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The Role of Plant-Breeding R&D in Tractor Adoption among Smallholders in Asia: Insights from Nepal Terai*

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Abstract

Combining agricultural census data from Nepal from 2001 and 2011 with various spatial agroclimatic data, we show that increase in yield potentials due to the introduction of high-yield technologies (particularly improved seed varieties) plays an important role in smallholders' tractor adoption in Nepal Terai. We use a novel instrumental variable, agroclimatic similarity between farmers' and plant breeding institutes' locations, to instrument the adoption of improved seed varieties. To our knowledge, our study offers the first direct evidence that mechanization growth among smallholders is partly induced by the introduction of high-yield technologies.

Keywords: tractor adoptions, smallholders, agroclimatic similarity, agricultural census, Nepal

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1 Introduction

While most countries have seen rising average farm size increase during periods of increased tractor use in South Asian countries like Nepal and India, a different trend has emerged. These countries seen growth in tractor use occurring alongside declining average farm sizes (Figure 1). Furthermore, in countries like Japan where farm size remained relatively small during periods of tractor use growth, smaller, two-wheel tractors (power tillers) dominated the total tractor horsepower provided. In South Asia, by contrast, four-wheel tractors have dominated in Nepal (especially in Terai) and India. This pattern defies conventional wisdom that mechanization growth accompanies farm size growth, and that only small, two-wheel tractors will be adopted by smallholders.

A knowledge gap exists regarding what factors induce smallholders to adopt tractor especially four-wheel tractors. Machinery is often believed to be complementary to land; tractor adoption by larger farmers can be explained largely by the increased returns to tractors de- rived from this complementarity (Foster and Rosenzweig 2011; Otsuka et al. 2013; Yamauchi 2016; Liu et al. 2016; Takeshima 2017a). The literature has attributed the rapid adoption of machinery among smallholders in Asia to increasing wage rates and the development of machine rental markets (Otsuka et al. 2013; Zhang et al. 2017).

In this paper, we provide another (previously unstudied) explanation to account for this observed pattern of tractor adoption in South Asia. Specifically, we examine the role of adoption of improved seed varieties, promoted by public-sector agricultural research and development (R&D) systems, in determining tractor adoption among smallholders in Nepal Terai. We hypothesize that, smallholders' adoption of tractors has been partially driven by the introduction of improved seed varieties. Smallholders are unable to extract tractors' complementarity with the land; therefore, raising total factor productivity (TFP) through the use of improved varieties may be critical for increasing returns to tractor use. Because the adoption of improved seed varieties in Nepal can be attributed largely to public-sector agricultural R&D, we hypothesize that agricultural R&D contributes to mechanization through its development and promotion of improved seed varieties.

We test these hypotheses using household-level National Sample Census of Agriculture 2001-2002 and 2011-2012 (Census 2001-2002 and Census 2011-2012, hereafter), in combination with various agroclimate datasets. The large sample size allows us to obtain precise estimates within sub-groups of specific farm sizes.

We estimate the effect of the adoption of improved seed varieties on machine use at the household level. The key identification challenge stems from the fact that farmers simultaneously make decisions about seed varieties and tractor adoption based on unobservables. To address this endogeneity issue, we use a novel instrumental variable (IV), agroclimatic similarity between farmers' location and the location of plant breeding institutes (PBIs), for the adoption of improved seed varieties. We argue that agroclimatic similarity affects the adoption of improved seed varieties but does not correlate with tractor adoption after effectively controlling for yield potential, market access and distance to PBIs.

We find that increased adoption of improved varieties has significantly positive effects on smallholders' adoption of tractors. These effects are much weaker among larger farmers. Regressing tractor adoption on agroclimatic similarity suggests that tractor adoption is higher among smallholders located in areas that share similar agroclimatic conditions with PBIs.

Our findings suggest that adoption of high-yield technologies (such as improved seed varieties) is an important driver of tractor adoption by smallholders. Public-sector agricultural R&D, which aims to raise overall productivity though activities including plant breeding, is a potentially significant determinant for the adoption of agricultural mechanization.

Our paper contributes to the literature in at least four ways. First, we provide the first evidence regarding the role of adoption of improved seed varieties in the process of machinery adoption. To date, the literature on the determinants of machinery adoption has focused on farm size, wages, market access, population density, etc. To our knowledge, no previous studies have identified the effect of adoption of improved seed variety on machinery adoption.

Second, this paper adds to the increasing literature on agricultural technology adoption induced by complementarity, which has shown evidence that the introduction of improved varieties induces the adoption of other inputs and production practices through complementarity (e.g., Emerick et al. (2016)).

Third, we provide new evidence regarding the important role of public-sector agricultural R&D in the process of economic transformation. Historically, the public sector has played a more important role in plant breeding than in R&D for mechanical technologies; these technologies have often been more directly transferred from abroad (Evenson 1988), especially in Nepal. Our finding suggests that public-sector agricultural R&D indirectly promotes mechanization through investment in improved seed varieties.

Fourth, methodologically, our study contributes to the literature by applying the concept of agroclimatic similarity between farmers' and PBIs' locations as one of the important sources of exogenous variations that affect variations in the introduction of improved varieties. Agroclimatic similarity is considered to be one of the factors determining "technological distance" between a technology source and the users of that technology (Evenson and Westphal 1995). Recent studies in other developing countries report that agricultural productivity is significantly positively associated with "agroclimatic similarity" (Takeshima & Nasir 2017; Takeshima 2017b).

The remainder of this paper is structured as follows. Section 2 discusses public-sector agricultural research and development in Nepal. Section 3 provides the conceptual frame- work. Section 4 describes the data and Section 5 discusses empirical method. Section 6 presents the results. Section 7 concludes.

2 Public-Sector Agricultural R&D in Nepal

In Nepal, the public sector has led agricultural R&D, particularly in regard to plant breeding, since the institutionalization of varietal development in the 1950s (Joshi 2017). Since 1958 when the first improved crop variety for rice (CH-45) was released, a total of 275 improved varieties of various crops (including first wheat varieties Lerma-52 and first groups of maize varieties Rampur Pahenlo) have been introduced, stemming from imported foreign varieties, indigenous varieties, or cross-bred varieties (Joshi 2017; NARC). The contributions of the private sector to plant breeding have been relatively small in Nepal.

Public-sector plant breeding in Nepal has been largely conducted by National Commodity Research Programs (e.g., National Rice Research Programs) and Regional Agricultural Research Stations (RARS) under the National Agricultural Research Council of Nepal. In some cases, universities, such as the Institute of Agriculture and Animal Sciences under Tribhuvan University system, have also been, given the plant-breeding mandate.

Most improved varieties released have been tested at Agriculture Farms where the head offices of Commodity Research Programs or the Regional Agricultural Research Stations are located, or Agronomy Farms that belong to Universities. The locations of these programs and stations (shown in Figure 2) were selected during the 1960s through the 1990s, based on various factors including the proximity to various administrative centers (often close to district headquarters) and the existence of suitable irrigation infrastructure and farm land. Some were originally established as Agricultural Training Centers to train retired military personnel (e.g., RARS in Lumle or Pakhribas). Similarly, the locations of some of the university plant breeding programs were selected based on the existing infrastructure. For example, the Institutes of Agricultural and Animal Sciences under Tribhuvan University moved to Rampur Campus in the 1970s because the infrastructure under the then Panchayat Training Center (land, buildings and facilities) was endowed to the institute (Sofranko and Odell 1984). Hereafter, we will refer to such public-sector R&D programs and stations as PBIs.

Improved varieties developed through the PBIs have spread gradually but successfully. For example, a number of rice varieties now account for a significant share of planted areas in various districts (Witcombe et al. 2001; Shrestha et al. 2012). Although representative figures are not available for 2001 which is one of the periods of our analysis, a number of studies show that improved rice varieties have gradually spread in different areas, including Radha-4 (released in 1995) and Khumal-4 (released in 1987) (Witcombe et al. 2002; Joshi and Witcombe 2003). Improved rice varieties that had been widely adopted by 2009-2010 include Radha-4 (30 percent adoption in Banke and 15 percent in Rupandehi), Radha-12 (40 percent in Sunsari), Hardinath-1 (close to 10 percent in Bara, Kailali). By 1990 and 2000, PBIS had released 25 and 33 rice varieties, 17 and 27 wheat varieties, 12 and 15 maize varieties, respectively in Nepal (NARC). Many improved wheat varieties have also gradually spread across Nepal by the early 2000s (Morris et al. 1994).

3 Conceptual Framework

Suppose a farm household has the following production function:

$$y = \mu f(L, M; A), \tag{1}$$

where y is output, μ is Total Factor Productivity (TFP), L and M are labor and mechanical force (proxied by tractor use), respectively, and A is land, which is assumed to be fixed. TFP growth is Hicks-Neutral and often induced by the adoption of improved varieties (Evenson and Gollin 2003). L and M are substitutes so that,

$$\frac{\partial^2 f}{\partial L \partial M} < 0$$

We assume that the household maximizes profitability and that the price of output serves as numeraire and denote the price of machine use and shadow price of labor by p and w, respectively. The household will choose to adopt machinery if

$$\mu \frac{\partial f(L^0, 0; A)}{\partial M} > p \tag{2}$$

where L^0 is the optimal level of labor if machinery is not adopted and L^0 satisfies

$$\mu \frac{\partial f(L^0, 0; A)}{\partial L} = w \tag{3}$$

The left-hand side of (2), marginal productivity of machinery use, tends to be larger for larger farms for two reasons. First, the existence of scale economies in machinery use implies that larger farmers tend to have higher $\partial f(L^0, 0; A)/\partial M$, keeping L0 constant (Foster and Rosenzweig 2011). Second, larger farmers often face higher shadow prices for labor and thus have lower L0 (Feder 1985; Benjamin and Brandt 2002), which in turn implies a larger $\partial f(L^0, 0; A)/\partial M$ given that L and M are substitutes. Therefore, larger farmers have a higher propensity for machinery adoption than smallholders.

However, increases in TFP also raise marginal productivity of machinery use, $\mu\partial f(L^0, 0; A)/\partial M$. Although the left-hand side of (3), marginal productivity of labor when machine is not used, also increases in this context, the rising shadow price of labor (mostly driven by growth of non-farm sectors during economic transformation) counteracts the effect of TFP on L^0. Therefore, increasing TFP and rising shadow labor wages will jointly lead to adoption of machinery by smallholders. Consequently, the factors that affect TFP, such as the adoption of improved varieties or its key drivers such as agricultural R&D, will affect smallholders' adoption of tractors. The role of TFP growth is particularly important if available tractors are larger and more expensive types (that is, four-wheel tractors as opposed to two-wheel tractors), which are less divisible, and if the costs of hiring services are further raised by liquidity constraints that limit the number of tractors purchased in the market. If larger farms have already experienced high rates of machinery adoption because of complementary between machinery and landholdings, we would expect the increase in TFP through the adoption of improved seed varieties to have higher effects on machinery adoption among smallholders.

4 Data

4.1 Data Source

Our main data come from the National Sample Census of Agriculture 2001-2002 and 2011- 2012 (Census 2001-2002 and Census 2011-2012, hereafter), collected by the Nepal Central Bureau of Statistics (CBSN 2002, 2012). Both Census datasets were collected through stratified multi-stage random sampling methods. For 2001, at the first stage, based on the total planting area of eight major crops (paddy, wheat, maize, millet, barley, sugarcane, oilseed and potato), districts were classified into four groups: 25 districts with the largest planting area of these crops, 25 districts in the second most important group, 15 in the third most important group, and 10 in the least important group. Fixed numbers of enumeration areas (EAs) were assigned for districts in each group (80, 70, 60 and 50 EAs per district, respectively, for the most important districts, second most important districts, and so forth) (CBSN 2002). In the 2011 census, similar methods were used for the numbers of EAs in each district, but the district classification was based on the average areas of nine major crops for the previous three years (CBSN 2012). For both the 2001 and 2011 census, at the second stage, all agricultural households were listed in the selected EAs, from which random samples were selected. For each round, a total of 5200 EAs were selected. The 2001 census includes a total of 125,000 households while the 2011 census includes 124,144 households (CBSN 2002, 2012).

We collect spatial agroclimatic data from various sources and merge these datasets with the census data. Soil-related information is obtained from (FAO et al. 2012). Historical averages of rainfall and temperature data between 1980 and 2000 come from (CRU). Elevation, slope and topography are obtained from The United States Geological Survey (Survey) 1996), and terrain ruggedness index is calculated following Riley et al. (1999) using this topography data. Euclidean distance to the nearest major river is calculated using the map of major rivers from Lehner et al. (2006). Groundwater table depth is from Fan et al. (2013).

For Census 2001-2002, information is available of the Ward to which each household belongs; we then extracted the agroclimatic data for these Wards and merged them with the Census household data. For Census 2011-2012, we can only identify the district (but not the Village Development Committee [VDC][1]. or Ward) to which each household belongs. As described in the result section, we therefore use agroclimatic data aggregated at the district level for Census 2011-2012.

Table 1 summarizes the descriptive statistics of variables from Census 2001-2002 and 2011-2012. The samples in our data are representative of the Terai region in each period and reflect the characteristics of farm households in this region. On average, sampled households are smallholders, with less than 1 ha of farm land in total, split into about three plots, with a further decrease in total farm size between the two rounds of censuses. Households are mostly male-headed with an average of six household members. Households' farming practices have been modernized between 2001-2002 and 2011-2012. The share of tractor using farm households increased from 17.9 percent to 48.4 percent during the study period, and the area share planted to improved crop varieties increased from 29.8 percent to 42.1 percent. The average number of own farm building also increased from 0.425 to 0.997. While the ownership of various agricultural equipment remains relatively limited, the average number of mechanical equipment increased over the period, except for relatively traditional tools like iron ploughs and animal-drawn carts. Importantly, the tractor ownership share has also remained largely unchanged between these two periods. Therefore, the substantial growth of tractor usages, mentioned above, had been through the growth of tractor hiring services provided largely by these tractor owners. While it is beyond the scope of this paper to investigate the evolution of hiring services, some of the factors leading to the growths of hiring services might include reduced transactions costs in meeting demand and supply for hiring services, partly enabled by the growing information & communication technology (ICT), continuous decrease of average farm sizes that make ownership relatively unprofitable compared to hiring-in, despite the overall

[1]VDC was the administrative unit under districts in Nepal, until 2017 when it was replaced by Gaunpalika. During 2001 and 2011 which was covered by our study, there were approximately 3,600 VDCs in Nepal (Takeshima et al. 2017)

rise in demand for mechanization services due to wage increases (Takeshima 2017a), among others.

The average ownership of livestock assets declined slightly between the two rounds of censuses, with the number of cattle and buffalo owned falling (although some of these were) replaced by goats. This trend may reflect some effects of substitutions of draft animals (such as buffalo and sometimes cattle) with tractors. On average, sample households are located in relatively humid, subtropical climates. Although our samples come exclusively from the Terai region, the agroecological conditions of farm households are still diverse in certain dimensions, including soil characteristics, elevation, terrain ruggedness, slope, groundwater table depths, etc.

4.2 Descriptive Results

In this section, we show descriptive results regarding how tractor use is associated with different factors depending on farm size.

4.2.1 Tractor adoption growth by farm size

Figure 3 shows the relationship between tractor adoption rates and farm size, and the evolution of the relationship between 2001 and 2011 in the Terai zone. The curves are estimated using local polynomial regression, with corresponding 95 percent confidence intervals. Figure 4 shows that 1) for farm size above 0.5 ha, tractor use growth has been broad-based, so that adoption rates have increased across a wide range of farm sizes; 2) growth in adoption rates has been relatively limited among households with farm size of below 0.5 ha. This further motivates our investigation of the factors that facilitate the tractor adoption among households with particularly small farm sizes (less than 0.5 ha).

4.2.2 Adoption rates of ploughs and tractors

Figure 4 shows the adoption rates of ploughs and tractors, by farm size, in Terai in 2001 and 2011. Adoption rates of ploughs are considerably higher than tractor adoption rates, particularly for farm sizes below 0.5 ha. When ploughs are not used with tractors, they are likely to be used with animals. As Figure 4 shows, there is sufficient demand for ploughs for land preparation even among small farmers; this implies that there would also be increased demand for tractors among these farmers if tractors were made more accessible. Ploughs and animals are less expensive and more divisible than tractors and are thus more accessible than tractors through ownership or rentals; these differences are particularly large for smallholders, for whom divisibility of technologies is critical. Potential roles of high-yield production systems in inducing tractor adoptions among small farms.

Figure 5 depicts the tractor adoption rate conditional on farm size in 2001 and 2011, for EAs with the proportion of households that adopted improved varieties above the sample median versus EAs with such proportion below the sample median. The figure suggests that tractor adoption rate among smaller farms (less than 0.5 ha) is higher in EAs where more improved varieties are adopted; the differences appear particularly large among smaller farms and less significant among larger farms. This result shows a positive association between improved varieties and tractor adoption among smaller farms. It is also consistent with the hypothesis that increased availability of high-yield varieties that respond to more intensive land preparation might play a role in inducing tractor adoption among smallholders.

4.2.3 Potential spatial correlation of the tractor adoptions

Another important pattern we find is the potentially strong spatial correlation of tractor adoption, including adoption among smallholders. Figure 6 depicts tractor adoption conditional on farm size in 2001 and 2011, for the EAs with a higher-than-median adoption rate in the sample versus those with lower-than-median rate. We see a large difference between the two curves, indicating that tractor adoption rates are spatially correlated, and that the propensity of tractor adoption among small farms is considerably higher in areas with high adoption rates. This result suggests that tractor adoption rates are affected by factors that vary across local areas (such as the distance to PBIs, potential for high-yield production systems, etc.), in addition to household specific factors.

Figure 7 illustrate the differences in the adoption curves between areas that share more similar agroclimatic environments with PBIs and areas that share less similar environments, separated at the median value of the agroclimatic similarity index in 2001 and 2011, respectively. Both periods in Figure 7 indicate that tractor adoption rates are higher in areas with higher agroclimatic similarity, particularly among the smaller farms. Tractor adoption rates also respond more positively to increases in farm size, even among farms cultivating less than 0.5 ha; this pattern is particularly strong in areas with high agroclimatic similarity. These patterns further motivate our analyses regarding whether higher agroclimatic similarity, which raises the productivity of improved varieties, also induces increased mechanization among smallholders.

4.2.4 Presence of tractor owners in the same Enumeration Areas

Another potential factor that can lead to spatial correlation of tractor adoption rates is the presence of tractor owners in the same local area. Tractor mobility is relatively low and tractor owners tend to provide hiring services only in their vicinity, especially in regions such as Nepal Terai, where large, four-wheel tractors dominate (Takeshima et al. 2015).

5 Empirical Methodology

Our main hypothesis is that adoption of improved seed varieties induces small farmers to adopt tractors and that such effects are less significant for large farmers who are able to extract complementarity between farm size and tractor use. Because PBIs have promoted the adoption of improved varieties in Nepal Terai, we further hypothesize a positive causal effect of PBIs on tractor adoption. The descriptive results show some interesting patterns that are consistent with our conceptual framework and hypotheses. We next explore the causal effects of PBIs and adoption of improved seed varieties on tractor adoption. To examine the effect of PBIs on tractor adoption, we estimate the following function:

$$y_i = \beta_0 + \beta_1 A_i + \beta_2 \sigma_i + \beta_3 A_i \times \sigma_i + \beta_4 d_i + \beta_5 A_i \times d_i + Z_i \beta_6 + E_i, \tag{4}$$

where y_i is a dummy variable indicating tractor adoption for household/farm i; A_i is farm size; σ_i is Agroclimatic similarity between the location of the farm and the location of the plant breeding institution which has the highest agroclimatic similarity with the farm; d_i is distance to the closest PBI; Z_i is other key factors that may also affect the demand for and supply of mechanization (such as the distance to an urban center, which affects the variations in farm wages, access to imported machines, and agroclimatic variables capturing yield potential); and E_i is the error term. Our key parameters of interest are β_2, β_3, β_4, and β_5, which capture the effect of PBIs.

Agroclimatic similarity (σ_i) is constructed as the measurement of similarity between areas where each household is located and areas where plant breeding institutions and their substations are located within Terai, in terms of soil, hydrological, and climate conditions (Bazzi et al. 2016; Takeshima & Nasir 2017; Takeshima 2017b). It is constructed as a weighted sum of the similarity measurements for each of soil, hydrological, and climate factors (see Appendix A for detail). The list of PBIs in Nepal is based on the list identified in Takeshima et al. (2016, 2017). Although evaluations and tests of potential improved crop varieties are conducted at various locations across the country, their intensities (number of varieties tested, the accuracy of evaluations, etc.) tend to be considerably higher in farms where headquarters of each program is located. Discoveries of successful varieties are often stochastic processes (Evenson and Kislev 1976) and thus depend crucially on such intensities of evaluations (intensive margins), rather than on the extensive margins. Therefore, improved varieties are more suitable for farms with the higher agroclimatic similarity with PBIs. In other words, higher agroclimatic similarity contributes to higher propensity of adoption of improved varieties. PBIs may also provide some extension services, which may affect farmers' adoption of improved varieties and other technologies (such as fertilizer and pesticides). We include Euclidean distance to the closest PBI and its interaction with farm size to capture such information effects.

Potential endogeneity of the agroclimatic similarity index arises if PBIs are established in areas with higher (unobserved) yield potentials which also affect tractor adoption. We deal with this concern by explicitly controlling for key agroclimatic variables at households' location. In addition, as discussed earlier, we argue that most of the PBIs which have taken over plant breeding activities in Nepal were originally established in the 1960s and 1970s (NARC; Yadav 1987), when the information of agroclimatic conditions and yield potentials tended to be lacking. Further, the locations of PBIs were selected based on different criteria, such as their suitability for training of ex-military personnel, rather than on their agroclimatic conditions. While some commodity-specific programs were established in the 1980s and 1990s, their locations were largely influenced by the pre-existence of infrastructure, such as the Agricultural Farms (for example, the National Rice Research Program was transferred in 1998 to an Agriculture Farm in Hardinath, Dhanusa, which had been in existence since the 1960s.

We were also concerned that the distance to the closest PBI is correlated with distance to urban centers as PBIs tended to be placed close to urban centers. Proximity to urban centers improves farmers' access to markets which can increase tractor adoption. To mitigate this concern, we include Euclidean distance to the nearest urban centers in Z_i.

Other socioeconomic variables in Z_i include the household size, the gender of the house- hold head, and the number of buildings owned. Asset indices are also included, which are constructed as the first principal components based on the number of each type of livestock owned (cattle, yak, buffalo, goats, sheep, pig, horse, rabbit, and any other animals), and the number of each type of farm equipment owned (iron plough, power tiller, shallow tubewell, deep tubewell, rower pump, tractor, thresher, pumping set, animal drawn cart, sprayer, and all the other pieces of equipment). Euclidean distance to the nearest Indian border is also included to control for any effects due to the proximity to the Indian border (including access to cheaper chemical fertilizers that are sometimes informally traded across the border) (Takeshima et al. 2017).

We next examine the effect of adoption of improved varieties on tractor use in the following equation:

$$y_i = \gamma_0 + \gamma_1 H_i + \gamma_2 A_i + \gamma_3 Z_i + E_i, \tag{5}$$

where H_i is share of cultivated area (aggregated across all field crops) in which improved varieties were adopted by household i. All the other variables are the same as in (4). We are interested in γ_1 which is expected to be positive following our conceptual framework.

H_i is endogenous because farmers likely make decisions regarding seed varieties and tractor use simultaneously. We use agroclimatic similarity and its squared term as IVs for H_i, and estimate (5) using Generalized Method of Moments (GMM). Among common linear IV-based estimation methods, GMM is more efficient than other methods such as two-stage- least squares where the idiosyncratic error term E_i is heteroskedastic or serially-correlated; this is often the case in the agricultural sector which is more susceptible to biotic/abiotic stresses that tend to be spatially correlated within a locality.

Our identification assumption is that agroclimatic similarity affects tractor adoption decisions only through the adoption of improved varieties and not through any other channels. This assumption is reasonable given that we control for numerous variables to capture other channels through which R&D may affect tractor adoption decisions. Particularly, the Euclidean distance to PBIs captures the diffusions of other technologies and access to extensions through PBIs, while the agroclimatic variables captures yield potential. This assumption can be tested using a test of over-identification (Hansen 1982).

To assess how the effects of various factors on tractor adoptions differ across farm sizes, as hypothesized in the conceptual framework, we estimate (4) and (5) for five sub-groups of farm households based on their farm size; under 0.1 ha, under 0.5 ha, under 1 ha, above 1 ha, and above 2 ha. For both 2001 and 2011, the farm size is the sum of owned land, rented land, mortgaged land, and land of other tenure. While these groupings are somewhat arbitrary, they account for approximately 10 percent, 50 percent, 67 percent, 33 percent, and 10 percent, respectively, of the total farm household samples in 2001. The distributions are similar for 2011 data, with slightly greater shares of smaller farms. We also estimate the models with different sub-groupings and find that the implications of our results are generally robust.

6 Results

Table 2 presents the estimation results from equation (4) using Census 2001 data, for house- holds with landholdings under 0.1 ha (columns 1-3), under 0.5 ha (columns 4-6), under 1.0 ha (columns 7-9), above 1.0 ha (columns 10-12), and above 2.0 ha (columns 13-15), respectively. We standardize the agroclimatic similarity index to z score and demean the explanatory variables with interaction terms. Thus, the coefficient of agroclimatic similarity is interpreted as the average partial effect of one standard deviation increase in this index. For each sub-group of households, we show results from three sets of explanatory variables (without asset or agroclimatic variables, with assets but with no agroclimatic variables, and full model with all explanatory variables). The results are robust across the three specifications for each subgroup. Our interpretation is thus based on the full model (columns 3, 6, 9, 12, and 15 of Table 2).

Consistent with our hypothesis, agroclimatic Similarity has statistically significant, positive effects on tractor adoption among farmers with less than 1 ha of farm land. The effects of agroclimatic similarity are weaker for farm households with more than 1 ha of land and even weaker for larger farm households with more than 2 ha of land. On average, an increase in agroclimatic similarity by one standard deviation increases the probability of tractor adoption by 1.5 percentage points for the under 0.1 ha group, by 1.3 percentage points for the under 0.5 ha group, and by 1.0 percentage points for the under 1 ha group. These effects translate into an increase in tractor adoption by 36 percent for the under 0.1 ha group, 10 percent for the under 0.5 ha group, and 6 percent for the under 1 ha group.[2]

Not surprisingly, farm size has positive effects on tractor adoption for each sub-group. Further, the interaction term of agroclimatic similarity and farm size is significant and positive for smallholders below 0.5 ha, suggesting that high-yield technologies are complementary to farm size with regards to the effects on tractor adoption by very small farms.

We conduct robustness checks by estimating the same model using the Census 2011 data. As

[2]The adoption rate of the three corresponding groups are 4.2 percent, 13.6 percent, and 16.0 percent, respectively.

mentioned previously, for 2011 data we can only identify the variations in agroclimatic similarity at the district level rather than at the Ward level. Results, shown in Table B1 in Appendix B, suggest that our findings in Table 2 still largely hold in 2011, by which time the overall tractor adoption rates had risen considerably from 2001.

Table 3 reports the effects of improved seed adoption on machinery adoption based on the GMM estimation in (5) using Census 2001 data for the five sub-groups. Our interpretation is based on the full model, which includes the complete set of explanatory variables (bolded in columns 3, 6, 9, 12, and 15). The share of areas using improved varieties has a significantly positive effect among farm households with less than 1 ha of land but has no significant effect among larger farms.

This result is consistent with our hypothesis that increased TFP through adoption of improved seed varieties plays a key role in inducing adoption of machinery among small- holders who, unlike their larger counterparts, fail to cultivate the complementarity between machinery use and landholdings. The result also suggests that the effects of agroclimatic similarity on tractor adoptions among smallholders in Table 2 operate through the adoptions of improved varieties.

Appendix Table B2 reports the results from a tobit regression of areas share of improved seed varieties on agroclimatic similarity and other variables in (4). As expected, agroclimatic similarity has a significantly positive effect on adoption of improved seed varieties for all specifications for the lower than 0.5 ha group, lower than 1 ha group, and higher than 1ha group.[3]

We check the robustness of our main results in Tables 2 and 3 by classifying farm households based on quintile of land holding sizes. Appendix Tables B3 and B4 summarize the results that correspond to Tables 2 and 3, respectively. As can be seen in these tables, our results and main implications in Tables 2 and 3 are generally robust against the uses of different landholding size classifications.

We also checked whether the results are robust if we exclude tractor-owning households, since, as described above, spatial variations in the accessibility to tractor service can still largely depend

[3]The effect is positive but insignificant for the remaining two groups with smaller sample size.

on the presence of tractors in the locality. Results are summarized in Tables B5 and B6, which correspond to Tables 2 and 3. As can be seen, our main results and key messages remain robust against the exclusions of tractor owning households in the analyses.

While our main interests are the effects of agroclimatic similarity and the adoption of high-yield varieties on tractor adoption, we also briefly discuss the signs of other coefficients, having in mind that it is more appropriate to interpret many of these results as associations rather than as causalities. Fuller results for Table 2 and Table 3 are shown in Tables B7 and B8 in Appendix B. As expected, key patterns of the relationships between each variable and tractor adoptions are largely consistent between Table B7 and Table B8.

First, tractor adoption is generally positively associated with greater landholding size (among both smallholders and large farmers), proximity to the nearest PBI and major urban centers, and higher shares of lowland-type plots. These relationships are consistent with the general hypotheses that demand for tractor uses is greater if more complementary factors (land) are used, if access to improved production technologies and extension services and major markets is better, and if the soil and hydrological characteristics of land are more conducive for more intensive land preparation. In some cases (particularly among larger farms), areas distant from major market centers may be more conducive for tractor use if the lower opportunity costs of land combined with economies of scale bring higher returns from mechanized extensive farming system, as is suggested by positive effects of interaction terms between farm size and distance to major urban centers.

Greater distance to the nearest Indian border generally positively affected tractor adoption in 2001. While counter-intuitive, this finding could be due to the fact that food commodities were generally flown from India to Nepal during the 2000s (Sanogo and Amadou 2010), which led to lower crop prices in areas closer to the Indian border and which discouraged intensive cultivations and reduced farm power use in these areas. However, as suggested in Table 3, this effect was likely to have been offset by the similar effects of distance on the accessibility of tractor hiring service providers, who are based in India but travel across the border to also serve Nepalese farmers.

Female household heads also have consistently positive effects, indicating that, if other household characteristics are controlled for (including production endowments, land quality, assets, etc.), having a female household head actually induces more intensive production systems, including the adoptions of tractors.

Having more farm buildings also has positive association with tractor adoption among smallholders but negative association among larger farms. For smallholders, a greater number of farm buildings, which proxy greater farm assets and storage space, may induce greater production intensification, including the use of mechanization. In contrast, large farmers, may induce more specialized production of higher-value crops for which tractors are not necessarily used. While it is beyond the scope of this paper to provide fuller evidence for such hypotheses, they nevertheless capture important effects on tractor adoption that should be separated from the effects of agroclimatic similarity and high-yield technologies, which are our main interests.

The coefficients of number of land parcels are negative for smallholders, which is consistent with findings of negative effects of land fragmentation on farm machinery uses in South Asia (K. Deininger K and Singh 2017). These coefficients are, however, positive for larger farmers (albeit with smaller effects). This may be because having more plots that are scattered (given the same size of total landholdings and other farm characteristics) can increase the chances of having plots that are relatively more easily accessible by tractors, instead of having plots concentrated in certain locations. For these larger farmers, fragmentation may be less constraining because each plot may be large enough for tractors to be used.

Coefficients of agricultural equipment assets are generally negative or insignificant for smallholders and are positive for larger farmers. Positive coefficients for larger farmers suggest that these sets of equipment often complement tractors, possibly because cultivating large farms require machinery for farming operations other than land preparation or transportation (such as pumping irrigation water, threshing, etc.). Negative coefficients for smaller farmers could be due to the fact that farm equipment other than tractors may sufficiently substitute for tractors because these farmers' overall farm power requirements are relatively small.

Coefficients of livestock assets are generally negative regardless of farm size, but with greater magnitude among larger farms. This may be because livestock production may compete with crop production for resources; large farmers with greater livestock holdings may specialize in livestock rearing rather than in field crop production. Magnitudes may be smaller for smallholders because livestock can also serve as assets that can be liquidated to alleviate credit constraints on inputs, including tractors. The coefficients of the number of different types of livestock are generally complicated, because animals can either substitute for machines in providing draft force or induce greater production of feed crops through greater uses of farm power. Our results suggest that accounting for these associations is important in correctly understanding the role that agroclimatic similarity and high-yield technologies play in tractor adoptions.

Lastly, agroclimatic factors are, other than their effects through agroclimatic similarity, directly associated with tractor adoption. Greater rainfall and higher temperature generally have positive effects, suggesting that mechanization potential is generally greater for relatively more tropical or sub-tropical crops (for example, rice) than for hardy crops (wheat, potato etc.). Given their rainfall and temperature, however, areas with higher elevation may often indicate greater solar radiation and thus greater yield responses to farm power, thus potentially leading to increased tractor adoption. Proximity to the nearest major rivers or groundwater table may also indicate a generally favorable environment for agricultural intensification, which raises returns to intensive land preparations (for example, greater plant growth potentials, even for varieties with shorter root lengths, because of higher soil moisture and higher soil nutrients supplied by river water). Other soil characteristics have significant effects as well, albeit at varying magnitude and signs, indicating the importance of controlling for these factors in understanding tractor adoption decisions.

7 Conclusions

Agricultural mechanization growth patterns in parts of South Asia, including the Terai zone of Nepal, have been unique, characterized by growing tractor use despite small and declining average farm sizes. While the complementarity between land and machinery has been well understood, a knowledge gap still exists regarding the factors that induce smallholders to adopt tractors.

We partly filled this key knowledge gap by testing hypotheses that tractor adoption by smallholders has been induced by yield-enhancing agricultural R&D; in contrast, for large farmers, tractor adoption has been driven by complementarity with landholdings. To do so, we use Agricultural Census data of Nepal, as well as various spatial agroclimatic data.

We find that tractor adoption among smallholders is induced by the similarity in agroclimatic conditions between areas where farmers are located and where plant-breeding activities are conducted. This is consistent with the hypothesis that the greater yield-potential of particular areas, given the current R&D systems in Nepal, is an important driver of tractor adoption by smallholders in those areas. This hypothesis was further supported by another set of findings through instrumental variable analyses that, increased adoption of improved crop varieties is in fact driving the adoption of tractors among smallholders. Our findings also suggest that these effects are generally much weaker among larger farmers.

These findings make important contributions to the literature on mechanization. While the conventional wisdom suggests that small farm size is a critical constraint for the adoption of modern machinery such as tractors, we show that this constraint may be overcome by raising yield potential through the adoption of improved crop varieties, which sufficiently raise the returns to and above willingness-to-pay for mechanization.

Lastly, our findings also have important policy implications in countries such as Nepal, which has recently formulated agricultural mechanization policies to support the mechanization of smallholders. The policy dialogue thus far has not considered the fact that the potential demand for mechanization among smallholders is closely linked to agroclimatic similarity with locations of public sector R&D, particularly plant-breeding activities. Our findings therefore offer important insights into how mechanization support for smallholders can be made more effective in Nepal.

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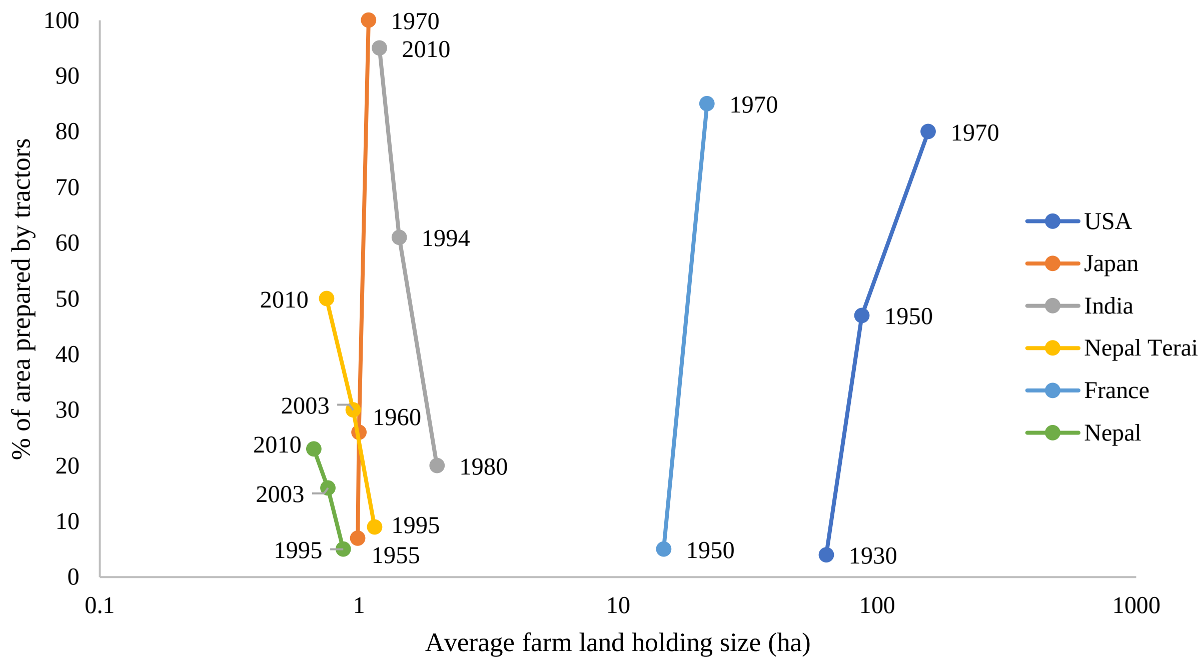
Figures and Tables

Figure 1. Mechanization growth among smallholders in South Asia



Source: Farm size - World Census of Agriculture except for South Asian countries. Japan – Hayami & Kawagoe (1989) for 1955, 1960 and 1970. Nepal – CBS.

Areas share (%) of tractored area.

India**:** Ugwuishiwu & Onluwal (2009) for 1994, assessed from figures for 2014 in Grant Thornton India LLP. (2015). Figures for 1980 were assessed proportionally using the number of tractors reported by FAO (2017) in 1980 and 1994.

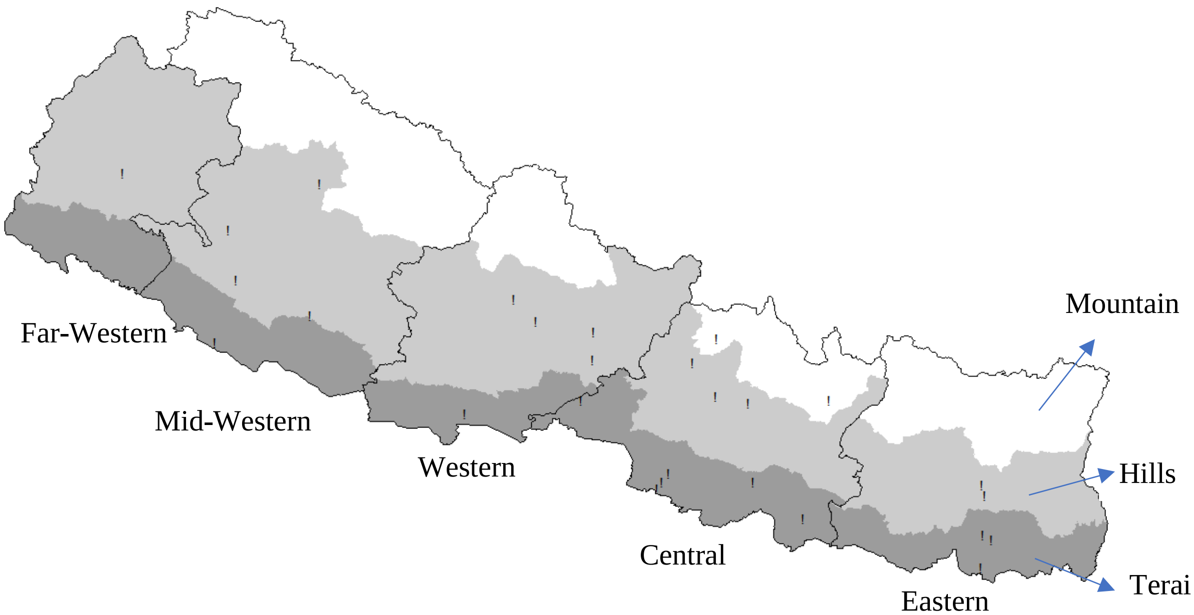
Japan: Economic Planning Agency (1962) for 1955 and 1960. Barker et al. (1985 Figure 8.1) suggests that by 1970, the adoption rate had reached almost 100 percent.

Nepal: Shares of tractor uses are approximated by the shares of households using tractors calculated from NLSS.

France: Approximate tractor use shares are estimated by comparing the numbers of working tractors at each period (Binswanger 1986) and those in 1980 (FAO 2017) by which the tractors would have covered 100%.

USA; Figures of the share of tractor-owning farm households (Olmstead & Rhode 2001) are used to approximate the share of areas prepared by tractors.

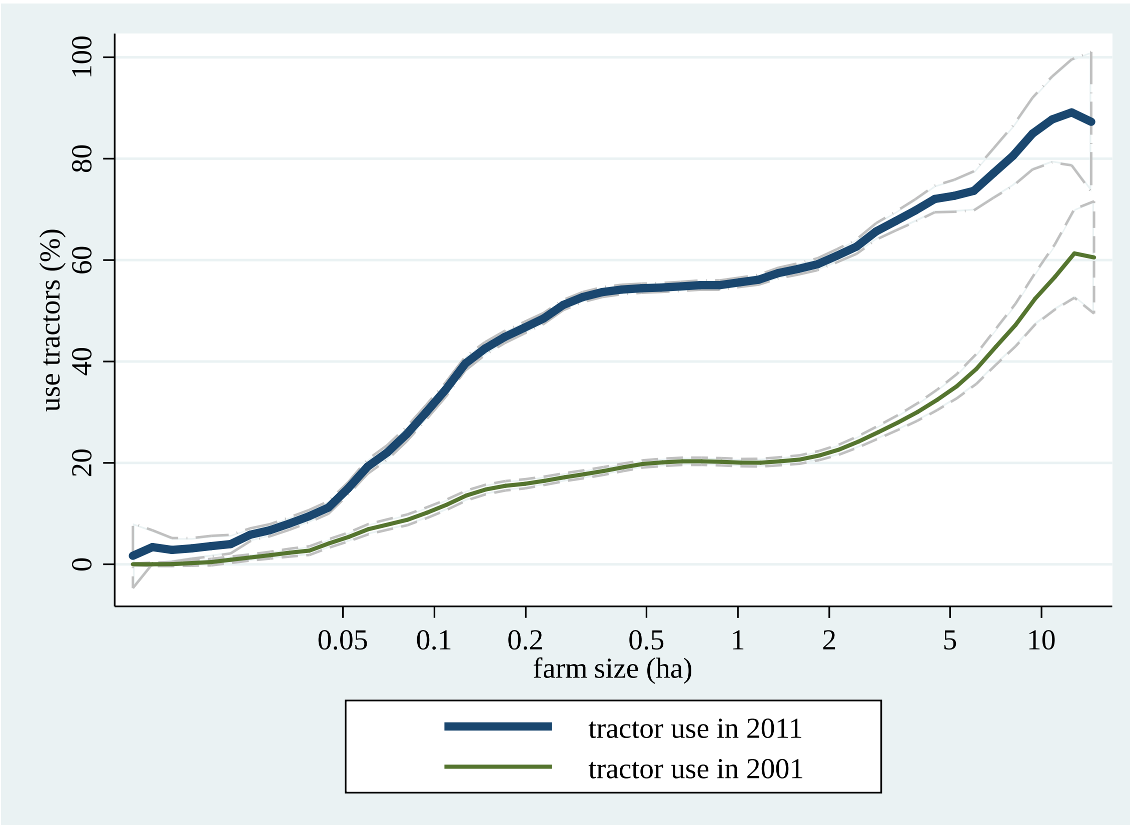
Figure 2. Three agroecological belts and five development regions in Nepal, as well as locations of Agriculture Research Stations and major universities with breeding activities



Source: Authors' compilations from various sources.

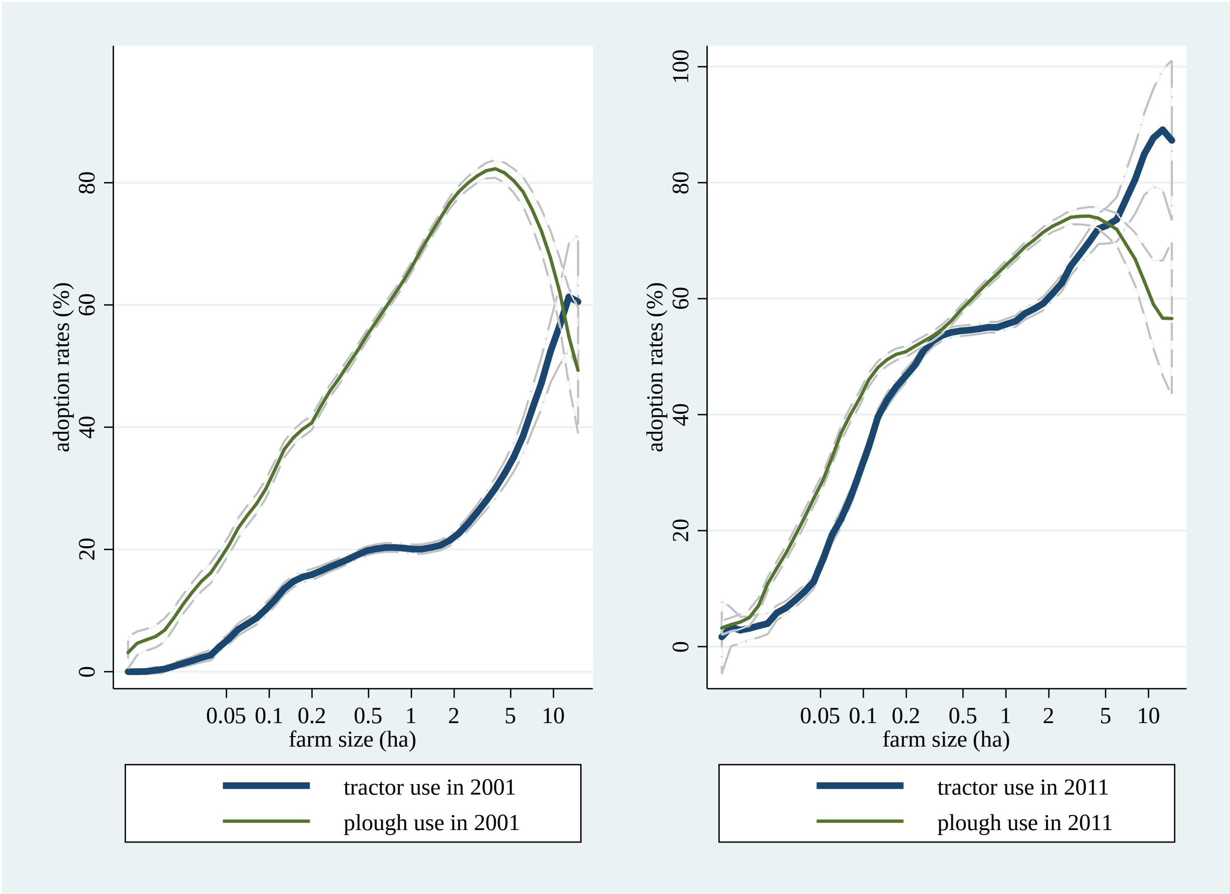
Note: Black dots indicate Agriculture Research Stations and key universities with plant-breeding activities.

Figure 3. Growth of tractor adoption rates in Nepal Terai between 2001 and 2011, by farm size



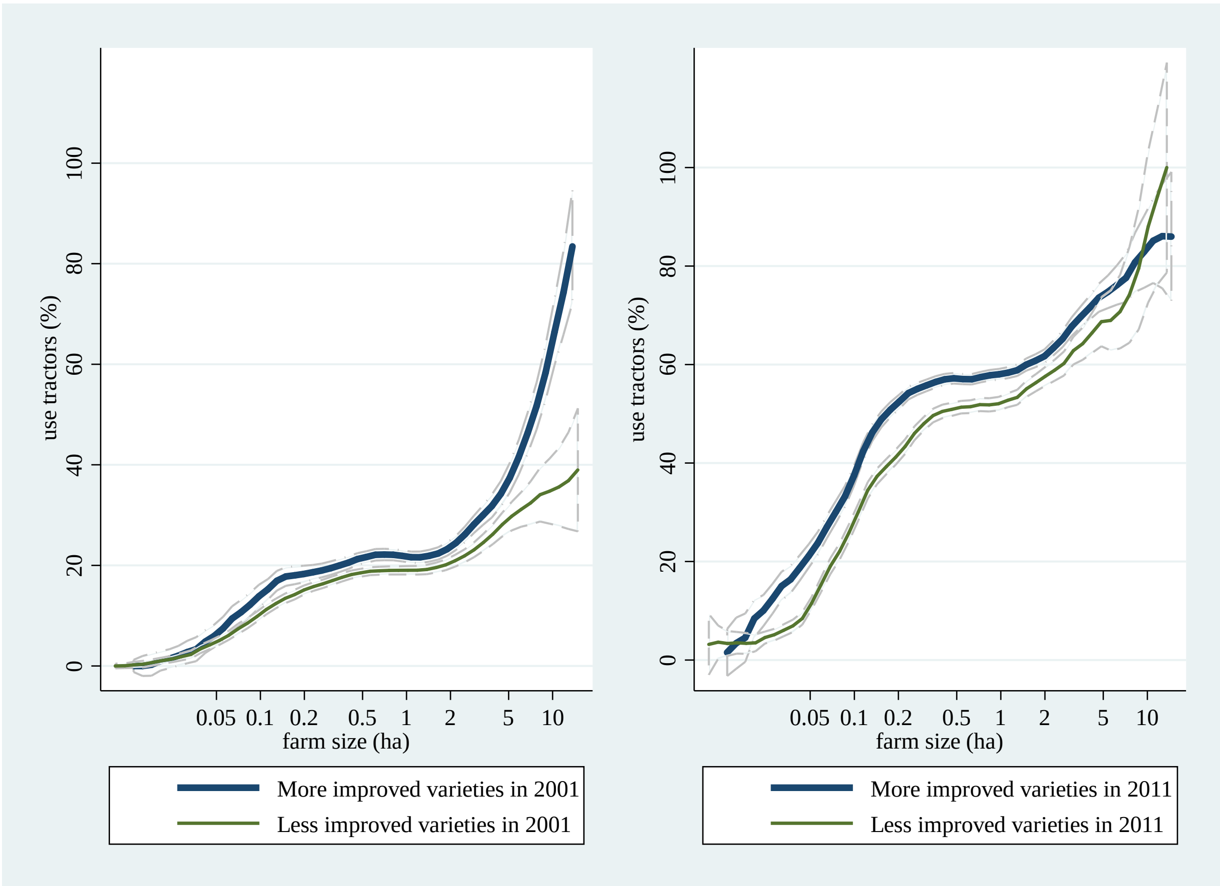
Source: Authors based on the Nepal Agricultural Census Data 2001 and 2011.

Figure 4. Relationship between adoptions rates of ploughs, tractors and farm size (Terai, 2001 and 2011)



Source: Authors based on the Nepal Agricultural Census Data 2001 and 2011.

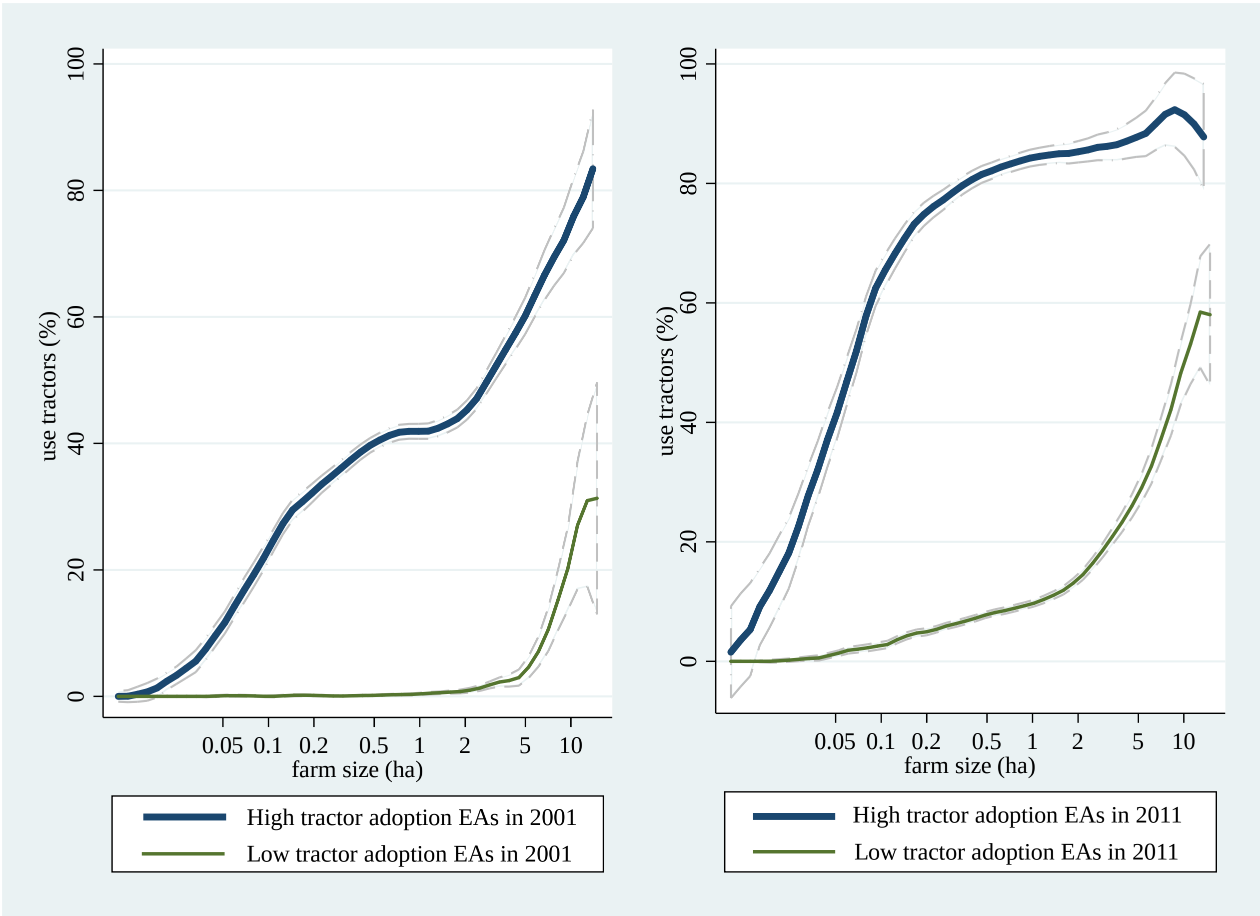
Figure 5. Tractor adoption rate and farm size, differentiated between enumeration areas with more / fewer households using improved varieties (Terai, 2001 and 2011)



Source: Authors based on the Nepal Agricultural Census Data 2001 and 2011.

[a]Samples are split into two group by taking the median value of area share of improved varieties at household level.

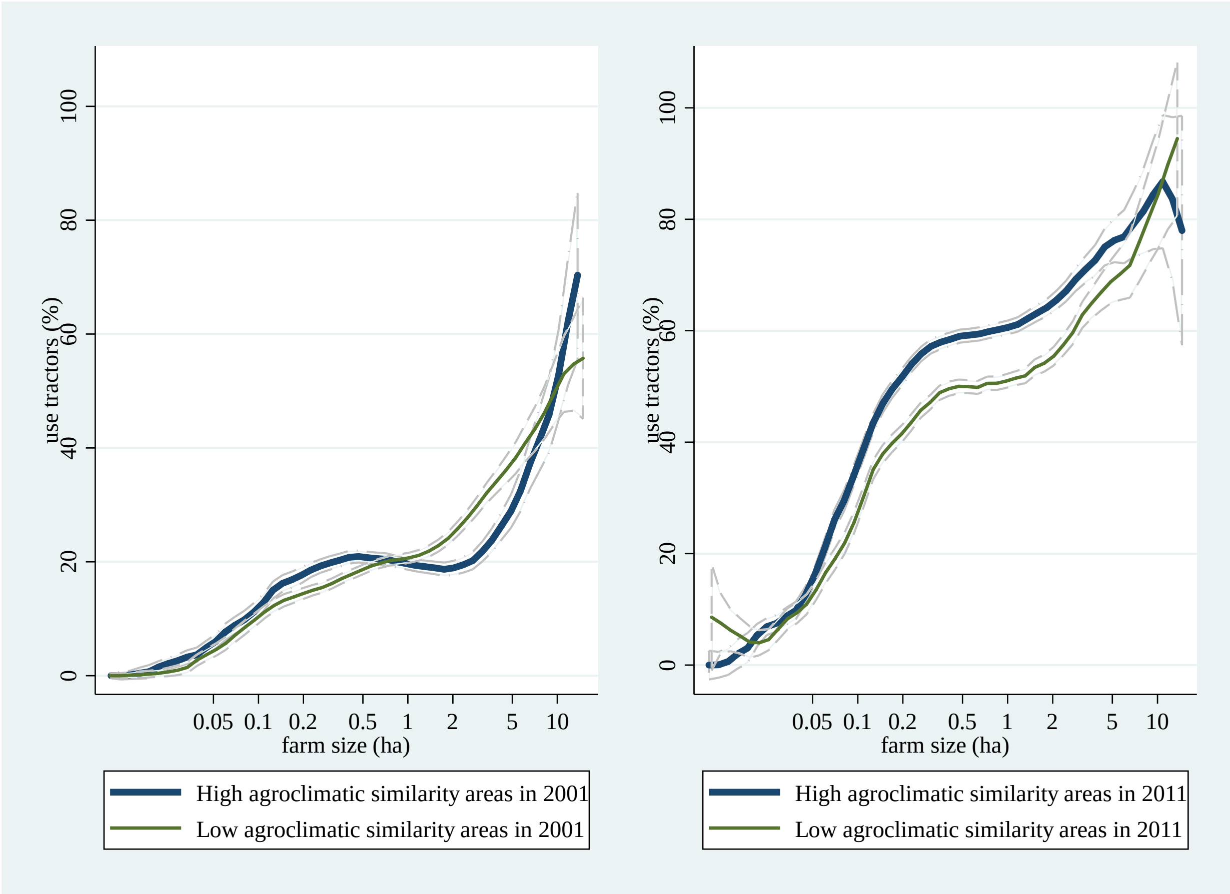
Figure 6. Tractor adoption rates, farm size, differentiated by the adoption rates in the local area (Terai, 2001 and 2011)



Source: Authors based on the Nepal Agricultural Census Data 2001 and 2011.

[a]Samples are split into two group by taking the median value of EA level adoption rates.

Figure 7. Tractor adoption rates, farm size, differentiated by Agroclimatic Similarity (Terai, 2001 and 2011)



Source: Authors based on the Nepal Agricultural Census Data 2001 and 2011.

Table 1. Descriptive statistics (Terai region, Nepal)

	Census 2001/02		**Census 2011/12**	
	Mean	Std.dev	Mean	Std.dev
Sample size	39650		42049	
Use tractors (yes = 1, no = 0)	0.179	0.383	0.484	0.500
Area share of improved varieties (improved non-hybrid + hybrid)	0.298	0.423	0.421	0.447
Agroclimatic similarity index	0.716	0.178		
Size of farm land (ha)[a]	0.950	1.305	0.786	0.955
Household size	6.281	3.174	5.804	2.798
Female household head (yes = 1, no = 0)	0.053	0.223	0.138	0.345
Number of own farm building	0.425	0.494	0.997	0.051
Number of land parcels	3.224	3.125	2.922	2.234
Euclidean Distance to the nearest ARS (Geographical minutes)[a]	0.314	0.219	0.326	0.211
Euclidean Distance to the nearest major urban center (Geographical minutes) [a]	0.282	0.193	0.289	0.184
Euclidean Distance to the nearest Indian border (Geographical minutes) [a]	0.124	0.103	0.125	0.084
Annual rainfall (mm) [a]	1333.872	261.107	1362.521	262.665
Temperature (°C)[a]	23.311	1.268	23.263	1.217
% of soils with poor drainage[a]	47.232	26.256	48.234	25.144
% of soils with excessive drainage[a]	0.000	0.000	0.000	0.000
Average soil sodicity (%)[a]	1.707	0.134	1.731	0.041
Average soil salinity (deciSiemens per metre)[a]	0.133	0.050	0.131	0.049
% of soil with coarse texture[a]	7.637	7.499	8.282	7.459
% of soil with fine texture[a]	4.270	10.300	3.518	7.203
% of soil with medium texture[a]	88.093	9.854	88.200	7.018
Organic carbon contents of the soil (% of weight)[a]	1.648	0.487	1.688	0.513
PH of the soil[a]	6.261	0.471	6.264	0.420
Euclidean distance to the nearest major river (Geographic minutes)[a]	0.013	0.008	0.011	0.002
Elevation (meter)[a]	191.019	248.935	178.639	230.231
Terrain ruggedness index[a]	45.333	116.599	28.197	79.467
Slope (%)[a]	0.783	1.954	0.497	1.344
Groundwater table depth (meter below the surface)[a]	6.525	17.756	4.404	13.427
Plot level area share of soil characteristics (self-reported)[b]				
sandy soil	.242	.428		
silty soil	.379	.504		
clayey soil	.051	.204		
loamy soil	.148	.349		
black soil	.306	.477		
brown soil	.390	.519		
yellow soil	.098	.284		
red soil	.036	.175		
Number of equipment owned				
Iron plough	0.518	0.642	0.415	0.587
Power tiller	0.005	0.112	0.004	0.060
Shallow tubewell	0.054	0.265	0.133	0.366
Deep tubewell	0.026	0.180	0.040	0.205
Rower pump	0.012	0.120	0.020	0.144
Tractor	0.018	0.142	0.020	0.142
Thresher	0.032	0.185	0.024	0.158
Pumping set	0.059	0.246	0.069	0.260
Animal drawn cart	0.120	0.331	0.087	0.283

Sprayer	0.036	0.204	0.091	0.296
Other pieces of equipment	0.496	1.437	0.041	0.199
Asset index: equipment (first principal component)	0.349	0.466	0.337	0.448
Number of livestock owned				
Cattle	1.917	2.400	1.414	1.820
Yak	0.000	0.000	0.000	0.000
Buffalo	0.898	1.470	0.755	1.316
Goat	1.439	2.512	1.853	2.775
Sheep	0.061	0.803	0.065	0.773
Pig	0.142	0.881	0.129	0.754
Horse	0.000	0.028	0.000	0.023
Rabbit	0.002	0.078	0.003	0.158
Other animals	0.001	0.024	0.004	0.146
Asset index: livestock (first principal component)	2.335	2.355	2.143	2.190

Source: Authors' based on Census 2001 and 2011.
[a]Figures for 2011 are district level averages.
[b]Plot level soil characteristics are not reported in 2011.

Table 2. Effects of agroclimatic similarity on tractor adoption decisions, differentiated by land holding size, in Nepal Terai in 2001[a,b]

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
	(1)	(2)	**(3)**	(4)	(5)	**(6)**	(7)	(8)	**(9)**	(10)	(11)	**(12)**	(13)	(14)	**(15)**
ln (farm size)	.034**	.033**	**.023****	.050**	.048**	**.045****	.045**	.045**	**.042****	.098**	.084**	**.094****	.157**	.135**	**.137****
	(.004)	(.004)	**(.004)**	(.002)	(.002)	**(.002)**	(.002)	(.002)	**(.002)**	(.009)	(.009)	**(.009)**	(.018)	(.018)	**(.018)**
Agroclimatic similarity	.017**	.017**	**.015***	.030**	.031**	**.012***	.028**	.029**	**.009***	.007†	.007*	**-.002**	-.004	-.004	**.001**
	(.003)	(.003)	**(.007)**	(.002)	(.002)	**(.005)**	(.002)	(.002)	**(.005)**	(.004)	(.004)	**(.008)**	(.007)	(.007)	**(.016)**
Agroclimatic similarity ×	.020**	.019**	**.017****	.006*	.005*	**.005***	.000	.000	**.001**	-.010	-.011	**-.003**	.033†	.028	**.031†**
ln (farm size)	(.006)	(.006)	**(.006)**	(.002)	(.002)	**(.002)**	(.002)	(.002)	**(.002)**	(.009)	(.008)	**(.008)**	(.018)	(.017)	**(.017)**
Distance to PBI	-.002	-.003	**-.027****	-.019**	-.018**	**-.041****	-.020**	-.020*	**-.036****	-.031**	-.033**	**-.045****	-.041**	-.042**	**-.059****
	(.004)	(.004)	**(.006)**	(.004)	(.004)	**(.004)**	(.003)	(.003)	**(.004)**	(.006)	(.006)	**(.007)**	(.011)	(.011)	**(.013)**
Distance to PBI × ln	.003	.003	**-.002**	-.005†	-.004	**.000**	-.007**	-.006*	**-.003**	-.018	-.014	**-.016**	-.017	-.002	**-.005**
(farm size)	(.006)	(.006)	**(.006)**	(.003)	(.003)	**(.003)**	(.003)	(.003)	**(.003)**	(.013)	(.013)	**(.012)**	(.028)	(.029)	**(.029)**
Other socioeconomic variables and intercept	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**
Other asset variables		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**
Other agroclimatic / soil variables			**Yes**			**Yes**			**Yes**			**Yes**			**Yes**
Number of observations	4,236	4,236	**4,236**	17,237	17,237	**17,237**	26,093	26,093	**26,093**	12,226	12,226	**12,226**	4,570	4,570	**4,570**

Source: Authors' estimations based on the census data.

Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%

[a]Both *agroclimatic similarity* and *ln (land holding size)* are demeaned within the corresponding samples. Therefore, coefficients for non-interacted variables are average partial effects for all corresponding samples.

[b]Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 3. Effects of the adoptions of improved varieties on tractor adoption decisions, differentiated by land holding size, in Nepal Terai in 2001[a]

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
	(1)	(2)	**(3)**	(4)	(5)	**(6)**	(7)	(8)	**(9)**	(10)	(11)	**(12)**	(13)	(14)	**(15)**
Area share of improved varieties	1.397*	1.488*	**1.809†**	2.039*	2.284†	**2.189†**	1.661**	1.815**	**1.733***	.125	.114	**.101**	-.523	-.630	**-.611**
	(.679)	(.745)	**(.961)**	(1.026)	(1.238)	**(1.129)**	(.712)	(.839)	**(.762)**	(.234)	(.250)	**(.239)**	(.507)	(.592)	**(.552)**
Other socioeconomic variables and intercept	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**
Other asset		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**
plot soil variables			**Yes**			**Yes**			**Yes**			**Yes**			**Yes**
Number of observations	4,236	4,236	**4,236**	17,237	17,237	**17,237**	26,093	26,093	**26,093**	12,226	12,226	**12,226**	4,570	4,570	**4,570**
p-value (H0: over-identification)	.242	.291	**.562**	.771	.858	**.710**	.741	.534	**.108**	.605	.398	**.305**	.383	.289	**.301**
p-value (H0: exogeneity)	.000	.000	**.000**	.000	.000	**.000**	.000	.000	**.000**	.669	.692	**.720**	.134	.124	**.108**

Source: Authors' estimations based on the census data.

Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%

[a]Numbers in parentheses are EA cluster-adjusted standard errors.

Appendix A

Agroclimatic similarity index

Agroclimatic similarity is constructed in the following way. Following Takeshima & Nasir (2017), raw similarity index for household i with respect to the breeding institute B ($D_{i.B}$) is,

$$D_{i.B} = -\sum_{\theta} w_{\theta}(\left|A_i^{\theta} - A_B^{\theta}\right|) \tag{A1}$$

where A_i^{θ} and A_B^{θ} are the values of key agroclimatic parameters θ in areas where farm household i and breeding institute B is located, respectively. $\left|A_i^{\theta} - A_B^{\theta}\right|$ is the absolute deviations. Weight for each θ (w_{θ}) captures the effect of the similarity of θ for the overall similarity with B. Following Bazzi et al. (2016), Takeshima & Nasir (2017), Takeshima (2017b), sample average values of θ is used as w_{θ}, so that absolute deviations are standardized relative to the unit of θ. $D_{i.B}$ is therefore the weighted sum of the absolute differences in the values of parameter θ between i with respect to B. With the negative "$-$" added in front of summation operator in (A1), an increase in $D_{i.B}$ indicates the increase in agroclimatic similarity.

The overall similarity index for the household i (D_i) is then,

$$D_i = f(D_{i,B}) \tag{A2}$$

in which f denotes various functions that translate $D_{i.B}$ to D_i. We primarily present the case where f is the average so that $D_i = \sum_B D_{i.B}/N_B$ in which N_B is the number of reference breeding institutes or stations. We then present the robustness of the results using different f, such as the maximum, average weighted by the number of improved varieties released (more details are provided in the results section).

D_i is then standardized so that they are distributed between 0 and 1, with 0 the least similar and 1 the most similar. This is simply for the ease of interpreting D_i.

Appendix B: Additional results

Table B1. Effects of agroclimatic similarity on tractor adoption decisions, differentiated by land holding size, in Nepal Terai in 2011[a, b]

Dependent variable =	Samples by land-holding size														
tractor adoptions (yes = 1)	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
ln (farm size)	.135**	.135**	.148**	.184**	.181**	.179**	.138**	.141**	.142**	.090**	.079**	.090**	.105**	.069**	.078**
	(.010)	(.010)	(.010)	(.003)	(.003)	(.003)	(.002)	(.002)	(.002)	(.011)	(.012)	(.012)	(.024)	(.024)	(.024)
Agroclimatic similarity	.067**	.067**	.136**	.084**	.083**	.152**	.086**	.086**	.140**	.060*	.063**	.065**	.045**	.048*	.052**
	(.008)	(.008)	(.010)	(.005)	(.005)	(.006)	(.004)	(.004)	(.005)	(.006)	(.006)	(.007)	(.010)	(.010)	(.011)
Agroclimatic similarity × ln (farm size)	.078**	.081**	.066**	.019**	.020**	.008	.014**	.014**	.002	-.026†	-.027†	-.018	-.092*	-.084**	-.072*
	(.016)	(.016)	(.017)	(.005)	(.005)	(.005)	(.004)	(.004)	(.004)	(.015)	(.014)	(.014)	(.031)	(.031)	(.031)
Other socioeconomic variables and intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other asset variables		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Other agroclimatic / soil variables			Yes			Yes			Yes			Yes			Yes
Number of observations	5,137	5,137	5,137	21,270	21,270	21,270	31,371	31,371	31,371	10,677	10,677	10,677	3,429	3,429	3,429

Source: Authors' estimations based on the census data.

Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%

[a]Both *agroclimatic similarity* and *ln (land holding size)* are demeaned within the corresponding samples. Therefore, coefficients for non-interacted variables are average partial effects for all corresponding samples.

[b]Numbers in parentheses are heteroskedasticity-robust standard errors.

Table B2. Effects of agroclimatic similarity on the area shares of improved varieties, differentiated by land holding size, in Nepal Terai in 2001 (two-sided tobit)[a]

Dependent variable = area shares of improved varieties, aggregated across all crops	Samples by land-holding size														
	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Agroclimatic similarity	.234	.241	.072	.130†	.124†	.376*	.106†	.105†	.301*	.153**	.149**	.165†	.117*	.108*	.127
	(.174)	(.174)	(.430)	(.078)	(.076)	(.185)	(.062)	(.061)	(.142)	(.046)	(.045)	(.099)	(.051)	(.049)	(.108)
Other socioeconomic variables and intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other asset variables		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Other agroclimatic / soil variables			Yes			Yes			Yes			Yes			Yes
Number of observations	4,236	4,236	4,236	17,237	17,237	17,237	26,093	26,093	26,093	12,226	12,226	12,226	4,570	4,570	4,570

Source: Authors' estimations based on the census data.

Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%

[a]Numbers in parentheses are EA-clustered robust standard errors.

Table B3. Robustness check for the results of Table 2 using different land-holding size classification[a, b]

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	1^{st} quintile			1^{st} ~ 2^{nd} quintile			1^{st} ~ 3^{rd} quintile			4^{th} ~ 5^{th} quintile			5^{th} quintile		
ln (farm size)	.046**	.044**	.029**	.043**	.041**	.035**	.042**	.041**	.036**	.077**	.065**	.074**	.130**	.112**	.113**
	(.003)	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.007)	(.007)	(.007)	(.012)	(.013)	(.013)
Agroclimatic similarity	.026**	.026**	.012*	.030**	.030**	.007	.030**	.031**	.008†	.009**	.009**	.002	.004	-.004	-.002
	(.003)	(.003)	(.007)	(.003)	(.003)	(.006)	(.002)	(.002)	(.005)	(.003)	(.003)	(.007)	(.005)	(.005)	(.011)
Agroclimatic similarity × ln (farm size)	.013**	.012**	.010**	.005*	.005*	.004	.003	-.002	.002	-.011	-.012†	-.006	-.001	.004	.001
	(.004)	(.004)	(.004)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.007)	(.007)	(.007)	(.012)	(.012)	(.012)
Distance to PBI	-.015**	-.016**	-.046**	-.019**	-.018**	-.041**	-.018**	-.018**	-.036**	-.031**	-.033**	-.045**	-.037**	-.039**	-.053**
	(.004)	(.004)	(.005)	(.004)	(.004)	(.004)	(.003)	(.003)	(.004)	(.005)	(.005)	(.006)	(.008)	(.081)	(.009)
Distance to PBI × ln (farm size)	-.011*	-.010*	-.009*	-.007*	-.006†	-.002	-.006*	-.005†	.002	-.013	-.011	-.011	-.020	-.012	-.009
	(.005)	(.005)	(.005)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.011)	(.011)	(.011)	(.019)	(.019)	(.019)
Other socioeconomic variables and intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other asset variables		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Other agroclimatic / soil variables			Yes			Yes			Yes			Yes			Yes
Number of observations	7,661	7,661	7,661	15,258	15,258	15,258	22,987	22,987	22,987	15,332	15,332	15,332	7,603	7,603	7,603

Source: Authors' estimations based on the census data.

Asterisks indicate the statistical significance: ** 1%, * 5%, 10%

[a]Both *agroclimatic similarity* and *ln (land holding size)* are demeaned within the corresponding samples. Therefore, coefficients for non-interacted variables are average partial effects for all corresponding samples.

[b]Numbers in parentheses are heteroskedasticity-robust standard errors.

Table B4. Robustness check for the results of Table 3 using different land-holding size classification[a]

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	1st quintile			1st ~ 2nd quintile			1st ~ 3rd quintile			4th ~ 5th quintile			5th quintile		
Area share of improved varieties	1.925** (.847)	1.936** (.867)	2.415* (1.184)	2.054† (1.086)	2.337† (1.345)	2.370† (1.319)	1.585* (.657)	1.795* (.811)	1.727* (.752)	.250 (.246)	.228 (.261)	.240 (.249)	-.083 (.255)	-.089 (.271)	-.100 (.258)
Other socioeconomic variables and intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other asset		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
plot soil variables			Yes			Yes			Yes			Yes			Yes
Number of observations	7,661	7,661	7,661	15,258	15,258	15,258	22,987	22,987	22,987	15,332	15,332	15,332	7,603	7,603	7,603
p-value (H0: over-identification)	.287	.283	.446	.965	.909	.961	.487	.606	.395	.824	.927	.711	.185	.103	.102
p-value (H0: exogeneity)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.347	.403	.358	.655	.693	.644

Source: Authors' estimations based on the census data.

Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%

[a]Numbers in parentheses are EA-cluster adjusted standard errors.

Table B5. Effects of agroclimatic similarity on tractor adoption decisions, differentiated by land holding size, in Nepal Terai in 2001 (excluding tractor owners from the sample)[a,b]

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
	(1)	(2)	**(3)**	(4)	(5)	**(6)**	(7)	(8)	**(9)**	(10)	(11)	**(12)**	(13)	(14)	**(15)**
ln (farm size)	.033**	.032**	.022**	.049**	.046**	.043**	.043**	.042**	.039**	.032**	.033**	.044**	.031†	.031†	.032†
	(.004)	(.004)	(.004)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.008)	(.009)	(.009)	(.018)	(.018)	(.018)
Agroclimatic similarity	.017**	.017**	.013*	.029**	.030**	.009†	.027**	.027**	.005	.006†	.006†	-.012	-.008	-.007	-.026†
	(.003)	(.003)	(.006)	(.002)	(.002)	(.005)	(.002)	(.002)	(.005)	(.003)	(.003)	(.008)	(.006)	(.006)	(.014)
Agroclimatic similarity ×	.019**	.019**	.017**	.006*	.006*	.005*	.000	.000	.001	-.022**	-.022**	-.011	.005	.006	.001
ln (farm size)	(.006)	(.006)	(.006)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.008)	(.008)	(.008)	(.018)	(.018)	(.018)
Distance to PBI	-.002	-.003	-.026**	-.018**	-.015**	-.037**	-.019**	-.016*	-.032**	-.039**	-.038**	-.046**	-.064**	-.063**	-.072**
	(.004)	(.004)	(.006)	(.003)	(.004)	(.004)	(.003)	(.003)	(.004)	(.006)	(.006)	(.007)	(.011)	(.011)	(.013)
Distance to PBI × ln	.002	.001	-.003	-.004	-.002	.002	-.006**	-.005*	-.002	-.045**	-.042**	-.044**	-.053†	-.045	-.049
(farm size)	(.006)	(.006)	(.006)	(.003)	(.004)	(.003)	(.002)	(.003)	(.003)	(.013)	(.013)	(.013)	(.032)	(.032)	(.032)
Other socioeconomic variables and intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other asset variables		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Other agroclimatic / soil variables			Yes			Yes			Yes			Yes			Yes
Number of observations	4,226	4,226	4,226	17,156	17,156	17,156	25,909	25,909	25,909	11,747	11,747	11,747	4,220	4,220	4,220

Source: Authors' estimations based on the census data.
Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%
[a]Both *agroclimatic similarity* and *ln (land holding size)* are demeaned within the corresponding samples. Therefore, coefficients for non-interacted variables are average partial effects for all corresponding samples.
[b]Numbers in parentheses are heteroskedasticity-robust standard errors.

Table B6. Effects of the adoptions of improved varieties on tractor adoption decisions, differentiated by land holding size, in Nepal Terai in 2001[a]

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
	(1)	(2)	**(3)**	(4)	(5)	**(6)**	(7)	(8)	**(9)**	(10)	(11)	**(12)**	(13)	(14)	**(15)**
Area share of improved varieties	1.324*	1.413*	**1.740†**	2.040†	2.319†	**2.218†**	1.651*	1.842*	**1.761***	.117	.127	**.120**	-.673	-.768	**-.733**
	(.644)	(.708)	**(.930)**	(1.044)	(1.279)	**(1.161)**	(.715)	(.860)	**(.781)**	(.224)	(.242)	**(.230)**	(.493)	(.604)	**(.558)**
Other socioeconomic variables and intercept	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**	Yes	Yes	**Yes**
Other asset		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**		Yes	**Yes**
plot soil variables			**Yes**			**Yes**			**Yes**			**Yes**			**Yes**
Number of observations	4,226	4,226	**4,226**	17,156	17,156	**17,156**	25,909	25,909	**25,909**	11,747	11,747	**11,747**	4,220	4,220	**4,220**
p-value (H0: over-identification)	.220	.265	**.523**	.797	.914	**.762**	.783	.932	**.679**	.730	.661	**.495**	.521	.465	**.448**
p-value (H0: exogeneity)	.000	.000	**.000**	.000	.000	**.000**	.000	.000	**.000**	.650	.641	**.651**	.040	.046	**.039**

Source: Authors' estimations based on the census data.

Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%

[a]Numbers in parentheses are EA cluster-adjusted standard errors.

Table B7. Effects of agroclimatic similarity on tractor adoption decisions, differentiated by land holding size, in Nepal Terai in 2001[a, b]

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
Agroclimatic similarity	.017**	.017**	.015*	.030**	.031**	.012*	.028**	.029**	.009*	.007†	.007*	-.002	-.004	-.004	.001
	(.003)	(.003)	(.007)	(.002)	(.002)	(.005)	(.002)	(.002)	(.005)	(.004)	(.004)	(.008)	(.007)	(.007)	(.016)
Agroclimatic similarity × ln (farm size)	.020**	.019**	.017**	.006*	.005*	.005*	.000	.000	.001	-.010	-.011	-.003	.033†	.028	.031†
	(.006)	(.006)	(.006)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.009)	(.008)	(.008)	(.018)	(.017)	(.017)
ln (farm size)	.034**	.033**	.023**	.050**	.048**	.045**	.045**	.045**	.042**	.098**	.084**	.094**	.157**	.135**	.137**
	(.004)	(.004)	(.004)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.009)	(.009)	(.009)	(.018)	(.018)	(.018)
Distance to PBIs	-.002	-.003	-.027**	-.019**	-.018**	-.041**	-.020**	-.020*	-.036**	-.031**	-.033**	-.045**	-.041**	-.042**	-.059**
	(.004)	(.004)	(.006)	(.004)	(.004)	(.004)	(.003)	(.003)	(.004)	(.006)	(.006)	(.007)	(.011)	(.011)	(.013)
Distance to PBIs × ln (farm size)	.003	.003	-.002	-.005†	-.004	.000	-.007**	-.006*	-.003	-.018	-.014	-.016	-.017	-.002	-.005
	(.006)	(.006)	(.006)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.013)	(.013)	(.012)	(.028)	(.029)	(.029)
Distance to urban centers	-.018**	-.017**	.006	-.036**	-.037**	-.003	-.038**	-.039**	-.007*	-.020**	-.020**	.006	-.008	-.009	.023*
	(.003)	(.003)	(.004)	(.003)	(.003)	(.004)	(.003)	(.003)	(.003)	(.005)	(.005)	(.006)	(.010)	(.010)	(.011)
Distance to urban centers × ln (farm size)	-.014**	-.014**	-.007	-.013**	-.014**	-.014**	-.007**	-.008**	-.009**	.026**	.024*	.026*	.056*	.041	.039
	(.005)	(.005)	(.005)	(.003)	(.003)	(.003)	(.002)	(.002)	(.002)	(.012)	(.012)	(.012)	(.026)	(.027)	(.027)
Distance to Indian border	.006†	.006†	.010	.011**	.011**	.015**	.006*	.007**	.021**	-.011**	-.006	.024**	-.010	-.005	.019
	(.004)	(.004)	(.006)	(.003)	(.003)	(.005)	(.002)	(.002)	(.004)	(.004)	(.004)	(.008)	(.007)	(.007)	(.014)
Distance to Indian border× ln (farm size)	.008†	.008	.001	.011**	.001	-.004	.006**	-.004*	-.006**	.004	.003	.012	.026	.022	.034*
	(.005)	(.005)	(.005)	(.003)	(.002)	(.024)	(.002)	(.002)	(.002)	(.008)	(.008)	(.008)	(.017)	(.017)	(.017)
Household size	-.002	-.002	-.002	-.001	.002	-.001	-.001	.002	-.003	.004	.007*	-.001	.007	.012*	.003
	(.004)	(.004)	(.004)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.005)	(.005)	(.005)
Gender of household head (female = 1)	.011**	.011**	.007*	.012**	.012**	.005**	.012**	.011**	.006**	.011*	.012*	.012*	.005	.007	.007
	(.003)	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.006)	(.005)	(.005)	(.010)	(.010)	(.010)
Number of owned farm buildings	.000	.001	.011**	.008**	.013**	.017**	.003	.007**	.012**	-.026**	-.024**	-.007†	-.024**	-.022**	-.003
	(.003)	(.004)	(.004)	(.003)	(.003)	(.003)	(.002)	(.002)	(.002)	(.004)	(.004)	(.004)	(.007)	(.007)	(.007)
Number of farm plots	-.052*	-.054*	.001	-.068**	-.068**	-.040**	-.043**	-.045**	-.026**	.019**	.015**	.007†	.022**	.018**	.008
	(.024)	(.024)	(.025)	(.007)	(.007)	(.007)	(.004)	(.004)	(.005)	(.004)	(.004)	(.004)	(.005)	(.005)	(.005)
Lowland type plots	.025**	.025**	.026**	.052**	.051**	.047**	.055**	.053**	.050**	.063**	.055**	.062**	.073**	.062**	.073**
	(.004)	(.004)	(.004)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.004)	(.005)	(.008)	(.008)	(.008)
Asset index (equipment)		.015	.010		-.010†	-.010†		.000	.001		.023**	.022**		.027**	.025**
		(.013)	(.013)		(.006)	(.006)		(.004)	(.004)		(.003)	(.003)		(.004)	(.004)
Asset index (livestock)		-.007	-.006		-.018**	-.017**		-.021**	-.021**		-.025**	-.018**		-.030**	-.020**
		(.005)	(.005)		(.003)	(.003)		(.003)	(.003)		(.003)	(.003)		(.006)	(.006)
Rainfall			.023**			.033**			.034**			.009†			-.004
			(.004)			(.003)			(.003)			(.005)			(.009)
Temperature			.065**			.125**			.138**			.127**			.119**
			(.008)			(.006)			(.005)			(.009)			(.018)
Sodicity of soil			.015**			.020**			.023**			.027**			.025*
			(.004)			(.003)			(.002)			(.005)			(.010)

Dependent variable =	Samples by land-holding size														
tractor adoptions (yes = 1)	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
Coarse soil			-.073**			-.117**			-.112**			-.076**			-.064**
			(.009)			(.012)			(.004)			(.008)			(.015)
Fine soil			.010†			.004			.004			.000			.011
			(.006)			(.005)			(.004)			(.009)			(.021)
Organic carbon contents			.044**			.086**			.092**			.076**			.067**
			(.010)			(.005)			(.004)			(.007)			(.014)
Elevation			.024**			.029**			.029**			.016			.010
			(.006)			(.006)			(.005)			(.010)			(.019)
Slope			-.005			-.004			.000			.023*			.028
			(.006)			(.007)			(.005)			(.009)			(.018)
Distance to the river			-.012**			-.013**			-.010**			-.006†			-.005
			(.003)			(.002)			(.002)			(.004)			(.007)
Ground water table			-.010†			-.007			-.010*			.005			.020
			(.006)			(.006)			(.005)			(.007)			(.014)
Sandy soil (plot)			-.006			.006			.009†			-.011			-.012
			(.007)			(.006)			(.005)			(.009)			(.016)
Silty soil (plot)			-.010			-.006			-.010†			-.025*			-.015
			(.008)			(.007)			(.006)			(.011)			(.018)
Clayey soil (plot)			.003			.006			.006†			-.014*			-.008
			(.005)			(.004)			(.003)			(.006)			(.009)
Loamy soil (plot)			-.002			.011*			.008†			-.017*			-.019
			(.007)			(.005)			(.005)			(.008)			(.013)
Black soil (plot)			.011			-.001			.001			.028**			.015
			(.008)			(.007)			(.006)			(.011)			(.018)
Brown soil (plot)			.020*			.013†			.016**			.032**			.027
			(.008)			(.006)			(.006)			(.011)			(.019)
Yellow soil (plot)			.003			-.004			-.005			.006			.001
			(.005)			(.004)			(.004)			(.007)			(.011)
Red soil (plot)			-.002			-.008**			-.008*			-.007			-.010
			(.003)			(.003)			(.002)			(.004)			(.007)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4,236	4,236	4,236	17,237	17,237	17,237	26,093	26,093	26,093	12,226	12,226	12,226	4,570	4,570	4,570

Source: Authors' estimations based on the census data. Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%

[a]Both *agroclimatic similarity* and *ln (land holding size)* are demeaned within the corresponding samples. Therefore, coefficients for non-interacted variables are average partial effects for all corresponding samples.

[b]Numbers in parentheses are heteroskedasticity-robust standard errors.

Table B8. Effects of the adoptions of improved varieties on tractor adoption decisions, differentiated by land holding size, in Nepal Terai in 2001[a, b]

Dependent variable =	Samples by land-holding size														
tractor adoptions (yes = 1)	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
Area share (%) of	1.397*	1.488*	1.809†	2.039*	2.284†	2.189†	1.653**	1.818**	1.724**	.125	.114	.101	-.523	-.630	-.611
improved varieties	(.679)	(.745)	(.961)	(1.026)	(1.238)	(1.129)	(.228)	(.274)	(.252)	(.234)	(.250)	(.239)	(.507)	(.592)	(.552)
ln (Farm size)	-.026	-.025	-.040	-.064	-.091	-.087	-.039**	-.056**	-.052**	.103**	.094**	.094**	.177**	.133**	.134**
	(.032)	(.032)	(.043)	(.061)	(.079)	(.073)	(.013)	(.016)	(.015)	(.015)	(.011)	(.011)	(.038)	(.030)	(.029)
Distance to PBIs	.016	.019	.027	.003	.030	.013	-.009	.003	-.004	-.019	-.020	-.021	-.051†	-.061	-.056
	(.028)	(.030)	(.036)	(.032)	(.021)	(.036)	(.007)	(.009)	(.008)	(.017)	(.019)	(.018)	(.031)	(.038)	(.035)
Distance to PBIs × ln	.066	.071	.087	-.022	-.019	-.018	-.018**	-.015*	-.014*	-.009	-.005	-.003	-.068	-.058	-.053
(farm size)	(.055)	(.060)	(.073)	(.023)	(.025)	(.024)	(.006)	(.007)	(.007)	(.015)	(.015)	(.015)	(.056)	(.060)	(.056)
Distance to urban centers	-.025	-.027	-.034	-.098*	-.114*	-.101**	-.101**	-.114**	-.101**	-.036	-.037	-.035	.019	.027	.024
	(.024)	(.025)	(.030)	(.044)	(.053)	(.046)	(.011)	(.014)	(.012)	(.023)	(.024)	(.023)	(.041)	(.049)	(.045)
Distance to urban centers	-.069	-.074	-.084	-.039†	-.046†	-.039	-.032**	-.036**	-.032**	.024†	.021	.020	.109*	.092†	.085†
× ln (farm size)	(.046)	(.050)	(.060)	(.024)	(.027)	(.025)	(.006)	(.007)	(.007)	(.014)	(.014)	(.014)	(.049)	(.050)	(.047)
Distance to Indian border	.016	.017	.018	.051†	.052	.044	.037**	.036*	.029**	-.008	-.004	-.003	-.012	-.005	-.005
	(.016)	(.017)	(.019)	(.029)	(.032)	(.028)	(.007)	(.007)	(.006)	(.009)	(.008)	(.008)	(.014)	(.015)	(.014)
Distance to Indian	-.001	.001	-.004	.010	.007	.007	.000	-.003	-.003	.005	.002	.002	.005	.004	.008
border× ln (farm size)	(.015)	(.015)	(.018)	(.011)	(.011)	(.011)	(.004)	(.004)	(.004)	(.011)	(.011)	(.011)	(.027)	(.025)	(.025)
Household size	-.030†	-.033†	-.039	-.022†	-.023	-.018	-.024**	-.023**	-.019**	.002	.005	.005	.001	.003	.001
	(.018)	(.020)	(.025)	(.015)	(.017)	(.015)	(.007)	(.007)	(.007)	(.005)	(.005)	(.005)	(.008)	(.009)	(.009)
Gender of household head	.003	.002	.000	.012†	.011	.008	.017**	.016**	.014**	.011*	.011*	.011*	.004	.005	.007
(female = 1)	(.008)	(.008)	(.010)	(.006)	(.007)	(.007)	(.004)	(.004)	(.004)	(.006)	(.005)	(.005)	(.012)	(.012)	(.012)
Number of owned farm	.011	.006	.009	.029	.040†	.033†	.028**	.037*	.031**	-.024**	-.022*	-.022*	-.040*	-.044†	-.043*
buildings	(.011)	(.012)	(.014)	(.018)	(.022)	(.019)	(.006)	(.007)	(.006)	(.009)	(.009)	(.009)	(.019)	(.023)	(.022)
Number of farm plots	-.196†	-.201†	-.212	-.117*	-.117*	-.077†	-.076**	-.077**	-.051**	.016†	.013	.015†	.032*	.028†	.026†
	(.102)	(.109)	(.132)	(.048)	(.052)	(.042)	(.011)	(.012)	(.011)	(.009)	(.009)	(.008)	(.016)	(.016)	(.013)
Lowland type plots	-.038	-.042	-.050	-.046	-.052	-.040	-.029*	-.031*	-.021	.062**	.056**	.056**	.100**	.085**	.082**
	(.035)	(.038)	(.046)	(.052)	(.059)	(.051)	(.013)	(.014)	(.013)	(.013)	(.012)	(.011)	(.026)	(.023)	(.021)
Asset index (equipment)		-.003	-.002		-.106†	-.102*		-.075**	-.071**		.012	.012		.037*	.035*
		(.024)	(.028)		(.056)	(.051)		(.013)	(.012)		(.009)	(.008)		(.017)	(.016)
Asset index (livestock)		.022	.025		.016	.009		.003	-.002		-.020**	-.020**		-.027**	-.022**
		(.019)	(.021)		(.021)	(.018)		(.006)	(.006)		(.004)	(.004)		(.007)	(.006)
Sandy soil (plot)			.033			.097*			.080**			.009			-.045
			(.035)			(.050)			(.014)			(.020)			(.046)
Silty soil (plot)			.022			.011			-.007			-.015			-.006
			(.036)			(.030)			(.013)			(.017)			(.029)
Clayey soil (plot)			.032			.049*			.040**			-.010			-.033
			(.021)			(.025)			(.008)			(.011)			(.028)

Dependent variable = tractor adoptions (yes = 1)	Samples by land-holding size														
	< 0.1 ha			< 0.5 ha			< 1.0 ha			> 1.0 ha			> 2.0 ha		
Loamy soil (plot)			.045			.076*			.053**			-.008			-.041
			(.033)			(.037)			(.011)			(.014)			(.032)
Black soil (plot)			-.052			-.054			-.038**			.010			.020
			(.047)			(.037)			(.013)			(.017)			(.034)
Brown soil (plot)			-.003			-.012			.000			.009			.021
			(.033)			(.031)			(.013)			(.017)			(.034)
Yellow soil (plot)			-.041			-.058†			-.049**			-.003			.022
			(.034)			(.033)			(.010)			(.012)			(.028)
Red soil (plot)			.001			-.003			-.003			-.010			-.020
			(.012)			(.013)			(.005)			(.007)			(.012)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4,236	4,236	4,236	17,237	17,237	17,237	26,093	26,093	26,093	12,226	12,226	12,226	4,570	4,570	4,570

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Asterisks indicate the statistical significance: ** 1%, * 5%, † 10%.

[a]Both *agroclimatic similarity* and *ln (land holding size)* are demeaned within the corresponding samples. Therefore, coefficients for non-interacted variables are average partial effects for all corresponding samples.

[b]Numbers in parentheses are EA-cluster adjusted standard errors.

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