HarvestChoice (2015b). Both the mean number of rainfall days and the average variation in the number of days may have relevance for intensification and machinery use. Areas with longer growing seasons will have higher agricultural potential and attract more investment in technologies. However, the greater the variation in the growing period, or the shorter the growing period, the more time constrained farmers will be to prepare their land. From qualitative work, timeliness is a major reason that farmers give for using mechanized plowing. Finally, a dummy variable is constructed to reflect whether the area has two growing seasons or a single growing season each year.

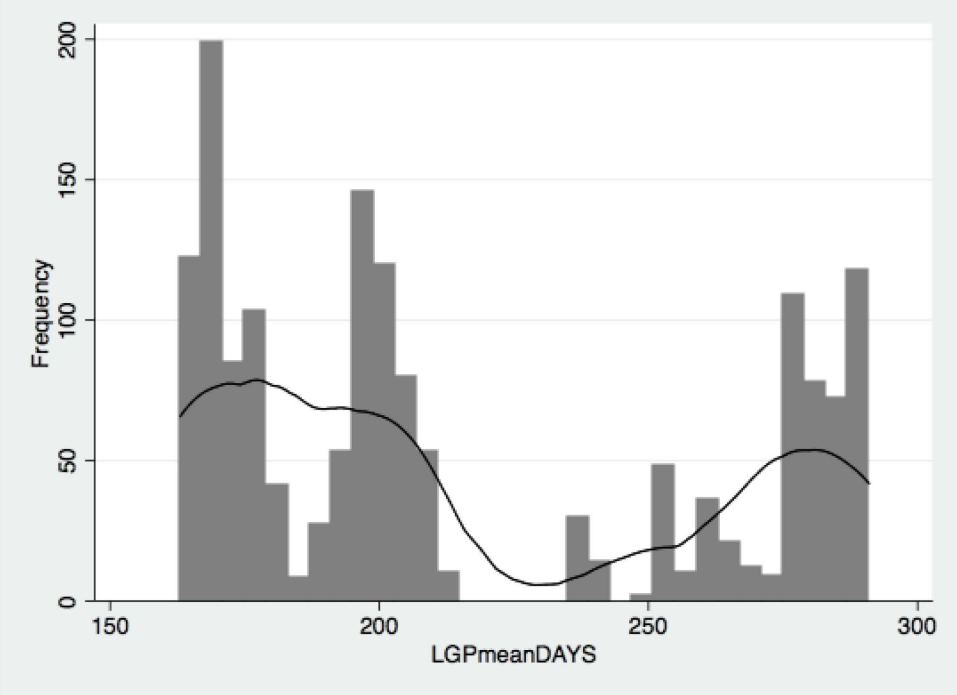
Table 3.4 shows, as expected, that the number of days in the growing period is highly correlated with the variation for the number of seasons. LGPcvABS is the number of days of variation in the growing period on average. This also is well correlated with the other measures. For the regression analysis, we will see that these variables by and large substitute one another. Figure 3.4 shows the density plot for the average length of growing period. This reflects the bimodal pattern, with some areas receiving more than 230 days of rainfall a year across two seasons and other areas receiving 160 to 220 days of rainfall and only one growing season.

Table 3.4 Correlation matrix for measures of agroecology

Variable	Average LGP (days)	Coefficient of variation of LGP	No. of growing seasons
Average length of growing period (days)	1	.670	.901
Coefficient of variation for length of growing period	.670	1	.716
Number of growing seasons (dummy)	.901	.716	1

Source: HarvestChoice (2015b).
Note: LGP = length of growing period.

Figure 3.4 Histogram and density plot of average length of growing period



Source: HarvestChoice (2015b).
Note: LGPmeanDAYS = Average length of growing period in days.

Market Access

Four measures of market access have been constructed using two datasets. The first two measures, *tt20k* and *tt50k,* draw on the estimated median travel time to the nearest settlement of 20,000 people and 50,000 people (HarvestChoice 2015e). Each household is assigned the median travel time for the enumeration area, based on the geospatial dataset from HarvestChoice (2015e) (10-square kilometer resolution). The

second two measures use data on primary and secondary roads. A dummy variable (*GoodRoad_dummy*) is created for each enumeration area that takes the value 1 when a primary or secondary road passes either through the enumeration area or within a 1-kilometer buffer of the road. At the district level, a variable is constructed capturing the number of kilometers of road (any type) per square kilometer (*roaddensity*). The correlation between these variables is shown in Table 3.5.

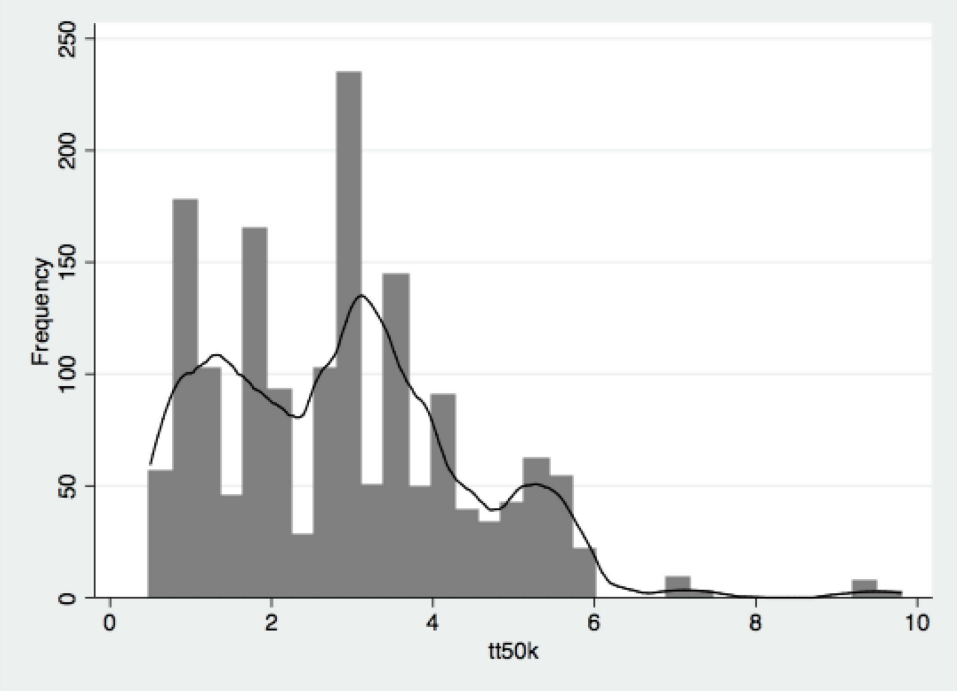
Table 3.5 Correlation matrix for measures of market access

Variable	Travel time to 20k town	Travel time to 50k town	EA contains good road	Length of roads per sq km
Median travel time to nearest 20k town	1	.754	-.051	-.183
Median travel time to nearest 50k town	.754	1	.129	-.173
EA contains good road (dummy)	–.051	.129	1	.297
Length of roads per square km	–.183	–.173	.297	1

Source: HarvestChoice (2015e) and Global Administrative Areas (2012).
Note: EA = enumeration area

As would be expected, the two measures of travel time—*tt20k* and *tt50k*—are strongly correlated. There is also some negative correlation between road density and the travel time measures. As the density of roads increases, the travel time will decrease. The travel time measure is a more meaningful measure of market access as it accounts for the different types of roads and estimates the travel time. As Figure 3.5 shows, there is good variation among enumeration areas of the travel time to a settlement of 50,000 people.

Figure 3.5 Histogram and density plot for median travel time to a settlement of 50,000 people



Source: HarvestChoice (2015e).
Note: tt50k = measure drawing on the estimated median travel time to the nearest settlement of 50,000 people.

Results

The estimation strategy is to use the measures of the independent variables to estimate the associated coefficients of the model outlined in section 2. The significance of the estimated coefficients will indicate whether the variable is significantly correlated with tractor use. The dependent variable is a binary variable for the individual farmer using machinery for land preparation for at least part of his or her cultivated area. Individual-farmer-level controls will be included for total land owned and whether the farmer has a plan to develop his or her farm business (a survey question designed to capture the entrepreneurial capacity of the farmer). The estimation is done using the linear probability model that seems to do a good job of estimation. Probit and logit models are used as a check on the coefficient estimation. The Stata command for survey data (svyset) was used to ensure standard errors are adjusted for clustering according to sampling strata. The sample stratification was by farm size (small: 0–5 hectares; medium: 5–12 hectares; large: >12 hectares) and by district.

The modeling approach used in this paper was confronted with issues in balancing the theoretical relevance of variables with the level at which data were available. The unit of analysis for the survey data was farm households. The households were sampled randomly in each district. With sample weights, the survey data are representative at the district level but not at the level of enumeration area. Global Positioning System coordinates were not recorded at the household level during the survey data collection; however, Global Positioning System information about the enumeration area (village) in which the household was situated has been adequate to match the geospatial datasets at the level of enumeration area. Combined with these data limitations, there are some variables, which in terms of theoretical relationship to the probability of mechanization use would be more or less relevant depending on the level of analysis. In particular, measures of market access and the density of roads at the enumeration area are less relevant than those of the district (or region) within which the household is situated. Road density is a proxy for access to markets for output sales and purchase of agricultural input, which is more likely to be procured from or via the district capital than from the enumeration area itself. However, the travel time to the nearest town is most relevant at the level of the individual household. The geospatial dataset is only at the level of a 1-kilometer grid, so the average travel time for the enumeration area is attributed to the household. Matching of geospatial data to the survey data was done using ArcGIS and data from the Ghana Statistical Service on the enumeration areas, which were used for the Ghana Living Standards Survey and the sampling frame for the International Food Policy Research Institute–Savannah Agricultural Research Institute survey.

The first three columns of Table 3.6 show the linear probability model estimation using only variables at the level of enumeration area and household-level controls. The only variable that is significant is the level of population density. Once population growth, at the district level, is included in columns 4 and 5, we find that both the length of the growing period and the travel time to the nearest large settlement have a weakly significant impact on the probability of a farmer's using agricultural machinery. The coefficient on population density is small and negative. Where there is a higher level of population density, there will be a slightly lower probability that the farmer will use machinery. Similarly, the length of the growing period has a small impact on the probability of tractor use. The rate of population growth and the travel time to the nearest large settlement seem to have the biggest importance in understanding the variation in machinery use across farmers. An increase in travel time of 10 hours would reduce the probability of machinery use by about 42 percentage points. A 1 percent higher population growth rate in the district during 2000–2010 increases the probability of tractor use by 11 percentage points. However, higher growth rates for population in the previous period, 1984–2000, actually reduced the probability of tractor use.

Table 3.6 Regression results: Linear probability model

Variables	Dependent variable: dummy for tractor use on at least one plot (1=yes, 0=no) (1)	(2)	(3)	(4)	(5)
Village Population Density (2012)	–0.001***	–0.001***	–0.001***	–0.001***	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density growth 2000-2010				0.116***	0.113***
				(0.018)	(0.017)
Population density growth 1984-2000				–0.166***	–0.163***
				(0.017)	(0.017)
Average length of growing period (days)	0.000		0.001	–0.002**	–0.002**
	(0.000)		(0.001)	(0.001)	(0.001)
Travel time to nearest 50k town	–0.036	–0.034	–0.035	–0.043*	–0.042*
	(0.023)	(0.026)	(0.023)	(0.019)	(0.019)
Coefficient of variation for LGP		0.007			
		(0.024)			
Farm has business plan			0.110*		0.081
			(0.049)		(0.046)
Land owned (ha)			0.004*		0.002
			(0.002)		(0.001)
_cons	0.704***	0.628	0.567***	1.552***	1.444***
	(0.165)	(0.399)	(0.165)	(0.178)	(0.180)
n	1,609	1,609	1,609	1,609	1,609
R^2	.141	.141	.158	.359	.366
F	23.41	24.41	17.54	39.74	29.48
pc_correct	0.712	0.717	0.737	0.855	0.855

Source: Author's calculations.

Note: LGP = Standard errors are in parentheses and significance level for each coefficient is indicated by $*p < .05$. $**p < .01$. $***p < .001$. N is the number of observations; R^2 is the R-squared for each regression model; F is the F statistic for each regression model; pc_correct is the percentage of the predicted values from the regression model that are consistent with the observed binary dependent variable.

As a goodness-of-fit measure, the percentage of predicted probabilities (using 50% percent as the threshold) is considered. For models including population growth, 85% percent of the predicted probabilities are correct. A common concern with the linear probability model is that there is no constraint on the predicted probabilities lying within 0 and 1. For models 4 and 5 in the table 3.6, only 41 observations resulted in predicted probabilities that were less than 0, with the rest being less than 1. This suggests that the linear probability model does a reasonable job in estimating the theoretical model.

As a check on the results from the linear probability model estimation, probit and logit models are run using the same specification as in models 4 and 5 in Table 3.6. The results are similar in terms of sign of the estimated coefficient and significance (Table 3.7). The goodness-of-fit measure indicates that more than 80 percent of the predicted probabilities for both the probit and logit models are correct. Furthermore, ordinary least squares and tobit models were estimated using the number of hectares on which machinery was used for land preparation as the dependent variable. These results are not shown, but the coefficients are of similar significance and sign as those in Tables 3.6 and 3.7.

Table 3.7 Regression results: Probit and logit models

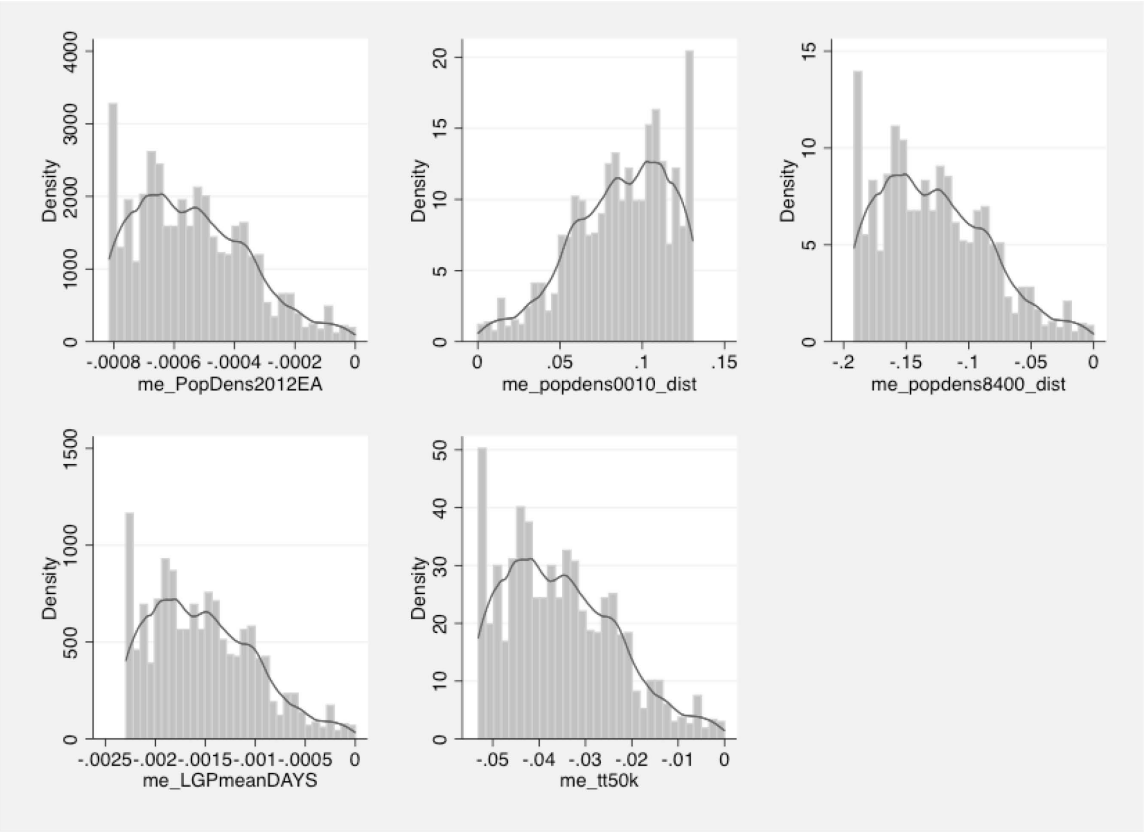
	Dependent variable: dummy for tractor use on at least one plot					
	Probit model			Logit model		
	(6)	(7)	(7a)	(8)	(9)	(9a)
Variables			APE at means			APE at means
Village population density (2012)	–0.002**	–0.002**	–0.001**	–0.004**	–0.004**	–0.001**
	(0.001)	(0.001)	(–2.99)	(0.001)	(0.001)	(–2.95)
Population density growth 2000-2010	0.335***	0.328***	0.131***	0.577***	0.567***	0.142***
	(0.060)	(0.059)	(5.53)	(0.104)	(0.104)	(5.47)
Population density growth 1984-2000	–0.489***	–0.480***	–0.192***	–0.849***	–0.839***	–0.210***
	(0.067)	(0.067)	(–7.18)	(0.124)	(0.126)	(–6.67)
Average length of growing period (days)	–0.007**	–0.006*	–0.002*	–0.012**	–0.011*	–0.003*
	(0.003)	(0.002)	(–2.34)	(0.004)	(0.004)	(–2.45)
Travel time to nearest 50k town	–0.132*	–0.133*	–0.053*	–0.209*	–0.210*	–0.053*
	(0.058)	(0.057)	(–2.33)	(0.096)	(0.093)	(–2.25)
Farm has business plan		0.257			0.483	
		(0.165)			(0.297)	
Land owned (ha)		0.008			0.019	
		(0.008)			(0.017)	
_cons	3.122***	2.759***		5.500***	4.852***	
	(0.606)	(0.602)		(1.108)	(1.087)	
n	1,609	1,609	1,590	1,609	1,609	1,590
F	18.83	13.09		15.08	10.33	
pc_correct	0.806	0.802		0.832	0.838	

Source: Author's calculations.

Note: Standard errors are in parentheses and significance level for each coefficient is indicated by *$p < .05$. **$p < .01$. ***$p < .001$. N is the number of observations; F is the F statistic for each regression model; pc_correct is the percentage of the predicted values from the regression model that are consistent with the observed binary dependent variable. 'APE at means' is the average partial effect calculated at the mean value of the independent variable.

To get an idea of the magnitude and stability of the estimated coefficients in the probit model, the average partial effects at the mean are calculated, shown in columns 7a and 9a of Table 3.7. The relative partial effects are similar in the linear probability, probit, and logit models. However, the absolute magnitudes are larger in probit and logit. In these models, the partial effect depends on the value of the independent variable. Figure 3.6 shows the density of the partial effects evaluated at each value of the independent variable to give an idea of how stable the average partial effect is. The evidence suggests that the average partial effect will give a decent representation of the marginal effect of changes in each explanatory variable, on the probability that a farmer uses agricultural machinery.

Figure 3.6 Distribution of marginal effects under probit model



Source: Author's calculations.

Note: Each graph shows the distribution of marginal effect of the explanatory variable on tractor use, at each value of the explanatory variable, from the probit estimation. me_PopDens2012EA is the marginal effect of village population density in 2012; me_popdens0010_dist is the marginal effect of population growth over 2000-2010; me_popdens8400_dist is the marginal effect of population growth over 1984-2000; me_LGPmeanDAYS is the marginal effect of the average length of the growing period; me_tt50k is the marginal effect of travel time to nearest 50k town.

4. DISCUSSION AND CONCLUSIONS

Given these results, what can be said about the proposed theoretical model? One caveat is that these results are from a single time period and seek to exploit the spatial variation in mechanization use to provide evidence for theoretical relationships. Causality cannot be established, but statements about the correlation between these variables can be made. Overall, the theoretical model that is proposed stands up to econometric testing. The variables for agroecological conditions, market access, and population density explain a considerable part of the variation in mechanization use by farmers that is observed across locations.

The importance of agroecological conditions in determining mechanization use varies somewhat with the length of the growing season. The marginal effect on mechanization use is higher for those areas with a shorter growing season. With a single growing season, a reduction in the number of growing days is associated with a higher probability of using a tractor. The number of days in the growing period ranges in the sample from 163 to 291 days. Therefore, in an area with 100 more growing days, farmers are approximately 20 percentage points less likely to be using machinery for land preparation. In considering the importance of timeliness as a reason for farmers to adopt mechanized land preparation, this result makes sense. When the time for cultivation is restricted by rainfall, there is a greater need to prepare the land quickly to maximize the time between planting and harvesting. In areas with two seasons and a longer growing period, there is more time to prepare the soil, and therefore the length of the growing period is less important in determining machinery use (at least for land preparation). We can conclude that agroecological conditions are important in considering the probability of mechanization use.

As indicated by Boserup (1965), the speed of population growth, at least in the most recent years, is strongly related to the uptake of agricultural machinery. Her theory was that faster population growth puts pressure on farmers to increase productivity rapidly and creates demand for productivity-enhancing technologies. The evidence here is somewhat mixed. The analysis finds a negative relationship between population growth in 1984–2000 and mechanization use in 2012, which appears contrary to theory. One explanation may be that higher population growth in this earlier period led to greater pressure on land use, leading to smaller land sizes and limited scope to harness mechanized technologies, which are arguably more efficiently utilized when farm sizes are larger. However, population growth in the most recent period, 2000–2010, does have a positive relationship with mechanization use in 2012. Those districts with higher population growth in 2000–2010 tend to have lower levels of population density and therefore less binding constraint on land (Figure 3.2). As discussed previously, the mechanisms through which population growth incentivizes more intensive agricultural production will be through well-functioning markets, which are supported by good infrastructure, efficient farmgate prices, and the availability of productivity-enhancing technologies. The mixed results of this analysis will reflect changes to these mechanisms in 1984–2010 and also variation in the functioning of these mechanisms across localities. The travel time variable will capture some of this but doesn't allow analysis over time. However, it is clear from this analysis that population growth in previous time periods is an important factor, in addition to the level of population density, in explaining mechanization use.

The travel time to the nearest settlement of 50,000 people ranges from 30 minutes to 10 hours in the sample. From the regression estimations, an increase of travel time of five hours is associated with a lower probability of mechanization by about 21–27 percentage points. There are several reasons for farmers to be less likely to use machinery when situated far from urban markets. The most immediate is that the farm, especially if relying on hiring in machinery services, will be less accessible for tractors. A tractor owner will prefer to serve farmers closest to accessible roads. A more indirect impact would be the importance of travel time in determining the farmers' ability to participate in marketing of agricultural outputs and also their access to other modern inputs, which are complementary to machinery use. Evidence from elsewhere is that travel time is strongly associated with commercialization and modern inputs use, both of which in turn will theoretically affect the probability of farmers' utilizing machinery

(Stifel and Minten 2008). The analysis presented here provides strong evidence of the negative relationship between travel time to urban centers and machinery use.

The empirical analysis presented in this paper provides evidence that all three independent variables are able to consistently predict the probability of farmer use of machinery. A more structural model would allow a greater understanding of the mechanisms through which population growth and nonagriculture-sector growth lead to agricultural intensification and machinery use. The analysis has not considered individual farmer characteristics such as the extent and quality of social networks, entrepreneurial capacity and education, access to credit, or the spillover effects of technology adoption. In particular, machinery is a relatively high-cost technology in terms of both the equipment and learning about its use and maintenance. Government and nongovernmental organization interventions have often sought to overcome this cost and promote mechanized technologies. The sustainability of such interventions will depend on capabilities of farmers, the appropriateness of the technology, and whether private investment is crowded out. However, unless the conditions in terms of agroecology, population, and market access create the incentives for farmers to adopt mechanized technology, it is likely that external interventions will not be sustained.

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