Geographic Heterogeneity and Technology Adoption*

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Abstract

This paper provides evidence that geographic heterogeneity affects the rates of adoption of modern agricultural technologies using data from the Direct Planting System (DPS) in Brazil. DPS is a no-till farming technique and its adoption requires adaptation to local conditions. Our results indicate that geographic heterogeneity decreases DPS adoption. This effect is robust to the inclusion of a large number of geographic and socioeconomic controls. Moreover, our results indicate that geographic heterogeneity does not reduce the adoption of technologies in which site-specific adaptation is not required. To rationalize these findings, we propose a model in which modern technologies require adaptation to site-specific conditions to be adopted and demonstrate that, in this context, geographic heterogeneity can decrease adoption by increasing the cost of learning about modern technologies.

JEL: *D83*, *O33*, *Q33*

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1 Introduction

Under-adoption of modern technologies is an important constraint on economic development. Several studies document that agricultural technologies often have low adoption rates despite having large returns (Duflo et al., 2008; Suri, 2011). The inefficiencies arising from this phenomenon can have substantial consequences since agriculture explains a large share of cross-country productivity differences (Caselli, 2005; Gollin et al., 2014). These consequences have motivated a substantial number of studies investigating the causes of under-adoption of modern agricultural technologies. The existing literature has associated under-adoption with factors that range from market failures to behavioral biases.[1]

This paper provides evidence that geographic heterogeneity is another important barrier to the adoption of modern technologies in agriculture. We combine fine-level geographic data with information on the adoption of the Direct Planting System (DPS) in Brazil to document that increases in geographic heterogeneity are connected to lower technology adoption.

The DPS is a no-till technique developed in southern Brazil in the 1970s in areas prone to land degradation. It later evolved into a full farming method with higher revenues and lower costs than the traditional methods used in the country (Inoue, 2003). The limited use of tillage also prevents soil degradation and the loss of nutrients which boosts productivity in the long run.[2] Despite these benefits, only one-tenth of farmers adopted the technique in 2006. Under-adoption is often connected to difficulties in the diffusion of information about this technology since farmers must adapt the DPS to site-specific conditions (Landers, 2005; Derpsch et al., 2010).

Our empirical exercise uses municipality-level information on DPS adoption and geographic heterogeneity in Brazil. Because the use of this technology is influenced primarily by soil characteristics, we use soil heterogeneity as a proxy of geographic heterogeneity. Soil heterogeneity is defined as the inverse of the Herfindahl index (HHI) of soil concentration. It can be interpreted as the effective number of soils observed in a given municipality.

[1] Foster and Rosenzweig (1995) and Conley and Udry (2010) emphasize the role of social learning in technology adoption in India and Ghana. Karlan et al. (2014) investigates the role of market failures in investments and technology adoption in Ghana. Suri (2011) emphasizes the role of comparative advantage in explaining under-adoption of modern technologies in agriculture in Kenya. Duflo et al. (2011) investigate the role of behavioral biases in explaining adoption decisions among Kenyan farmers.

[2] DPS adoption is also associated with an increase in carbon sequestration and a reduction in greenhouse gas emissions in agriculture. See West and Post (2002) and Metay et al. (2007) for evidence on these gains in different settings.

To ensure that technology adoption does not influence this measure of heterogeneity, we construct it using a physicochemical classification of soil types that is invariant to land use.

We regress the DPS adoption rate on this measure of soil heterogeneity controlling for geographic characteristics (soil types, rainfall, temperature, land gradient, altitude, latitude, longitude, and potential yields). This empirical model examines whether the variance of soils affects DPS adoption conditional on the mean geographic characteristics.

Our estimates provide evidence that municipalities with more heterogeneous soils have significantly lower DPS adoption rates than municipalities with less heterogeneous soils. Including state fixed effects and socioeconomic characteristics such as education, number of farms, farm revenues, government technical assistance, land use, presence of cooperatives, and learning facilities and access to credit does not influence the results. Robustness tests indicate that the results do not change when different soil heterogeneity definitions and sample selection methods are considered. The main specification indicates that an increase of one standard deviation in soil dissimilarities reduces DPS adoption by 1.5 percentage points.

We perform placebo tests to examine whether more heterogeneous municipalities also have lower adoption rates of technologies that do not require site-specific adaptation. The results suggest that soil heterogeneity neither affects the use of general-purpose technologies such as electric power nor the use of agricultural technologies such as harvesters.

Because geographic heterogeneity does not influence the costs and benefits from adoption directly, it is essential to discuss the mechanisms that might explain the documented relationship between geographic heterogeneity and technology adoption. The robustness of the results to the inclusion of socioeconomic controls rule out explanations based on the link between fragmentation and the provision of public goods (Alesina et al., 1999; Michalopoulos, 2012). However, the absence of effects of geographic heterogeneity on technologies that do not require site-specific adaptation indicates that the results might be tied to difficulties in the diffusion of information about modern technologies in heterogeneous areas (Ellison and Fudenberg, 1993; Diamond, 1997; Munshi, 2004).

We propose a theoretical model to formalize the idea that information barriers are the mechanism connecting geographic heterogeneity and technology adoption. In the model, profit-maximizing farmers must decide whether to adopt a new technology that requires adaptation to site-specific conditions. Non-adopters must adapt the new technology from the current adopters and adaptation entails a cost that increases as the difference between farmers geographic characteristics increases. These assumptions capture the intuition that farmers learn from their peers (e.g., Foster and Rosenzweig (1995) and Conley and Udry (2010)) and that it is easier to learn from similar peers than from different ones (e.g., Ellison and Fudenberg (1993) and Munshi (2004)). This model predicts that adaptation costs will be greater in more heterogeneous regions than in more homogeneous ones because farmers are located farther from each other in the former regions than in the latter ones. As a consequence, less farmers will find it profitable to adopt the DPS in regions where geographic heterogeneity is high. The results obtained using OLS regressions are consistent with this prediction.

The model also predicts that geographic heterogeneity will not affect adoption when adoption rates are either too low or too high. In the former case, adoption is so limited that there will not exist enough adopters to learn from at all levels of geographic heterogeneity. In the latter, the opposite situation occurs, and there will exist enough adopters to learn from regardless geographic heterogeneity. For intermediate adoption levels, the impact of geographic dissimilarities will be the highest.[3]

The results obtained using quantile regressions are consistent with this supplementary prediction. Estimated obtained using the unconditional quantile estimator from Firpo et al. (2009) indicate that the effects of soil heterogeneity on DPS adoption are stronger at intermediate adoption levels. The estimates are larger in absolute value than the OLS estimates for adoption levels from 20 to 50%.

Our findings support Diamond (1997)'s assertion that the diffusion of agricultural technologies is slower in areas with large geographic dissimilarities.[4] However, we provide evidence that this assertion is compelling just for technologies that require site-specific modifications to be successfully adapted. The results from our paper are also related to Munshi (2004). This author proposes a model in which farmers learn with their peers about the profits of new technologies that predicts farmers' choices should respond more to their neighbors choices when the population is homogeneous than when the population is more heterogeneous. He then provides empirical support for this prediction. However, it is not possible to rule out that unobserved factors drive the relationship between het-

[3]It should be noted that this non-monotonic pattern is related to the traditional S-curve which describes adoption levels over time. It is nearly flat when adoption levels are either too low (because there are few adopters to be imitated) or too high (because there are few non-adopters to imitate). The present model captures a similar effect over quantiles of the unconditional distribution of adoption. See Jackson (2010) for a theoretical discussion of the S-curve and Foster and Rosenzweig (1995) for evidence that the diffusion of agricultural technologies follows the S-curve.

[4]See Blouin (2014) for evidence supporting this hypothesis in the context of the Bantu migration in Africa.

erogeneity and adoption in his setting. Our approach mitigates this concern by using direct information about geographic heterogeneity to test the proposition that heterogeneity across agents obstructs technology adoption. This enables us to contribute to the growing literature linking social learning on technology adoption (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010).

The use of direct geographic information also links our paper to a growing number of studies documenting the impact of the variation in geographic characteristics on different determinants of economic development such as trust, fractionalization and state centralization (Durante, 2010; Michalopoulos, 2012; Fenske, 2014). Our evidence indicates that the variation in geographic characteristics can also affect economic development through its impact on the adoption of agricultural technologies. This evidence complements other studies that document the impact of mean geographic characteristics on agricultural outcomes like Hornbeck (2012).

The remainder of this paper is organized as follows. Section 2 describes the Direct Planting System and its diffusion in Brazil. Section 3 describes the data. Section 4 discusses the empirical model used to test the hypothesis that geographic heterogeneity obstructs technology adoption. Section 5 reports the estimates and robustness tests. Section 6 presents the theoretical model. Section 7 concludes and discusses implications for future research.

2 Background

2.1 The Direct Planting System (DPS)

The DPS is a no-till technique developed in Brazil at the beginning of the 1970s. No-till techniques can be described as agricultural practices in which tillage is absent and crop residue is left on the surface. These practices reduce the loss of nutrients and erosion, but their use in large-scale agriculture requires the presence of effective herbicides because tillage is an important tool for weed control. Indeed, the substantial benefits of tillage in terms of weed control implied that it was worth using despite its cost in terms of land degradation and erosion until the development of more effective herbicides after the 1940s. Technological developments in weed control triggered more research about no-till techniques in the following decades. These techniques have become popular among proponents of sustainable agricultural practices because of their positive environmental consequences (Baker et al., 2007).

The DPS is a distinct no-till method in which the absence of tillage is permanent and the use of green manure crops to cover soils is widespread (Derpsch et al., 2010). These features resulted from efforts to adapt no-till techniques to the specific geographic conditions that farmers face in southern Brazil, where the technique was developed in the 1970s. The DPS has since became popular in other South America regions such as the *Pampas* in Argentina and the *Cerrado* in Brazil.

The DPS is novel production technology as adopters continue to use similar inputs and reach a higher output. Its adoption may thus be characterized as the adoption of a different production process that uses the same inputs. This feature is important for the empirical investigation because it is often difficult to separate technology under-adoption from input under-use (Foster and Rosenzweig, 2010).[5]

DPS adoption is associated with public and private gains. Table 1 describes the benefits from DPS adoption. Its public gains are presented in Panel A. The main benefits are derived from both lower carbon emissions and higher carbon sequestration. Both changes have positive externalities to the environment and mitigate climate change (West and Post, 2002; Metay et al., 2007). Other gains have been reported in terms of reduced environmental contamination and increased biodiversity (Derpsch et al., 2010). The technology's private gains are presented in Panel B. These benefits are derived from a combination of higher revenues and lower costs. The DPS reduces soil degradation and erosion and improves soil properties, resulting in higher revenues. The expenditures with associated with herbicides increase, but the reduction in the use of machines more than compensates this increase and total costs decrease (Derpsch et al., 2010; Baker et al., 2007).

A number of studies have quantified the benefits farmers obtain from DPS adoption. Inoue (2003) presents evidence that DPS adoption increases productivity in soy cultivation by 17% in Brazil. The author also presents evidence that average costs decrease by 9% with DPS adoption. Sorrenson and Portillo (1997) report that DPS increases net income by 33% in the first year of adoption among farmers in Paraguay. The authors also argue that the benefits gained from the DPS increase over time. Trigo et al. (2009) estimates substantial economic benefits from DPS adoption in Argentina derived from both increases in production and decreases in costs. Simulations reported by Ringler et al. (2013) indicate that widespread adoption of no-till techniques would increase yields of staple crops, even considering the effects of climate change on temperature and rainfall. The authors therefore argue that no-till is a promising farming technique for mitigating climate change's

[5] The optimal choice of inputs often changes under a new technology. However, this is different from change of inputs given a technology.

impact on agriculture.

An important feature of the DPS is that neither credit constraints nor incomplete insurance appear to be barriers to its adoption because the technology does not have relevant upfront costs and does not increase risk exposure. DPS adoption also does not require additional infrastructure. However, information appears to be an important barrier to DPS adoption. Derpsch (1999) argues that adjustment required to make the DPS suitable are unique to the type of soil considered (although there are some general practices that must be implemented in all contexts). The author suggests that a lack of "site specific knowledge" has been a significant barrier to the diffusion of DPS in Latin America. Indeed, his first two recommendations for farmers willing to adopt such techniques are:

1. "Improve your knowledge about all aspects of the system but especially in weed control."
2. "Analyze your soil. (...)"

2.2 DPS Diffusion

The DPS was first implemented at the beginning of the 1970s in southern Brazil among farmers cultivating sorghum and wheat. The technique was developed to fight rain erosion affecting soils in the region of *Ponta Grossa* in the state of *Paraná*. Pioneer farmers studied no-till techniques abroad and incurred the risk of importing equipment and knowledge and testing the method on a large scale. These farmers exerted significant influence over the development of the DPS in Brazil, inducing research about the DPS among seed producers, machines manufacturers and research institutes.

Anecdotal evidence suggests that large farmers in the *Ponta Grossa* region started adopting the DPS in 1976. Technological diffusion was concentrated in southern Brazil in the first decade after the technique's implementation. Diffusion to other regions began later. The DPS became particularly successful in the *Cerrado* biome where its use expanded among crop producers. Diffusion has accelerated in all regions since the 1990s.

An important feature of the DPS's diffusion was the creation of an association called Clube da Minhoca[6] (henceforth CM) in 1979. The CM is located in *Ponta Grossa* and is a diffusion center whose goal is to spread knowledge about the technology. The organization promoted meetings in which farmers (adopters and non-adopters) would discuss issues

[6] Translated as "Earthworm club" as the presence of earthworm is a sign of soil vitality.

related to farming. It also organized national meetings and sponsored the publication of technical material about the DPS.

The CM inspired the creation of private associations with a similar objective in other areas. These associations are called Clube Amigos da Terra[7] (henceforth CAT). The first CAT was established in 1982 in the state of Rio Grande do Sul. These associations were an essential tool for the diffusion of the DPS throughout Brazil. The CATs coordinate learning efforts and information exchange among farmers. The CATs and other organizations that promote the technique were essential to spread information and knowledge about the method. Indeed, these private organizations appear to have been more important to DPS diffusion than public extension services.

However, the presence of these associations was not sufficient to induce most Brazilian farmers to adopt the DPS. Almost 90% of farmers did not adopt the technique despite the substantial increase in adoption since the 1990s depicted in Figure 1. Adoption rates are similar across farm sizes and are higher in the crop-intensive areas in southern and central Brazil.

3 Data

3.1 Soil Heterogeneity

We build the soil heterogeneity measure using detailed GIS information from a Brazilian soil map developed by Embrapa, the Brazilian Agricultural Research Corporation (EMBRAPA, 2011). The data are based on an international soil classification system. This classification uses a hierarchical taxonomy: A hypothetical soil 'Aa1' belongs to order 'A', suborder 'a', and group '1'. 'Order' is the first and most general classification level and the following levels are subdivisions. Although the classification system allows for finer levels, the map does not report information beyond the third level. Information is presented at a scale of 1:5.000.000 for each level.

The classification system is based on soils' physicochemical composition. This composition is a major determinant of the physical properties of each type of soil. Physical properties, in turn, define the suitability for different agricultural methods. For example, in the case of the DPS, high soil temperature often calls for a thick layer of residue on the surface

[7] Translated as "Friends-of-the-earth club".

to decrease exposure to sunlight and avoid excessive heat. Hence, a different type of soil calls for some adjustment (a micro-innovation) in the use of the DPS. This classification system is smooth in the sense that, for agricultural purposes, the difference in physical properties between two soils is roughly the same for each soil pair.

The baseline empirical specification considers the most general level (order) to construct the soil heterogeneity measure. This level has the advantage of being invariant to land use. Although different practices may either enrich or impoverish the soil by affecting the levels of several nutrients, this process cannot go as far as to change its basic chemical structure. Therefore, this measure is independent of the adoption of the DPS or other agricultural practices. We provide evidence in the robustness section that results remain unchanged when one considers 'orders', 'sub-orders', and 'groups' to construct the soil heterogeneity measure.

There are 35 different orders across Brazil. We merge the soil map with the map of municipalities to build a measure of the share of each municipality covered by each soil order. We use the same procedure to build measures for the other levels. These shares are used to construct a Herfindahl index (HHI) of soil types for each municipality. The index varies from zero to one. High values indicate homogeneity and low values indicate heterogeneity.

Soil heterogeneity (S) is defined as the inverse of a municipality's Herfindahl index of soil concentration. In line with the industrial organization literature, we interpret this index as a measure of the effective number of soils. S is chosen because it is simple to interpret. The variation in the data also makes it difficult to use other measures from the existing literature. It is important to highlight that S is an artificial variable with no direct impact on agricultural production. Panel A in Table 2 reports descriptive statistics for the main soil heterogeneity measure. We trim the upper 1% tail of S's distribution to remove some extreme outliers. The average value of S is 1.69 with variance 0.69.

It is important to note that our approach for measuring heterogeneity of growing conditions stands in contrast to that used by Munshi (2004). The author classifies regions as more or less heterogeneous using information on the crops cultivated in these regions. Our approach uses direct geographic information, being more similar to the approach of Durante (2010), Michalopoulos (2012) and Fenske (2014) who correlate similar heterogeneity measures to determinants of economic development.

3.2 Agricultural Data

The outcome used in our empirical exercises is the Direct Planting System adoption rate. This measure is defined as the percentage of farms that use the DPS and it is constructed using data from the 2006 Brazilian Agricultural Census. We restrict the baseline estimates to municipalities with adoption levels above 5% to ensure that we are investigating adoption in municipalities in which the DPS is viable. The results are robust to including municipalities below this threshold. We also exclude municipalities without information of one or more control variables. The results are also robust to including these municipalities in the specification without the full set of controls. The final sample has 1,681 municipalities.

Table 3 reports the distribution of adoption rates in Brazil. In the sample used in the empirical analysis, the average adoption rate is 30%. DPS adoption is above 40% in the states from South Brazil (Rio Grande do Sul, Santa Catarina, and Paraná) and close to 20% in the states from Central Brazil (Goiás, Mato Grosso do Sul, and Mato Grosso). Adoption rates are approximately 10% in the other states. The adoption rates in the full set of municipalities are considerably lower than in the sample used in the empirical analysis.

Our empirical exercises further use the Brazilian Agricultural Census to construct controls used in the regressions. We build the following municipality-level controls: number of farms, average farm revenues, share of farms with tractors, share of farmers with more than 11 years of schooling, share of farmers with access to technical assistance, and share of farmers associated to cooperatives.

Moreover, we use a administrative data on diffusion centers (CAT) to calculate the distance (in kilometers) to the nearest diffusion center and administrative data on the location of bank branches to calculate the number of bank branches in each municipality. We calculate the number of Banco do Brasil and non-Banco do Brasil bank branches because this financial institution is the principal supplier of rural credit in Brazil. Table 2, Panels B-C reports descriptive statistics of these variables.

3.3 Geographic Data

The empirical specifications include several other geographic and socioeconomic variables as controls. Average temporary rainfall and temperature for the period 1970 to 2010 are calculated for each observation using gridded data on rainfall and temperature obtained from the Terrestrial Air Temperature and Precipitation Version 3.01. Rainfall is measured in millimeters of precipitation, while temperature is measured in degrees Celsius. Land gradient is calculated using raster data collected from the 90-meter Shuttle Radar Topography Mission (SRTM) radar. We combine this data with a municipalities map to construct the average land gradient at the municipality-level. The gradient is measured in degrees. Agronomic potential is measured using raster data from the FAO Global Agro-Ecological Zones (GAEZ) dataset. We combine this data with a municipalities map to calculate the average agronomic potential to cultivate at the municipality-level for each of the six main crops cultivated in Brazil (soy, maize, sugarcane, rice, beans, and cotton). Our measure of agronomic potential is based on potential yield for rain-fed cultivation in the high-input regime. The results are robust to suing the intermediate input-level instead. Latitude, longitude, and altitude were obtained through the Ipeadata website. Table 2, Panels D-F reports descriptive statistics of these variables.

4 Empirical Framework

The literature on technology diffusion emphasizes the dynamic nature of this process (Young, 2009; Jackson, 2010; Foster and Rosenzweig, 2010). Technologies typically diffuse in a given group following a S-curve which implies that the level and the growth of adoption rates in a period depend on the adoption rate from the previous period. Hence, an empirical model including geographic heterogeneity as an additional determinant of technology adoption in a given group should allow it to influence both the level and the rate of change of technology adoption.

Let A_{mt} denote the DPS adoption in municipality m and period t and S_m denote the level of soil heterogeneity in municipality m. Let also ε_{mt} be an error term of municipality m and period t. We depict the relationship between DPS adoption and soil heterogeneity using the following empirical model:

$$A_{mt} = \alpha_m + \rho A_{mt-1} + \beta_1 S_m + \beta_2 S_m * t + \varepsilon_{mt} \quad (1)$$

This empirical model explicitly considers the dynamic nature of the diffusion process emphasized in the literature on the S-curve (e.g., Jackson (2010) and Foster and Rosenzweig (2010)) since technology adoption in each period is influenced by technology adoption in the previous periods. Moreover, it enables heterogeneity to influence different features of this process through the parameters β_1 and β_2.

Separately identifying the parameters from equation (1) requires data on technology adoption for several periods. This is a problem in our setting because data on DPS adoption is available only for one period. Nevertheless, it is possible to shown that the relationship between DPS adoption and geographic heterogeneity in one period is informative about the magnitudes of these structural parameters.

Because equation (1) is valid for all periods, we can write the technology adoption as a function of initial adoption and soil heterogeneity:

$$A_{mt} = \sum_{\tau=1}^{t} \rho^{t-\tau}\alpha_m + \rho^t A_{m0} + \left(\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_1 + \sum_{\tau=1}^{t} \rho^{t-\tau}\beta_2\tau\right) S_m + \sum_{\tau=1}^{t} \rho^{t-\tau}\varepsilon_{mt} \qquad (2)$$

Suppose we can approximate the municipality fixed effect α_m using observable geographic characteristics $\mathbf{X}_m$. Moreover, notice that the term $\rho^t A_{m0}$ converges to zero since initial adoption is zero. Then, it is possible to re-write equation (2) as:

$$A_{mt} = \alpha + \beta S_m + \gamma' \mathbf{X}_m + \varepsilon_m, \qquad (3)$$

in which $\alpha + \gamma' \mathbf{X}_m = \sum_{\tau=1}^{t} \rho^{t-\tau}\alpha_m$, $\beta = \left(\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_1 + \sum_{\tau=1}^{t} \rho^{t-\tau}\beta_2\tau\right)$ and $\varepsilon_m = \sum_{\tau=1}^{t} \rho^{t-\tau}\varepsilon_{mt}$. Equation (3) can be estimated using cross-sectional information on DPS adoption and soil heterogeneity. The parameter β is the cumulative effect of soil heterogeneity on DPS adoption. Since technology adoption is persistent ($\rho > 0$), the sign of this parameter is informative about the relative magnitudes of the effects of geographic heterogeneity on the level and the growth of technology adoption across the municipalities in our sample. A negative β indicates either that both effects are negative or that the negative effect dominates the positive one while a positive β indicates either that both effects are positive or that the positive effect dominates the negative one.[8]

[8] It is possible to formalize the discussion from the main text using the following expressions:

$$\beta < 0 \Longleftrightarrow \begin{cases} \beta_1,\ \beta_2 \leq 0, \text{ and } \beta_1 < 0 \text{ or } \beta_2 < 0 \\ \beta_1 < 0,\ \beta_2 > 0, \text{ and } \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_1\right| > \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_2\tau\right| \\ \beta_1 > 0,\ \beta_2 < 0, \text{ and } \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_1\right| < \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_2\tau\right| \end{cases}$$

$$\beta > 0 \Longleftrightarrow \begin{cases} \beta_1,\ \beta_2 \geq 0, \text{ and } \beta_1 > 0 \text{ or } \beta_2 > 0 \\ \beta_1 > 0,\ \beta_2 < 0, \text{ and } \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_1\right| > \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_2\tau\right| \\ \beta_1 < 0,\ \beta_2 > 0, \text{ and } \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_1\right| < \left|\sum_{\tau=1}^{t} \rho^{t-\tau}\beta_2\tau\right| \end{cases}$$

The parameter β will be identified under the assumption that (conditional on the vector of covariates) soil heterogeneity is not correlated with the error term. This assumption will not be satisfied if there are geographic characteristics that are correlated both with soil heterogeneity and DPS adoption. The vector $\mathbf{X}_m$ includes numerous geographic characteristics to mitigate this concern. We include soil types, temperature, rainfall, altitude, land gradient, latitude, longitude, and agronomic potential for the six main crops cultivated in the country in this vector. We also include state fixed effects to control for unobservable characteristics of the states that might correlated with both soil heterogeneity and DPS adoption.

It is important to notice that because soil heterogeneity in neighboring municipalities might be correlated. Therefore, the error term from equation (3) might be spatially correlated. This creates problems for estimating standard errors using methods (e.g.: standard errors robust to heteroscedasticity) that assume the error term is independent across observations. To account for this issue, we cluster the standard errors at the micro-region level. This allows for arbitrary correlation in the errors of municipalities located in the same micro-region. There are 360 micro-regions in our main sample. In robustness tests, we use the Conley (1999)'s method to estimate standard errors robust to the presence of spatial correlation using three different distance cutoffs (50km, 100km, and 150km).

Measurement error is another important issue for estimation of equation (3) because our index of heterogeneity probably measures the relevant heterogeneity with noise. This will bias the estimates of the parameter β. Hence, we perform robustness tests using other indexes of soil heterogeneity to test whether our estimates are robust to the choice of heterogeneity index.

5 Results

5.1 The Effect of Soil Heterogeneity on Technology Adoption

Table 4 reports estimates of equation (3). Column 1 reports the results from the regression of the DPS adoption rate on soil heterogeneity controlling for soil types, altitude, and gradient. The coefficient on soil heterogeneity is negative and significant at the 5% level. Its magnitude suggests that an increase of one standard deviation in soil heterogeneity (0.69) reduces the DPS adoption rate by 1.6 percentage points.

Column 2 includes measures of agronomic potential as additional controls. These controls mitigate the concern that the relationship between soil heterogeneity and DPS adoption is driven by differences in DPS profitability for different crops. The estimates indicate that soil heterogeneity continues to exert a negative and significant effect on DPS adoption. In this specification, an increase in one standard deviation in soil heterogeneity is connected to a 1.5 percentage points reduction in DPS adoption.

Column 3 includes temperature and rainfall in the vector of covariates. These variables help to ensure that differences in climate not captured in the measures of agronomic potential drive the relationship between soil heterogeneity and DPS adoption. The coefficient on soil heterogeneity decreases but continues negative and significant at the 5% level. Its magnitude suggests that an increase in one standard deviation in soil heterogeneity reduces DPS adoption in 1.3 percentage points.

Column 4 further includes latitude and longitude as controls. These coordinates help to mitigate the concern that our results are driven by some geographic characteristic not included in the controls from the previous columns. The coefficient on soil heterogeneity of this specification is quite close to the coefficient estimated in column 2.

Column 5 further includes state fixed effects as controls. The fixed effects control for state-specific unobserved geographic characteristics that might influence both soil heterogeneity and DPS adoption. This is our preferred specification. The coefficient on soil heterogeneity continues significant at the 5% level with magnitude close to the coefficient estimated in the previous column.

We also estimate the standard errors using the method proposed by Conley (1999) to account for spatial correlation in the error term. The method enables estimation of consistent standard errors in the presence of spatial correlation by imposing a structure on the correlation of the error term across spatial units using their relative distance. We calculate standard errors allowing for spatial correlation of the error term using 50, 100 and 150 kilometers cutoffs. Appendix Table A1 reports the results. The results from our preferred specification continue significant at the usual statistical levels regardless the cutoff used.

Table 4 provides support to the hypothesis that geographic heterogeneity influences technology adoption. While we are unable to separate whether the effect of soil heterogeneity comes from a level or a growth effect, our results strongly indicate that the net effect of geographic heterogeneity coming from these two mechanisms is negative. Because the results are robust to the inclusion of numerous geographic controls, this does not appear to be a consequence of correlation between our heterogeneity measure and other geographic factors that influence adoption.

5.2 Mechanisms Linking Soil Heterogeneity and Technology Adoption

Soil heterogeneity is a variance measure that does not influence the costs and benefits from using technologies directly. Therefore, it is essential to discuss the mechanisms that might explain the documented relationship between soil heterogeneity and DPS adoption. Table 5 examines whether this connection is mediated by the following mechanisms: mechanization, farm size, access to public goods, access to credit, access to information.

We begin by investigating whether farm size drives the relationship between soil heterogeneity and DPS adoption. Farms with different sizes might have different costs and benefits from using the DPS. Moreover, differences in the distribution of farm size might influence the diffusion of this technology. Therefore, to the extent to which soil heterogeneity influences the size distribution of agricultural establishments, this mechanism might explain the results presented in the previous subsection. Table 5, column 1 investigates this possibility by including the log of the number of farms and the log of farm revenues as additional controls in the specification from Table 4, column 5. The coefficient on soil heterogeneity declines less than one fifth from -2.16 to -1.84 the inclusion of these controls. This effect is significant at the 5% and implies that an increase in one standard deviation in soil heterogeneity generate a decline in 1.3 percentage points.

We then examine whether mechanization drives this connection. The use of tractors, harvesters and other agricultural machines might facilitate the adaptation of farmers to the DPS, thereby, increasing its use. Therefore, to the extent to which soil heterogeneity influences mechanization, this mechanism might explain the estimates obtained in Table 4. Table 5, column 2 examines whether this is the case by including the log of the number of tractors as an additional control. The coefficient on soil heterogeneity barely changes, suggesting that this mechanism does not drive the relationship between soil heterogeneity and DPS adoption.

We further investigate whether access to public goods, credit, and information drive the relationship between soil heterogeneity and DPS adoption. Heterogeneity might exacerbate collective action issues (e.g., Alesina et al. (1999) and Michalopoulos (2012)) which might reduce the provision of public goods like education or extension services. Heterogeneity might also reduce the supply of credit by increasing the dispersion of borrower types and making the acquisition of information about them more difficult. It might as well discourage the formation of cooperatives and diffusion centers, leading sources of knowledge about the DPS. To the extent that public goods, credit and information affect DPS adoption, this could explain the relationship documented in Table 4.

Table 5, columns 3-5 examines these hypotheses. Column 3 includes controls for schooling and access to extension services. Column 4 adds controls for the presence of Banco do brasil and *non*-Banco do Brasil bank branches. Column 5 includes controls for the presence of cooperatives and diffusion centers. We find no evidence that these mechanisms drive the relationship between soil heterogeneity and DPS adoption. The impact of soil heterogeneity on DPS adoption remains statistically significant and quite close to the impact estimated in the other columns.

The findings presented above are not consistent with the hypothesis that the effect of soil heterogeneity on economic outcomes mediates its impact on DPS use. Other hypothesis is that soil heterogeneity reduces technology adoption by creating barriers to the diffusion of information about modern technologies in heterogeneous areas (Ellison and Fudenberg, 1993; Diamond, 1997; Munshi, 2004). To the extent that farmers learn from their peers how to use modern technologies, this might be a mechanism connecting soil heterogeneity and technology adoption. This mechanism might be of particular importance in the case of technologies that require site-specific adaptation such as the DPS. While we are not able to test this hypothesis directly, we can test it indirectly by examining whether the connection between soil heterogeneity and DPS adoption exists for technologies that do not requite site-specific adaptation.

Table 6 reports estimates of the relationship between soil heterogeneity index and the use of electric power and harvesters. Columns 1 to 3 present the results for the former variable while columns 4 to 6 present the results for the latter. Columns 1 and 4 control for geographic characteristics. Columns 2 and 5 add state fixed effects. Columns 3 and 6 further add socioeconomic controls.

Columns 1-3 indicate that the use of electricity is not influenced by soil heterogeneity. The estimates indicate that soil heterogeneity does not influence the adoption of this technology. The coefficients are not significant at the usual statistical levels in all specifications. Moreover, the standardized effect of soil heterogeneity on electricity use are considerably smaller than the standardized effect of soil heterogeneity on DPS use regardless the specification. The evidence presented in columns 4-6 is compatible with the evidence from columns 1-3. We find no evidence of effects of soil heterogeneity on harvester use. The coefficients are modest and statistically insignificant in the three specifications.

The results reported in Table 6 suggest that geographic heterogeneity does not influence technologies which do not require adaptation to local conditions. This result provides further evidence in favor of the hypotheses in which soil heterogeneity influences technology use through its effect on the costs of learning and, thereby, adapting the new technology to a different context.

5.3 Robustness to Different Measurement Strategies

Table 7 considers the robustness of the results to different measurement strategies. Columns 1 and 2 examine the robustness of the results to different definitions of soil heterogeneity. First, we build a measure of heterogeneity using more refined information from the soil map. While the original measure uses information of the most general soil class available in the map ('order'), this measure uses information of the more detailed class available ('order', 'suborder' and 'group'). Because soil groups might be influenced by agricultural practices, this different measure is not invariant to land use as the original one. However, it uses more variation to construct the soil heterogeneity index than the baseline measure. Second, we build a measure of heterogeneity using information on soils from neighboring municipalities. The measure is the weighted average of the soil heterogeneity from the micro-region the municipality is located. The weights are the areas of each spatial unit. This alternative measure considers that farmers can learn from farmers located in other municipalities as well.

Table 7, column 1 reports the results obtained using the soil heterogeneity classification built using information on soils 'orders', 'sub-orders', and 'groups'. The specification is the same as the one used in Table 4, column 5. The coefficient on soil heterogeneity is negative and statistically significant at the 1% level. It implies that an increase in one standard deviation in this index of soil heterogeneity (about 0.92) reduces DPS adoption in about 1.8 percentage points. This is about 20% more than the results obtained using the original soil heterogeneity classification.

Table 7, column 2 reports the results obtained using the soil heterogeneity of the whole micro-region in which the municipality is located. The coefficient on soil heterogeneity continues negative and becomes significant at the 1% level. Its magnitude increases substantially with an increase in one standard deviation in soil heterogeneity (about 0.89) reducing the rate of DPS adoption in 2.2 percentage points. This is roughly 50% more than the effect obtained using the original measure. Thus, the results from columns indicate that we can interpret the baseline estimates as a lower bound of the impact of soil heterogeneity on DPS adoption.

We also consider the robustness to alternative samples. The baseline specifications exclude municipalities with low adoption levels to ensure we are restricting attention to municipalities in which the technology is viable. However, we examine whether the baseline results are sensitive to sample selection by considering alternative samples including either all Brazilian municipalities with information on the relevant variables or all Brazilian municipalities in which DPS adoption is positive.

Table 7, column 3 the municipalities in which DPS adoption is positive. The sample increases to 4,480 municipalities. The coefficient on soil heterogeneity becomes significant at the 1% level. However, its absolute value is smaller. Because learning from peers is not relevant in municipalities with few adopters, this result is consistent with hypotheses in which soil heterogeneity influences DPS use through its effect on the costs of learning. Table 7, column 4 using all observations. The sample increases to 5,331 municipalities. The coefficient on soil heterogeneity continues negative and significant at the 1% level. Its magnitude is roughly 10% smaller than the coefficient from the previous column.

5.4 Heterogeneous Effects across Adoption Rates

The impact of soil heterogeneity on adoption rates is not necessarily monotonic and might change depending on the adoption rate itself. In particular, to the extent that soil heterogeneity influences adoption by increasing adaptation costs, we expect this effect to be highest for intermediate adoption levels. When adoption is either too high or too low, heterogeneity should be less relevant since the costs of adapting the technology will be either too high or too low regardless soil heterogeneity. The impact of soil heterogeneity on DPS adoption should be U-shaped if adaptation is the actual mechanism.[9]

Testing this prediction requires computing the impact of soil heterogeneity at different quantiles of the distribution of DPS adoption across municipalities (F_A). These estimates cannot be computed using traditional quantile regression developed by Koenker and Bassett Jr (1978) because these methods compute effects over the distribution of the dependent variable conditional on the set of covariates ($F_{(A|X)}$). Recovering unconditional quantile estimates from conditional quantile estimates is not straightforward and several distributional assumptions are required to compute the marginal distributions from the conditional ones (Machado and Mata, 2005).

We address this issue using the estimator developed by Firpo et al. (2009). The authors use a simple estimation method that involves OLS estimation to compute unconditional

[9] If adoption is close to zero, it is difficult to find a previous adopter to adapt DPS from. If adoption is close to 100%, it becomes easier to find a previous adopter.

quantile effects of a regressor on the dependent variable. This estimator is based on the concept of influence function. The influence function $IF(A, \nu, F_A)$ of a distributional statistic $\nu(F_A)$ is the influence of an individual observation on that statistic. The IF can be used to compute the Re-centered Influence Function (RIF) which is $RIF(A, \nu, F_A) = \nu(F_A) + IF(A, \nu, F_A)$ for a general distributional statistic and $RIF(A, q_\tau, F_A) = \nu(F_A) + IF(A, q_\tau, F_A)$ for the τth quantile of the distribution of the dependent variable.

Firpo et al. (2009) prove that the marginal effect of a change in the distribution of covariates on the unconditional quantile of the distribution of the dependent variable is the coefficient from a regression of $RIF(A, q_\tau, F_A)$ on the covariates. Therefore, we can estimate the impact of soil heterogeneity on technology adoption on the τth quantile of the distribution of DPS adoption by regressing $RIF(A, q_\tau, F_A)$ on soil heterogeneity and other covariates.[10]

We use this estimator to test whether the impact of soil heterogeneity on DPS adoption is U-shaped. We use the same specification from Table 4, column 5. Figure 2 reports the results and the 95% confidence intervals. The results are consistent with the theoretical model. The impact is zero or small at either low or high adoption rates and negative at intermediate adoption rates. The coefficients are significant and above the average effect for adoption rates ranging from 20 to 50% in the sample (percentiles 50 to 75). The impact of soil heterogeneity on DPS adoption reaches its maximum at the adoption rate of 40%. An increase of one standard deviation in soil heterogeneity decreases DPS adoption by 6.0 percentage points in this quantile. This impact is four times the average impact estimated in the previous section. These results provide further support for the adaptation costs mechanism.

6 A Possible Theory

In this section, we present a model of adoption that formalizes the intuition that geographic heterogeneity might reduce technology adoption by creating barriers to the diffusion of information about modern technologies and, as a consequence, increasing the costs of adapting the technology to a specific context.

[10]The authors describe three different methods for estimating the unconditional partial effect of a change in an explanatory variable in the distribution of the dependent variable. We use the RIF-OLS method, which is implemented in Stata and is consistent if the distribution of the dependent variable conditional on the explanatory variables is linear in the explanatory variables. Firpo et al. (2009) provides evidence that estimates obtained using the RIF-OLS are quite similar to those obtained using RIF-Logit (which considers this distribution to be logistic) or RIF-NP (which is non-parametric).

Suppose there is a continuum of farmers with mass normalized to 1. Each farmer i has a soil $\theta_i \in R^N$. Soils are distributed according to a single-peaked twice differentiable joint distribution $G(\theta;\sigma^2)$ with associated density g. The variance of this distribution, σ^2, is strictly positive and determines how much soils differ: soil heterogeneity is captured by a higher σ^2. We assume that the probability that $\theta_i = \theta_j$ is zero for all $i \neq j$.[11]

There are two technologies available for crop production: a traditional and a new technology. The (discounted) profits under the new technology, $\overline{\pi}$, are larger than under the traditional one, $\underline{\pi}$. The difference in profits can be expressed as $\Delta\pi = \overline{\pi} - \underline{\pi} > 0$. Farmers decide which technology to use. The adoption decision is described by a_i:

$$a_i = \begin{cases} 1, & \text{if farmer adopts the technology} \\ 0, & \text{otherwise} \end{cases}$$

Farmers must adapt the new technology (a micro-innovation) to adopt it in a different type of soil. This feature creates an adaptation cost that farmers must incur before adopting the new technology. This cost is assumed to be a decreasing function of the number of adopters with similar soils in the farmer's neighborhood. This assumption captures the idea that farmers can learn from their peers and that learning from similar peers is easier than learning from different ones (Ellison and Fudenberg, 1993; Munshi, 2004).

To formalize the adaptation cost, we define the distance between farmers soils as $d(\theta_i, \theta_j)$. A farmer i can learn from peers located in the following neighborhood:

$$N(\theta_i) = \{\theta_j : d(\theta_i, \theta_j) < R\} \tag{4}$$

This set's mass is $\int_{N(\theta_i)} g(\theta) d(\theta)$. The set of adopters in this neighborhood is:

$$N_A(\theta_i) = \{\theta_j : d(\theta_i, \theta_j) < R \text{ and } a_j = 1\} \tag{5}$$

This set has mass $M(N_A(\theta_i)) = \int_{N_A(\theta_i)} g(\theta) d(\theta)$. We can thus define the adaptation costs for non-adopters as $c(M(N_A))$, a decreasing function of this mass. This cost is equal to zero for adopters. It should be noted that adopters will never switch from the new technology to the traditional one because the adoption cost is paid once and $\Delta\pi > 0$. This model's feature implies that the set of adopters never decreases, distinguishing our adop-

[11]This hypothesis is done for simplicity but its interpretation is straightforward: two types of soil are never exactly equal even when their differences are irrelevant for the farmer's choices.

tion environment from other environments in which adoption costs are paid in all periods and changes in these costs induce switching behavior.[12]

We assume there is an exogenous initial distribution of adopters $N_A^0(\theta_i)$. The new technology's profits, adaptation costs and the initial distribution of adopters determine the farmers choices. Timing is straightforward. The initial distribution of adoption determines adaptation costs for non-adopters. Farmers observe this cost and adopt the new technology when $\Delta\pi \geq c(M(N_A^0)$. This decision creates a final distribution of adopters $N_A^1(\theta_i)$.

We can therefore describe adoption choices using the following rule:

$$a_i = 1 \iff \Delta\pi \geq c(M(N_A^0)) \tag{6}$$

Equation 6 enables us to characterize the model's equilibrium and its comparatives statistics. We introduce additional assumptions that will facilitate the equilibrium characterization. First, we introduce an assumption on the adoption distribution. Define $\overline{M} = c^{-1}(\Delta\pi)$ as the lowest mass of adopters that enables diffusion and define $\overline{M}^U = M(N_A^0)$ as the initial mass of adopters under the uniform distribution in the same neighborhood. We assume that $\overline{M} > \overline{M}^U$, which implies that the initial adoption rate cannot trigger diffusion when the distribution is flat. Therefore, the diffusion process cannot be reduced to a contagion model because it is not enough to have adopters in the neighborhood.[13] Second, we introduce restrictions on the cost function. We assume that $c(0) > \Delta\pi$ and that $c(m) < \Delta\pi$ for some $m < 1$. The former condition ensures we are modeling technology diffusion, whereas the latter ensures the technology is viable.

Let an allocation be a vector of adoption choices $\{a_i\}_i$. The model's equilibrium is the set of allocations $\{a_i^*\}_i$ for which equation 6 is valid.

Define A as the final share of adopters. We expect this share to depend on the soil's variance (σ^2) because more dispersion reduces the likelihood that there will be enough adopters in the neighborhood to make adoption profitable. The following proposition establishes this result:

Proposition 1. *An increase in σ^2 reduces the aggregate adoption level A for some $A \in (0,1)$.*

[12]See Suri (2011) for an example.

[13]This assumption is not essential for the main results and is made for simplicity. This assumption is trivially satisfied if the support of types is unbounded.

Proof. Since the distribution $G(.)$ is single-peaked and $\overline{M} > \overline{M}^U$, the set of farmers such that adoption is profitable decreases when the variance (σ^2) increases. Therefore, adoption will be lower. ■

The model also implies that the shape of the relationship between soil dispersion and adoption will differ across adoption quantiles. On the one hand, when adoption is too low, there are few peers to learn from, and diffusion is slow regardless of soil heterogeneity. On the other hand, when adoption levels are too high, adoption will be so widespread that farmers will be able to adapt no matter how different their soils are, and diffusion will be fast regardless of soil heterogeneity. It follows that the impact of soil heterogeneity on adoption will be small in these extreme cases. Nevertheless, at intermediate levels, an increase in soil heterogeneity reduces adoption to a greater extent because it reduces the chances a farmer will find a peer from whom to adapt the technology. The following proposition establishes this result:

Proposition 2. *Assume that $A(\sigma^2)$ is continuously differentiable and has one local minimum labeled A^c. The effect of σ^2 on aggregate adoption A is therefore U-shaped. It reaches a minimum at $A^C < 1$ and it is decreasing for $A < A^C$ and decreasing for $A > A^C$.*

Proof. Consider an initial situation in which $a_i = 0$ for all i. Then $c(0) > \Delta\pi$ implies that it is not profitable for any agent to adopt the new technology. Adaptation cannot take place in the absence of adopters in the neighborhood and $A(\sigma^2) = 0$ for all σ^2. The reasoning is similar for a profile $\{a_i^*\}_i$ such that $M(N_A(\theta_i)) > m$ for all i, in which m is the threshold such that $c(m) < \Delta\pi$. Then it is profitable for all agents to adopt the new technology and $A(\sigma^2) = 1$ for all σ^2. Therefore, A^C is smaller than 1 and the derivative $\partial A^t/\partial\sigma^2$ is increasing for $A^t \in [0, A^c)$ and decreasing for $A^t \in (A^c, 1]$. ■

As noted, the non-monotonicity of the impact of heterogeneity on adoption implies that a higher adoption rate can be associated either with a higher impact or a lower one. This observation does not rely on any assumption on the cross derivative of adaptation costs and alternative adoption channels. The interval of adoption levels where soil heterogeneity and alternative channels are substitutes - i.e., the presence of an alternative adoption channel would lead to a lower impact of heterogeneity on adoption - would be larger (smaller) when this derivative is positive (negative). However, there is no qualitative change in the results.

This framework may be immediately extended to an arbitrary number of periods: the initial distribution generates adoption decisions that give rise to a new distribution of adoption, based on which new adoption decisions will be made, and so on. Since the mass of adopters is non-decreasing and bounded above by one, it must converge over time to some long-term distribution (in fact, this holds for the sequence of individual adoption decisions). The propositions above hold without change.

It is worth highlighting a more general interpretation of the model above. Adaptation costs may depend on previous adoption or, more generally, on the existing stock of knowledge about the new technology. Previous adoption adds to this stock, but it is not the only possibility: agronomic research may develop an adaptation to a specific soil even in the absence of any adopters. Again, the results above go essentially unchanged as long as one interprets "mass of adopters" as "mass of types of soil for which the new technology has been adapted for".[14]

The model discussed above formalizes the intuition that geographic heterogeneity might reduce technology adoption by creating barriers to the diffusion of information about modern technologies and, as a consequence, increasing the costs of adapting the technology to a specific context. Its comparative statics are consistent with our empirical findings. We estimate a negative effect of soil heterogeneity on technology adoption that is not generated by correlation between soil heterogeneity and other determinants of adoption and that is not present for technologies in which site-specific adaptation is not required. We also find this effect to be stronger at intermediate adoption rates.

7 Conclusion

Low adoption of modern technologies is the object of extensive research in economics because of its impact on economic development. This paper provides evidence indicating that low adoption of modern technologies in agriculture is deterred by geographic heterogeneity using data from the adoption of the Direct Planting System (DPS) in Brazilian agriculture.

Conditional on geographic characteristics and socio-economic characteristics, we estimate

[14]Notice that this interpretation implies that all farmers should react in the same way to the availability of agronomic information. This is the case, for example, if there are no relevant barrier from agronomic knowledge to farming practices, and a newly-developed adaptation to a given type of soil is immediately used by the farmer that has that type of soil. If some farmers have more access to agronomic research then others, then the impact of soil heterogeneity on adoption may exist even for adoption close to zero, as some farmers may react to new adaptations even before they are used for adoption by other farmers. As long as this asymmetric impact is not too large, the results in this section hold unchanged.

a negative relationship between an index of soil heterogeneity and DPS adoption. We also estimate that this effect is higher at intermediate adoption levels. The results also indicate no relationship between soil heterogeneity and technologies in which adaptation costs are not relevant. These findings are consistent with a diffusion mechanism that relies on adapting DPS from previous adopters to site-specific conditions. We propose a model in which the need for such adaptations before adoption implies that adaptation costs will be higher in more heterogeneous regions than in more homogeneous ones. Therefore, the adoption rates will be smaller in the former regions than in the latter in all periods.

These findings illustrate that the process of learning can be deterred by dissimilarities across adopters and supports the theoretical mechanism highlighted by Ellison and Fudenberg (1993) within a context where large-scale agriculture is prevalent and for a production technique with important private and public benefits. The results have important implications for policies aimed at promoting technology adoption. Provisional and focused training can induce substantial adoption in homogeneous areas because social learning will induce technological diffusion in these areas. Nevertheless, lasting and widespread investments in training will be needed to induce adoption in more heterogeneous areas because adaptation will be more difficult in these areas.

References

ALESINA, A., R. BAQIR, AND W. EASTERLY (1999): "Public goods and ethnic divisions," *The Quarterly Journal of Economics*, 114, 1243–1284.

ANGRIST, J. D. AND J.-S. PISCHKE (2008): *Mostly Harmless Econometrics: An empiricist's companion*, Princeton University Press.

BAKER, C., K. SAXTON, W. RITCHIE, C. W., D. REICOSKY, AND M. E. A. RIBEIRO (2007): *No-tillage Seeding in Conservation Agriculture*, FAO, second edition ed.

BANDIERA AND RASUL (2006): "Social Networks and Technology Adoption in Northern Mozambique," *Economic Journal*, 116.514, 869–902.

BLOUIN, A. (2014): "Culture, Isolation and the Diffusion of Knowledge: Evidence from the Bantu Expansion," *Mimeo*.

CASELLI, F. (2005): "Accounting for cross-country income differences," *Handbook of economic growth*, 1, 679–741.

CONLEY AND UDRY (2010): "Learning about a new technology: pineapple in Ghana," *American Economic Review*, 100.1, 35–69.

CONLEY, T. G. (1999): "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics*, 92, 1–45.

DERPSCH (1999): "Frontier in conservation tillage and advances in conservation practice," Working Paper.

DERPSCH, FRIEDRICH, KASSAM, AND HONGWEN (2010): "Current status of adoption of no-till farming in the world and some of its main benefits," *International Journal of Agricultural and Biological Engineering*, 3, n. 1.

DIAMOND, J. (1997): *Guns, Germs, and Steel: The Fates of Human Societies*, W. W. Norton and Company.

DUFLO, E., M. KREMER, AND J. ROBINSON (2008): "How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya," *American Economic Review*, 98, 482–88.

——— (2011): "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya," *American Economic Review*, 101, 2350–90.

DURANTE (2010): "Risk, cooperation and the economic origins of social trust: an empirical investigation," Working Paper.

ELLISON, G. AND D. FUDENBERG (1993): "Rules of Thumb for Social Learning," *Journal of Political Economy*, 101, 612–43.

EMBRAPA (2011): "O Novo Mapa de Solos do Brasil," *MAPA*.

FENSKE, J. (2014): "Ecology, Trade, and States in Pre-Colonial Africa," *Journal of the European Economic Association*, 12, 612–640.

FIRPO, FORTIN, AND LEMIEUX (2009): "Unconditional quantile regressions," *Econometrica*.

FOSTER AND ROSENZWEIG (1995): "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture," *The Journal of Political Economy*, 1176–1209.

——— (2010): "Microeconomics of technology adoption," Working Paper.

GOLLIN, D., D. LAGAKOS, AND M. E. WAUGH (2014): "The Agricultural Productivity Gap," *The Quarterly Journal of Economics*, 129, 939–993.

HORNBECK, R. (2012): "The Enduring Impact of the American Dust Bowl: Short-and Long-Run Adjustments to Environmental Catastrophe," *American Economic Review*, 102, 1477–1507.

INOUE (2003): "Sistema de preparo do solo e o plantio direto no Brasil," *Agropecuaria Tecnica*.

JACKSON, M. O. (2010): *Social and Economic Networks*, Princeton University Press.

JEPSON, W. (2006): "Producing a modern agricultural frontier: firms and cooperatives in Eastern Mato Grosso, Brazil," *Economic Geography*, 82, 289–316.

KARLAN, D., R. OSEI, I. OSEI-AKOTO, AND C. UDRY (2014): "Agricultural Decisions after Relaxing Credit and Risk Constraints," *The Quarterly Journal of Economics*, 129, 597–652.

KOENKER, R. AND G. BASSETT JR (1978): "Regression Quantiles," *Econometrica*, 46, 33–50.

LANDERS (2005): "Plantio direto. Histórico, características e benefícios do plantio direto," Working Paper.

MACHADO AND MATA (2005): "Counterfactual decomposition of changes in wage distributions using quantile regression," *Journal of Applied Econometrics*, 20.4, 445–465.

METAY, A., R. OLIVER, E. SCOPEL, J.-M. DOUZET, J. A. A. MOREIRA, F. MARAUX, B. J. FEIGL, AND C. FELLER (2007): "N2O and CH4 emissions from soils under conventional and no-till management practices in Goiânia (Cerrados, Brazil)," *Geoderma*, 141, 78–88.

MICHALOPOULOS (2012): "The Origins of Ethnolinguistic Diversity," *American Economic Review*, 102.4, 1508–1539.

MUNSHI (2004): "Social learning in a heterogeneous population: technology diffusion in the indian green revolution," *Journal of Development Economics*, 73.1, 185–213.

RINGLER, C., N. CENACCHI, J. KOO, R. ROBERTSON, M. FISHER, C. COX, N. PEREZ, K. GARRETT, AND M. ROSENGRAN (2013): "The Promise of Innovative Farming Practices Global Food Policy Report," in *Global Food Policy Report*, ed. by IFPRI, International Food Policy Research Institute.

SORRENSON AND PORTILLO (1997): "Paraguay Soil conservation Project. Economic of no-tillage and crop rotations policy and investment implications," Working Paper.

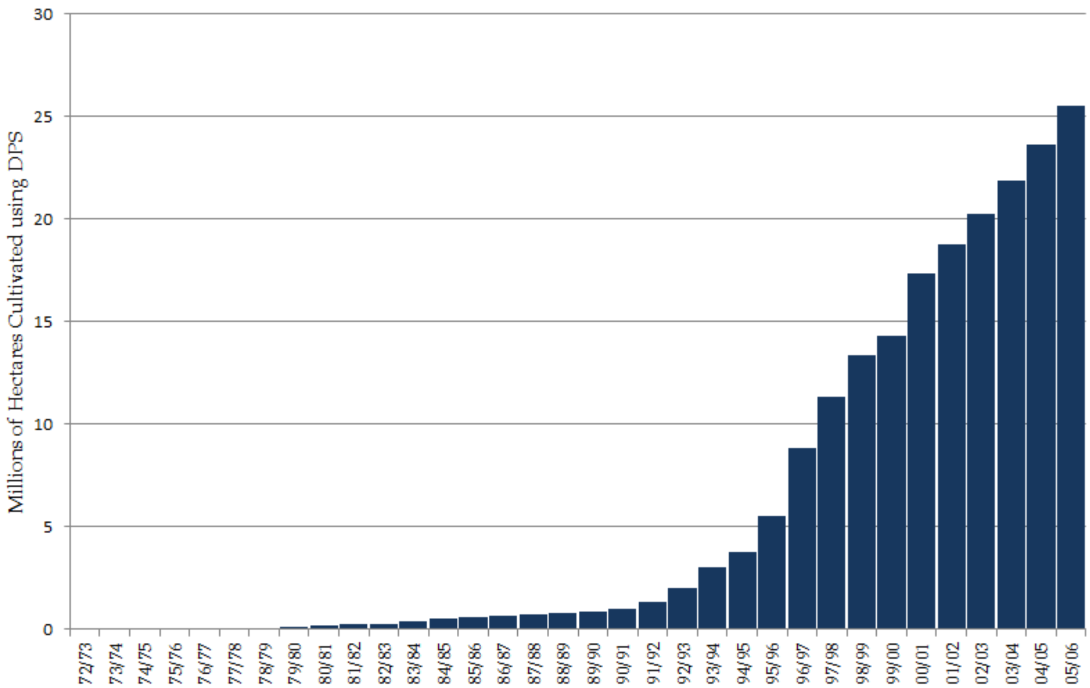
SURI, T. (2011): "Selection and comparative advantage in technology adoption," *Econometrica*, 79, 159–209.

TRIGO, E., E. CAP, V. MALACH, AND F. VILLAREAL (2009): "The Case of Zero-Tillage Technology in Argentina," *IFPRI Discussion Papers 915*.

WEST, T. O. AND W. M. POST (2002): "Soil organic carbon sequestration rates by tillage and crop rotation," *Soil Science Society of America Journal*, 66, 1930–1946.

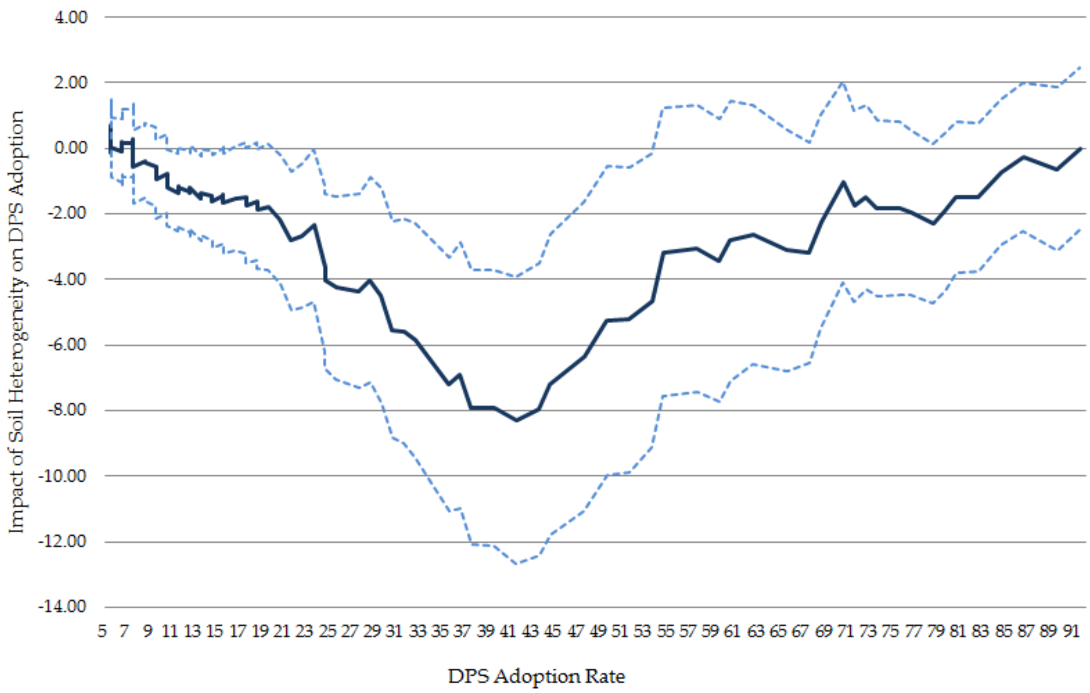
YOUNG (2009): "Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning," *The American Economic Review*, 99.5, 1899–1924.

Figure 1: Evolution in DPS Adoption Over Time



Notes: The figure reports the number of hectares cultivated using the Direct Planting System (DPS) from its introduction in Brazil to 2005/2006.

Figure 2: Quantile Effects of Soil Heterogeneity on DPS Adoption



Notes: The figure reports the effect of soil heterogeneity on DPS adoption for different adoption levels. The solid line plots the coefficients and the dashed lines their 95% confidence intervals. The estimates are constructed using the estimator proposed by Firpo et al. (2009) (described in detail in the main text).

Table 1: Costs and Benefits from DPS Adoption

Panel A: Public	Costs	Benefits
Environmental		Lower carbon emission Increase in carbon and nitrogen stocks Less contamination
Panel B: Private	Costs	Benefits
Economic	Higher herbicide use	Lower fuel consumption Lower fertilizer use Increase in machinery durability Time reduction in soil preparation Time reduction between harvest and sowing
Environmental	Lower germinative capacity of plants	Lower evaporation Lower soil temperature Deeper roots Reduction in soil preparation Smaller water loss Increase in organic matter Lower water and soil shedding Lower thermal and hydraulic amplitude Erosion Reduction Soil protection from solar radiation

Table 2: Descriptive Statistics

	Obs.	Mean	S.D.	Min.	Max.
Panel A: Geographic Heterogeneity					
Soil Heterogeneity	1681	1.69	0.69	1.00	7.89
Panel B: Agriculture					
log(Number of Farms)	1681	6.58	0.87	2.56	9.20
log(Average Revenues)	1681	2.97	1.47	-1.60	8.38
Tractors (% of farms)	1681	20.36	17.93	0.00	94.38
Technical Assistance (% of farms)	1681	14.83	15.06	0.00	87.12
11+ years of schooling (% of farmers)	1681	13.30	10.04	0.79	69.57
Cooperatives	1681	48.64	22.34	0.00	96.08
Diffusion Centers (distance in 100km)	1681	3.45	3.06	0.00	19.78
Panel C: Banks					
Banco do Brasil (# of branches)	1681	0.74	4.48	0.00	153.00
non-Banco do Brasil (# of branches)	1681	2.22	24.51	0.00	961.00
Panel D: Geography					
Gradient (degrees)	1681	5.65	3.32	0.71	15.97
Altitude (meters)	1681	468.85	276.45	0.68	1263.33
Latitude	1681	-19.71	8.69	-31.77	4.48
Longitude	1681	-48.91	5.79	-72.65	-34.91
Panel E: Climate					
Rainfall - Summer	1681	175.51	55.26	36.51	471.10
Rainfall - Autumn	1681	119.05	57.26	14.49	456.12
Rainfall - Winter	1681	84.30	53.27	3.31	222.74
Rainfall - Spring	1681	140.87	54.25	6.86	383.66
Temperature - Summer	1681	23.51	1.90	18.10	28.42
Temperature - Autumn	1681	19.56	3.99	12.68	27.69
Temperature - Winter	1681	18.93	4.60	11.14	28.69
Temperature - Spring	1681	22.60	2.92	16.17	29.19
Panel F: Agronomic Potential					
Potential Yield - Rice	1681	8.12	2.08	0.00	10.27
Potential Yield - Beans	1681	3.71	0.33	0.00	4.42
Potential Yield - Maize	1681	8.94	2.29	0.00	14.14
Potential Yield - Soybeans	1681	4.26	0.49	0.00	5.11
Potential Yield - Sugarcane	1681	8.85	3.09	0.00	13.05

Notes: The sample excludes municipalities with less than 5% of the farmers adopting the Direct Planting System (DPS). It also excludes municipalities with soil heterogeneity index in the upper 1% tail of the heterogeneity distribution and without information for one or more of the variables.

Table 3: Adoption Rate per State

	Adoption > 5%		All	
	Mean	Obs.	Mean	Obs.
Rondônia	7.23%	14	3.60%	52
Acre	15.09%	11	8.28%	22
Amazonas	11.48%	7	1.98%	62
Roraima	8.90%	4	3.21%	15
Pará	13.80%	40	4.91%	141
Amapá	14.90%	3	3.09%	16
Tocantins	11.96%	25	2.83%	139
Maranhão	13.37%	74	5.49%	216
Piauí	14.16%	66	5.05%	221
Ceará	11.84%	49	4.03%	184
Rio Grande do Norte	11.87%	8	1.01%	158
Paraíba	11.90%	34	2.55%	202
Pernambuco	11.93%	32	2.96%	169
Alagoas	12.10%	18	2.98%	97
Sergipe	6.56%	2	0.75%	67
Bahia	9.87%	71	2.52%	409
Minas Gerais	12.81%	191	3.95%	829
Espírito Santo	6.42%	3	1.32%	75
Rio de Janeiro	6.04%	2	1.04%	86
São Paulo	17.39%	82	3.17%	608
Paraná	41.67%	301	32.38%	392
Santa Catarina	42.57%	206	31.61%	281
Rio Grande do Sul	53.25%	331	39.69%	449
Mato Grosso do Sul	19.99%	28	8.06%	76
Mato Grosso	22.49%	34	6.88%	126
Goiás	17.58%	44	4.00%	238
DF	13.48%	1	13.48%	1
Total	30.07%	1,681	10.22%	5,331

Notes: The statistics are computed excluding municipalities in the upper 1% tail of soil heterogeneity and without information for one or more of the control variables.

Table 4: Soil Heterogeneity and Technology Adoption

	Dependent Variable: DPS Adoption				
	(1)	(2)	(3)	(4)	(5)
Soil Heterogeneity	-2.388**	-2.179**	-1.938**	-2.187**	-2.166**
	(0.938)	(0.896)	(0.863)	(0.888)	(0.856)
Soil Types	Yes	Yes	Yes	Yes	Yes
Gradient and Altitude	Yes	Yes	Yes	Yes	Yes
Agronomic Potential	No	Yes	Yes	Yes	Yes
Temperature and Rainfall	No	No	Yes	Yes	Yes
Latitude and Longitude	No	No	No	Yes	Yes
State FE	No	No	No	No	Yes
R2	0.403	0.515	0.605	0.606	0.640
N	1681	1681	1681	1681	1681

Notes: The table reports the results from estimating equation (3). "Soil types" refer to share of the municipality covered by 35 different soil orders. "Gradient and Altitude" refer to the land gradient and the altitude of the municipality's main district. "Temperature and Rainfall" refer to the municipality's temperature and rainfall in each season. "Latitude and Longitude" refer to the latitude and longitude of the municipality's centroid. All variable definitions are presented in the main text. Standard errors clustered at the micro-region level are reported in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Table 5: Mechanisms

	Dependent Variable: DPS Adoption				
	(1)	(2)	(3)	(4)	(5)
Soil Heterogeneity	-1.837**	-1.963**	-1.935**	-1.908**	-1.850**
	(0.877)	(0.842)	(0.837)	(0.840)	(0.840)
Geographic Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Farm size	Yes	Yes	Yes	Yes	Yes
Mechanization	No	Yes	Yes	Yes	Yes
Bank Branches	No	No	Yes	Yes	Yes
Training	No	No	No	Yes	Yes
Information	No	No	No	No	Yes
R2	0.643	0.673	0.674	0.673	0.686
N	1681	1681	1681	1681	1681

Notes: The table reports the results from estimating equation (3). "Geographic Controls" refers to the controls included in the specifications from Table 4. "Farm size" refers to the log of the number of farms and the log of average farm revenues. "Mechanization" refers to the share of farms which uses tractors. "Bank Branches" refer to the number of Banco do Brasil and *non*-Banco do Brasil bank branches. "Training" refers to the share of farmers with eleven or more years of schooling and the share of farms with access to technical assistance. "Information" refers to the share of farmers associated to cooperatives and the distance to the nearest diffusion center. All variable definitions are presented in the main text. Standard errors clustered at the micro-region level are reported in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Table 6: Soil Heterogeneity and Other Technologies

	Electricity Use			Harvester Use		
	(1)	(2)	(3)	(4)	(5)	(6)
Soil Heterogeneity	-0.941	-0.607	-0.140	-0.378	-0.212	-0.109
	(0.740)	(0.605)	(0.607)	(0.263)	(0.216)	(0.162)
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
Socioeconomic Controls	No	No	Yes	No	No	Yes
R2	0.501	0.616	0.635	0.388	0.456	0.671
N	1681	1681	1681	1681	1681	1681

Notes: The table reports the results from estimating equation (3) using different measures of technology use as dependent variables. Columns 1-3 use the share of farmers who use electricity as the dependent variable while columns 4-6 use the share of farmers who use harvesters as the dependent variable. "Geographic Controls" refers to the controls included in the specifications from Table 4. "Economic Controls" to the additional controls included in the specifications from Table 5. Standard errors clustered at the micro-region level are reported in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table 7: Robustness

	Dependent Variable: DPS Adoption			
	Heterogeneity		Selection	
	Soil Groups	Micro-region	Adoption > 0	All
	(1)	(2)	(3)	(4)
Soil Heterogeneity	-1.987***	-2.446***	-1.043***	-0.918***
	(0.565)	(0.912)	(0.382)	(0.342)
Geographic Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R2	0.641	0.643	0.659	0.655
N	1681	1681	4480	5331

Notes: The table reports the results from estimating equation (3). Columns 1 and 2 report the results of regressing DPS adoption on different measures of soil heterogeneity. Column 1 uses an index of soil heterogeneity constructed with information of soil 'orders', 'sub-orders', and 'groups'. Column 2 uses an index of soil heterogeneity constructed with information on all municipalities in the micro-region. Columns 3 and 4 report the result of regressing DPS adoption on soil heterogeneity using differet sample selection procedures. Column 3 uses municipalities with positive DPS adoption. Column 4 uses all municipalities. "Geographic Controls" refers to the controls included in the specifications from Table 4. All variable definitions are presented in the main text. Standard errors clustered at the micro-region level are reported in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table A1: Soil Heterogeneity and Technology Adoption

	Dependent Variable: DPS Adoption				
	(1)	(2)	(3)	(4)	(5)
Soil Heterogeneity	-2.388	-2.179	-1.938	-2.187	-2.166
	(0.922)***	(0.846)***	(0.788)**	(0.803)**	(0.776)**
	[0.863]***	[0.877]**	[0.883]**	[0.905]**	[0.870]**
	{1.016}**	{1.047}**	{1.036}*	{1.067}**	{1.057}**
Soil Types	Yes	Yes	Yes	Yes	Yes
Gradient and Altitude	Yes	Yes	Yes	Yes	Yes
Agronomic Potential	No	Yes	Yes	Yes	Yes
Temperature and Rainfall	No	No	Yes	Yes	Yes
Latitude and Longitude	No	No	No	Yes	Yes
State FE	No	No	No	No	Yes
R2	0.740	0.788	0.827	0.828	0.843
N	1681	1681	1681	1681	1681

Notes: The table reports the results from estimating equation (3). The specifications are the same from Table 4. Standard errors allowing for spatial correlation in the error term computed using Conley (1999) are reported in parentheses (50km cutoff), brackets (100km cutoff), and braces (150km cutoff). *** p<0.01; ** p<0.05; * p<0.10