CLIMATE POLICY INITIATIVE
NÚCLEO DE AVALIAÇÃO
DE POLÍTICAS CLIMÁTICAS
PUC-Rio

High Productivity Agricultural Techniques in Brazil: Adoption Barriers and Potential Solutions

Climate Policy Initiative

Juliano Assunção
Arthur Bragança
Pedro Hemsley

October 2013

Technical Paper

Descriptors

Sector	Land Use, Agriculture
Region	Brazil
Keywords	agriculture, no-till farming, Direct Planting System, social learning, soil dissimilarity
Contact	Juliano Assunção juliano@cpirio.org

Acknowledgements

Ana Ribeiro and Fabio Magrani provided excellent research assistance. We acknowledge Clarissa Gandour, Romero Rocha, Rodrigo Soares, Dimitri Szerman and Alban Thomas and for their helpful comments. We also thank EMBRAPA and IBGE for methodological support. Lastly, we are grateful to Manoel Henrique Pereira, head of the Brazilian Federation of Direct Planting, for kindly welcoming our team and answering our questions.

About CPI

Climate Policy Initiative is a team of analysts and advisors that works to improve the most important energy and land use policies around the world, with a particular focus on finance. An independent organization supported in part by a grant from the Open Society Foundations, CPI works in places that provide the most potential for policy impact including Brazil, China, Europe, India, Indonesia, and the United States.

Our work helps nations grow while addressing increasingly scarce resources and climate risk. This is a complex challenge in which policy plays a crucial role.

Geographic Heterogeneity, Social Learning and Technology Adoption: Evidence From The Direct Planting System in Brazil*

Juliano Assunção† Arthur Bragança‡ Pedro Hemsley§

October 2013

Abstract

We study the diffusion of a new agricultural technology in Brazil: the Direct Planting System. This system achieves higher revenue and lower cost than traditional farming; however, the adoption rate in 2006, more than thirty years after the original innovation, was very low (around 10%). While the usual deterrents to adoption (such as upfront costs or increased risk) are absent, the system needs to be adapted to specific site conditions, configuring a learning barrier that makes adoption costly when geographic heterogeneity is large. We develop a model to show that the impact of heterogeneity on adoption should be non-monotonic if learning is the diffusion channel: zero if adoption is either too low or too high, and negative for intermediate levels. This can be used as an indirect way to test for the presence of social learning. Using data on soil characteristics and adoption rates, we apply an unconditional quantile approach to show that the model's predictions are consistent with the empirical evidence.

Keywords: Social Learning, Technology Diffusion, Agricultural Technology.

JEL classification: D83, O33, Q33.

*We are grateful to Clarissa Gandour, Romero Rocha, Rodrigo Soares, Dimitri Szerman and Alban Thomas for valuable comments and suggestions. We also thank seminar participants at CPI San Francisco, at the European Meeting of the Econometric Society (ESEM), at the North-American Summer Meeting of the Econometric Society (NASM) and at USP. We are grateful to Ana Ribeiro and Fabio Magrani for excellent research assistance. All mistakes are our own.

†PUC-Rio and Climate Policy Initiative. Department of Economics, Rua Marquês de São Vicente, 225, Gávea, Rio de Janeiro, RJ, 22451-900, Brasil. Email: juliano@econ.puc-rio.br.

‡PUC-Rio and Climate Policy Initiative. Department of Economics, Rua Marquês de São Vicente, 225, Gávea, Rio de Janeiro, RJ, 22451-900, Brasil. Email: arthur.braganca@econ.puc-rio.br.

§Climate Policy Initiative. Estrada da Gávea, 50, 4º andar, Gávea, Rio de Janeiro, RJ, 22451-263, Brasil. Email: pedro.hemsley@cpirio.org

1 Introduction

Geographic heterogeneity constrains the spread of food production since the earliest accounts of agriculture. In a classic book, Jared Diamond shows that "even among all those areas where food production did spread in the prehistoric era, the rates and dates of spread varied considerably. At the one extreme was its rapid spread along east-west axes: from Southwest Asia both west to Europe and Egypt and east to the Indus Valley; (...) and from the Philippines east to Polynesia. (...) At the opposite extreme was its slow spread along north-south axes. (...) Localities distributed east and west of each other at the same latitude share exactly the same day length and its seasonal variations. To a lesser degree, they also tend to share similar diseases, regimes of temperature and rainfall, and habitats or biomes."[1] This paper shows evidence that geographic heterogeneity still plays an important role in the dissemination of agricultural technology, working through a specific mechanism of social learning.

In the 1970s, a new technology known as Direct Planting System (DPS), based on previous experiences with no-till farming, was developed in Southern Brazil. No-tillage refers to any way of preparing the soil for planting in which tillage is limited or even absent and crop residue is left on the surface. However, as opposed to traditional farming, it is not a general method: it needs to be adapted to the specific geographic conditions of each site where it is to be used (Derpsch (1999)). The DPS was initially developed as a version of no-tillage specific to the conditions of Southern Brazil - in particular, zones prone to rain erosion. It evolved into a full farming method with higher revenues and lower costs than the traditional (tillage-based) practices. For example, Inoue (2003) reports a reduction in costs of 9% and an increase in productivity around 17% in the case of soybean cultivation. The limited use of tillage also prevents soil degradation and the loss of nutrients due to plowing, which increases the long-run productivity of land. Moreover, greenhouse gas emissions are significantly lowered: carbon is one of the nutrients lost when soil is revolved (Derpsch and Moriy (1998); Alvarenga et al. (2006); Camargo et al. (2011)).

There are two key aspects of DPS. First, adoption configures an actual technology innovation, different from a change in input use. Indeed, it only requires learning about the new way of combining inputs for production and minor modifications in machinery. Second, other factors that often constrain technology adoption are not relevant in this case. Credit constraints play no role, as there are no significant upfront costs to switch to the new method; in fact, costs are usually lower, and revenues are higher, even in the first year of operation. The performance of a recent public policy illustrates this point. In 2010, the Brazilian federal government launched the Low-Carbon Agriculture program (*Programa ABC - Agricultura de Baixo Carbono*), which aims at reducing carbon emissions from the agricultural sector through subsidized rural credit. The low uptake of the program, after three years, suggests that credit was not the main barrier to the adoption of emission-reducing methods.

DPS also decreases risk exposure as it allows farmers to use the same land to produce

[1] See Diamond (1997), pages 178 and 183.

additional crops. There is no additional infrastructure needed to implement the DPS. Detailed accounts of these features include Derpsch et al. (2010), UFRPE (2009), Inoue (2003), Sorrenson and Portillo (1997) and Landers (2005). Moreover, Brazilian agriculture is mostly a competitive business; hence, generalized underuse cannot be explained by forgone opportunities due to lack of competition. Adoption rates are similar among small and large farmers, suggesting that advantages usually associated with large-scale operations are not relevant.

It is well-established that the main barrier to the diffusion of DPS is lack of knowledge. Specifically, the system must be adapted to different conditions. Sorrenson and Portillo (1997) state that the adoption of no-tillage techniques "necessitates the learning and mastering of an array of new crop management skills". According to Derpsch (1999), "site specific knowledge of the no-tillage system has most likely been the main limitation to the spread of the system in (...) Latin America.".

The DPS spread rapidly as of the 1990s and reached over 20 million hectares in 2006; however, this amounted to only 9.8% of Brazilian farmers[2]. The features of the DPS provide an empirical context to investigate a pure technology diffusion process, in which low adoption can be interpreted as evidence of relevant learning costs. The literature depicts two ways of testing social learning. First, there are studies based on direct inference on social networks, relying on comprehensive datasets that are often difficult to gather (Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010). Second, Young (2009) provides indirect inference on social learning. The author derives empirical implications of social learning that do not require data on the social networks. We follow this second route and explore geographical heterogeneity as a potentially important hindrance for social learning in the case of technology adoption in agriculture.

We present a simple theoretical model in which social learning becomes more difficult when farmers observe successful adoption experiences under different geographic conditions, either because these experiences are not informative enough or because adaptation costs are too high. The model predicts that adoption rates will be lower when heterogeneity is high. In addition to that, it predicts that this relationship should be non-monotonic: the impact of soil heterogeneity should be zero when adoption rates are either too low or too high. In the first case, social learning cannot take place because there are not enough adopters to learn from. In the latter, the new technology is so widespread that most farmers will probably find a neighbor operating under similar geographic conditions. For intermediate adoption levels, when social learning is present but feasible, the model predicts the impact of heterogeneity to be higher.

Hence social learning leaves a distinctive mark on the relationship between adoption levels and soil heterogeneity (or, more generally, any deterrent of social learning). This may be used to evaluate social learning indirectly, which is important when direct information on social relationships is hard or impossible to collect.[3] Moreover, this relationship holds for any given

[2]If one restricts attention to areas with significant production of the main crops raised in the country (soybean, sugarcane and maize), this figure raises to 13.5%.

[3]Young (2009) explores differences in the adoption rates over time (known as the S-curve) to identify social

moment in time; cross-section data can then be used to evaluate the social learning channel.

Notice that this pattern is closely related to the traditional S-curve, which depicts adoption levels over time[4]: it is nearly flat when adoption levels are either too low (as there are few adopters to be imitated) or too high (when there are few non-adopters to imitate). Although driving forces are not exactly the same, a non-monotonic behavior also arises: the derivative of the S-curve is increasing within a given range and then starts decreasing. The present model captures a similar effect not over time, but over quantiles of the unconditional distribution of adoption.

We take the model predictions to the data using detailed GIS soils information and the 2006 Brazilian agricultural census. We use soil heterogeneity as a measure of geographic diversity since soils affect the return of different crops and production methods. We build this measure based on a physicochemical classification of soil types; the composition of each type affects its physical properties, such as soil temperature. This particular measure of geographical heterogeneity determine how the DPS should be used. For example, a higher temperature may call for a thicker layer of residue on the surface. However, this measure does not have any direct impact on farming - it does not affect output or the use of other inputs (such as tillage machinery).

We first use OLS regressions to provide evidence that higher soil heterogeneity decreases technology adoption. The average impact estimated using OLS is robust to the inclusion of a large set of covariates as additional controls and implies that a one standard deviation increase in heterogeneity decreases adoption by one percentage point. We then use an unconditional quantile regression estimator proposed by Firpo et al. (2009) to investigate if the impact of soil heterogeneity is non-monotonic. Results are consistent with the model predictions. The impact of soil heterogeneity is typically higher than the average impact when adoption rates are between 18 and 50% (percentiles 50 to 75 in the sample). It peaks at an adoption rate of 40% (percentile 70) in which one standard deviation increase in soil heterogeneity reduces technology use by 5.8 percentage points.

We also investigate whether the impact of soil heterogeneity changes when formal learning channels, such as producers' associations and diffusion centers, are present. The theoretical model is ambiguous about the effect of these institutions on the relationship between heterogeneity and adoption. Producers' associations and diffusion centers decrease learning costs and increase adoption rates. These adoption rates may be associated with a higher or lower impact of soil heterogeneity on technology adoption, since this impact is non-monotonic. We find that the presence of producers' associations and diffusion centers is associated with a steeper relationship between soil heterogeneity and adoption rates: social learning and formal channels are complements in this setting. This is in contrast with previous findings: Conley and Udry (2010), for example, report that extension services substitute social learning.

In addition to the studies cited above, these results contribute to two fields of the literature.

learning as the actual diffusion channel.

[4] A description may be found in chapter 7 of Jackson (2008) and references therein. Foster and Rosenzweig (1995) estimate that technology adoption in agriculture follows the S-curve.

First, it contributes to the strand that investigates the economic consequences of geography. A large literature documents the impact of geography on several determinants of economic development as historical institutions, ethnic fractionalization and cultural formation (Durante 2010; Fenske 2012; Alsan 2012; Michalopoulos 2012). We provide evidence that social learning is another channel through which geography influences economic outcomes. Our results support the view that geographic similarities facilitate socioeconomic development as in Diamond (1997).[5]

Second, we contribute to the literature on technology adoption in agriculture. This strand stresses the relevance of both formal training (including educational levels) and social learning (or "learning-from-peers") (Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010). Several papers have argued that market failures such as credit and insurance market failures hinder technology adoption in agriculture due to large setup costs and risks often involved in the adoption of new technologies (Udry 2010; Karlan et al. 2012). We provide evidence that technology adoption can be restricted even when financial constraints and other market failures seem not to be relevant[6].

The paper is organized as follows. Section 2 describes the Direct Planting System and its diffusion in Brazil. Section 3 presents the theoretical model. Section 4 describes the data. Sections 5 and 6 report the main results and present some robustness exercises, respectively. Section 7 briefly concludes. Tables and figures are collected in the appendix.

2 Direct Planting

2.1 Overview of the Direct Planting System

No-tillage can be briefly described as an agricultural method in which: (1) tillage is limited or absent; and (2) crop residue is left on the surface. Soil is then preserved: loss of nutrients due to plowing and rain erosion decreases. However, tillage is a major tool for weed control; no-tillage can only take place if effective herbicides are available. Changing from traditional farming to the no-till system effectively characterizes the adoption of a new technology: based on essentially the same inputs, higher output can be achieved. It is a new production process, and not the adoption of formerly underused inputs.

The novelty of the no-till system comes from defying a well-established notion in agriculture: the importance of tillage. The plow was developed in the early days of agriculture and was one of the main drivers of agricultural development in early human history as it increased yields significantly by facilitating weed control. A second revolution took place in the 17th

[5]Acemoglu et al. (2002) provides evidence that institutions can revert geographic determinants in the long run (measured in centuries). We consider a relatively short period of time (around 35 years), when the institutions that affect Brazilian agriculture suffered no dramatic changes as those evaluated in their paper.

[6] Comin and Ferrer (2013) provide evidence that a large part of income inequality among countries can be explained by technology penetration rates (while adoption lags have converged). Our paper suggests that these rates may be affected by geographic heterogeneity.

century when plows able to invert soil layers were developed. The following centuries witnessed developments that allowed significant advances in agricultural production. As Derpsch (1997) put it, "because the modern plough saved Europe from famine and poverty it became a symbol of "modern" agriculture (...)". Colonies in America, Asia and Africa simply followed the European pattern. It was always worth paying the price in terms of soil erosion and degradation in order to get weed control and to scarify the soil.

The history of the no-till system then goes back to primitive societies that did not have power (either animal or mechanical) to till significant areas. Modern no-till farming began in the 1940s when new weed killers became available. The following decades witnessed the development of new forms of weed control, making the costs of tillage more apparent and triggering research on no-till.

While "no-tillage" refers generally to any system with the characteristics (1) and (2) mentioned above, DPS is a particular version developed in Brazil in the 1970s (as described in the next subsection). According to Derpsch et al. (2010), it has two distinct features: no-tillage is practiced permanently (while 90% of no-till in the United States is rotatory); and the use of green-manure cover crops is widespread. Both features resulted from an effort to adapt no-tillage to the specific geographic conditions Brazilian farmers were faced with.

The system used in Brazil is known for both public and private gains (as opposed to other conservationist techniques with ambiguous private return): greenhouse gas emissions are lower, productivity increases and formerly useless soil becomes productive. Private gains, described in Table 1, come from lower soil degradation, due to lower erosion and nutrient loss (consequences of revolving systematically the soil); and lower soil compaction, due to the systematic employment of heavy machinery. Soil properties are improved and yields remain higher over longer periods. These gains usually outweigh increased herbicide expenditures even in the first years (when adoption costs might be a concern). Use of fertilizers, machinery and fuel is significantly reduced. Inoue (2003) reports that soybean productivity increased by 17%, while on average costs are 9% lower.

According to Sorrenson and Portillo (1997), farmers in Paraguay achieved a higher net income under the DPS in the first year (33%) and this difference would grow constantly over time. It follows that eventual credit constraints are not relevant in the decision to adopt the new system: there are no upfront costs. Sorrenson and Portillo (1997) also conclude that risks are "considerably lower" compared to conventional cropping: yields are higher and more stable due to improved soil structure; exposure to crop-price risk is lowered through crop diversification, as crop rotation becomes possible (and is, in fact, useful in the adoption of the DPS); lower exposure to oil-price risk as machinery use, and hence fuel demand, is reduced. Imperfect financial markets then do not prevent DPS adoption; in fact, imperfect risk sharing should push farmers towards the new system, as risk is reduced. Lastly, Brazilian agriculture is mostly a competitive business; under-adoption cannot be traced to restrained transactions.

Public gains from the DPS - presented in Table 2 - are unambiguous and come from lower carbon emissions. Carbon, among other substances, is released into the atmosphere when soil is revolved. As a consequence of lower emissions, biodiversity increases beyond the farmer's area. Lower use of chemical products, in its turn, decreases soil and water contamination (Derpsch and Moriy (1998), Camargo et al. (2011)).

Derpsch (1999) describes the kind of adjustments needed to use the DPS in tropical soils, which are frequently "acid or have toxic aluminum". Although there are general methods to achieve these adjustments (such as liming), techniques to make no-tillage suitable are specific to the type of soil under consideration - for example, it may depend on the available organic matter. The conclusion about no-till in general, and DPS in particular, is clear: "The superiority of the no-tillage system over conventional tillage has generally been proven under a great variety of conditions worldwide. It is necessary now to develop and adapt the system locally and make sure that the technology works under the special environmental and socio-economic conditions of each specific site." Specifically, the first two recommendations for farmers are:

"1- Improve your knowledge about all aspects of the system but especially in weed control.

2- Analyze your soil. (...)"

According to Derpsch (1999), the need for "site specific knowledge" has been a major barrier to the diffusion of DPS in Latin America. The next subsection describes the diffusion process in Brazil.

2.2 The Diffusion of the Direct Planting System in Brazil

Brazil is a large country (the fifth largest in the world). It is traditionally divided into five regions. These regions differ along several dimensions; in particular, agricultural suitability varies significantly. DPS was first implemented in the beginning of the 1970s in the South, a region that comprises three states: Rio Grande do Sul, Santa Catarina and Paraná. These states have average income and educational levels above the rest of the country and the farm size is much lower. Climate is mostly sub-tropical. The states still present some features from massive European immigration in the late 19th century[7].

The first trials with DPS in Brazil took place in the end of the 1960s with sorgho and wheat. Most of the research was concentrated in the states of Rio Grande do Sul and Paraná. Research effort was coordinated by private institutes, public universities and by EMBRAPA (Brazilian Company of Agricultural Research), a state-owned company that would play a major role in the development of agricultural innovations. One of the main reasons for the success of this effort was the combination of highly-qualified farmers and soils prone to erosion in the north of Paraná (the state that would become the most important diffusion center in the country); in particular, rain erosion was the main concern. Farmers invested in innovation and assumed the risks and costs of a technology that had not been tried in a significant scale. The pioneering producers studied no-till systems abroad and imported machinery and knowledge.

In 1972, IAPAR (Agronomic Institute of Paraná - a private institution) was founded; in 1975, it launched the Soil Conservation Program and promoted the National Meeting of

[7] Migration was a major source of human capital in Brazilian agriculture.

Research on Soil Erosion, in which the importance of DPS was emphasized. From a method to reduce rain erosion, DPS started to be studied as a complete production system. It was then directed to the diversification (rotation) of cultures instead of the simple soy-wheat pattern that was dominant in the early days. In 1976, major producers started adopting the DPS. It started spreading into different types of soil and topology. In 1979, farmers who adopted the DPS established in Ponta Grossa (state of Paraná) the "Clube da Minhoca"[8] (henceforth CM), an association of adopters that aimed at spreading the system. This association was one of the main drivers of the expansion of DPS in the region and throughout the country as it tried to identify and overcome problems. In particular, it promoted meetings where farmers (adopters and non-adopters) would discuss issues related to farming.

The first national meeting on DPS, organized by the CM, took place in 1981 in Ponta Grossa. The following two meetings were held in 1983 and 1985 in the same place. The first national publication on DPS came out in July 1983. In the beginning of the 1980s, the government of Paraná supported experiments and the implementation of DPS in different regions of the state - in particular, studies on crop rotation and crop residue. From 1982 on, the state of Rio Grande do Sul started developing private associations based on the CM: the "Clube Amigos da Terra"[9] (henceforth CAT). They are still a major tool for the development of the system throughout the country as it is the basic cell where DPS adopters coordinate efforts and exchange information.

The first college-level course on DPS was established in 1983 at the State University of Paraná. In the state of Sao Paulo, the richest of the federation, the first trials were implemented by IAC (Agronomic Institute of Campinas) as of 1979. In 1983, the "Direct Planting Week" was held in the state. In the 1980s, there was intense cooperation among South-American countries (politically aligned due to similar military dictatorships), which enabled the DPS to start spreading over South America.

In the 1980s, the first attempts to implement DPS in the Cerrado biome[10] took place. It was the first time the system would have to be adapted to a significantly different ecosystem - which was the major agricultural frontier in the country. In 1982, the system was presented as a major solution to serious erosion problems in the region. The beginning of the 1990s witnessed the creation of many Foundations and Associations - in particular, the APDC (Direct Planting Association of the Cerrado) and many CATs. Between 1992 and 2001, APDC and CATs organized six regional and two national meetings, which were essential for the evolution of DPS planted area. In 1990, the "DPS Journal" came out. The first international seminar in DPS took place in 1992 in Paraná. In July 1992, the FEBRAPDP (Brazilian Federation of Direct Planting) was established in Paraná in order to "gather and represent associated entities"; it would become the most important association for the diffusion

[8]Literally translated as "Earthworm club", as the presence of earthworm was a sign of soil vitality.

[9]Literally translated as "Friends-of-the-earth club".

[10]Sometimes referred to as Brazilian Savannah, the Cerrado it is strongly associated with the Center-West region. It is the second largest bioma in Brazil, after the Amazon, accounting fofr 21% of the country's territory. It has a tropical climate and is characterized by very dry seasons in the winter.

and meetings - a private effort.

In spite of this effort, in 2006 only 10% of Brazilian farmers adopted the system, mostly concentrated in the South and in the Center-West regions. The adoption rate was the same for both small farmers and large-scale operations. DPS planted area achieved around 20 million hectares in that year (Figure 1).

The next section proposes a formal model to deal with the need to adjust the DPS for different geographic conditions - specifically, different soil types. Notice that such differences have no direct impact on agriculture: we only analyze soil types where agriculture is viable in the first place under both traditional tillage and DPS. We interpret them as a thwarter of social learning, which is not immediate as it is necessary to adapt this technology to any type of soil where it has not been formerly used[11]. As Munshi (2004) puts it, "social learning is evidently weak, and diffusion rates will be slow, if the individual is unable to observe his neighbors' experiences perfectly." A main component of "neighbors' experiences" in agricu is soil characteristics. It follows that when soil is heterogeneous, social learning, and hence technology diffusion, should be slower.

3 Technology Adoption under Learning Costs

Consider a simple economy with a mass 1 of agents (farmers). Each farmer i has a $\theta_i \in \mathbb{R}^N$ which we interpret as his soil type. There are two technologies available for crop production: a base technology everyone has access to and a new technology that may be adopted conditional on some non-pecuniary cost (described below).

Timing is as follows. An exogenous distribution of adopters is drawn in period 0. In the following periods $t = 1, 2, ...$ farmers make an adoption decision: $a_{it} = 1$ if he adopts the technology and $a_{it} = 0$ otherwise. Each farmer i is then characterized by a sequence $(\theta_i,$

Farmers are distributed according to a single-peaked joint distribution of types $G\left(\theta\right.$ with associated density g. The variance σ^2 is assumed to be strictly positive (i.e., G is degenerate). We assume that the probability that $\theta_i = \theta_j$ is zero for all $i \neq j$.[12] The i mass of adopters for each θ is $g_A^0(\theta) = \alpha g(\theta)$ for some $\alpha \in (0, 1)$.

The parameter σ^2 determines how much soils differ: soil heterogeneity is captured by a higher variance. We assume (discounted) profits under the new technology $\overline{\pi}$ are larger under the current one, $\underline{\pi}$: $\Delta\pi = \overline{\pi} - \underline{\pi} > 0$. This is the main feature of the DPS technology we make use of. Other restrictions (such as imperfections in the credit market) play no role.

[11] An alternative interpretation is related to the informational content of an experience performed under different conditions. The agent then updates his prior on the profitability of the new technology based on the conditions his neighbors were faced with and the results they achieved. Although the model in the next section is able to accommodate this Bayesian interpretation, we choose the 'adaptation cost' view as it captures more precisely the features of the DPS.

[12] This is done only for simplicity but its interpretation is straightforward: two types of soil are never exactly equal - even if any differences are irrelevant for the farmer's decision.

For simplicity and without loss of generality, profits are the same for every farmer conditional on the chosen technology.

Each farmer must learn how to use the new technology before adopting it. The first possibility is to learn from some other agent who previously adopted it and is "close" to him in a sense to be made precise. However, learning is costly. We interpret this cost as the need to make some kind of adjustment in the technology (a micro-innovation) in order to use it in a different type of soil. Intuitively, the cost of farmer i in period t depends on the previous adopter j with the 'most similar' type of soil, i.e., it should depend on $\min_j d\left(\theta_i - a_{jt}\theta_j\right)$, in which d is the Euclidean distance.

In order to define this cost for a continuum of farmers, define initially the R-neighborhood of farmer i as:

$$N\left(\theta_i\right) = \left\{\theta_j : d\left(\theta_i, \theta_j\right) \leq R\right\}$$

Notice that this set can be defined directly in terms of farmer's types θ_j: since types are never equal, it is possible to define a bijection $i \rightarrow \theta_i$. This set has a mass $M\left(N\left(\theta_i\right)\right) \equiv \int_{N(\theta_i)} g\left(\theta\right) d\theta$. Define accordingly the set of adopters in i's neighborhood in period t as:

$$N_A^t\left(\theta_i\right) = \left\{\theta_j : d\left(\theta_i, \theta_j\right) \leq R \textit{ and } a_{jt} = 1\right\}$$

with mass $M\left(N_A^t\left(\theta_i\right)\right) \equiv \int_{N_A^t(\theta_i)} g\left(\theta\right) d\theta$.

The cost of learning depends on the mass $M\left(N_A^t\left(\theta_i\right)\right)$. Learning is not viable beyond the threshold R. The cost function $c\left(M\left(N_A^t\left(\theta_i\right)\right)\right)$ is assumed to have the following properties:

1. $c\left(0\right) > \Delta\pi$.
2. $c\left(\right)$ is decreasing in M and there is $m < 1$ such that $c\left(m\right) < \Delta\pi$.

Assumption 1 means that the cost of the original innovation is too high: The farmer will not adopt the new technology if there are no neighbors to learn from (and no alternative diffusion channel). Hence, we are modeling only the diffusion and not the initial innovation process.

The learning channel is captured in assumption 2: the presence of adopters in the R-neighborhood decreases the cost of learning and it pays off to choose the new technology for at least some levels of adoption. Agents can learn how to operate a technology by observing other agents operating it in a neighborhood. However, operational details differ with the type of soil and some adjustment is called for. The higher the share of adopters with similar soils, the easier it will be for a farmer to learn how to use the new technology (i.e., adjust it to his type of soil). For interpretation purposes, one may think in terms of the discrete counterpart to this model[13]: the expected distance to the closest adopter decreases.

In any period, the agent may also have access to some alternative learning source, which will be interpreted as any formal diffusion channel for the new technology and will be labeled $F_t \geq 0$ such that $F_t = 0$ represents the absence of such channel in that period. The total cost

[13] In fact, it is straightforward to rewrite the model with a discrete distribution G. Results are unchanged.

of learning may now be defined as:

$$c\left(M\left(N_A^t\left(\theta_i\right)\right)\right) - F_t$$

Notice initially that $\Delta\pi > 0$ implies that adopters never switch back to the base technology: $a_{it} = 1 \Rightarrow a_{it'} = 1$ for all $t' > t$. At the beginning of every period, non-adopters observe the previous distribution of adoption and make their decisions. Timing is as follows:

$t = 0$: exogenous and independent distributions of types (θ_i) and initial adopters (a_i^0) are drawn;

$t = 1$: beginning-of-period: Non-adopters decide whether to adopt the new technology based on (θ_i, a_i^0).

$t = 1$: end-of-period: New distribution of adopters is observed by all agents.

$t = 2$: beginning-of-period: Non-adopters decide whether to adopt the new technology based on (θ_i, a_i^1).

And so forth.

Loosely speaking, an agent will choose the new technology whenever the gain in profit is higher than the cost of learning. The decision rule is simple: a farmer i will switch to the new technology in period t (i.e., $a_{it} = 1$) if and only if:

$$\Delta\pi \geq c\left(M\left(N_A^{t-1}\left(\theta_i\right)\right)\right) - F_t$$

Let $\overline{M} \equiv c^{-1}(\Delta\pi)$; this is simply the lowest mass of adopters, in a given neighborhood, that allows for diffusion. Define $M^U \equiv M\left(N_A^0\left(\theta_i\right)\right)$ as the initial mass of adopters around θ_i under the uniform distribution, and notice that it must be the same for all i. Assume lastly that $\overline{M} > M^U$: if the distribution of types is uniform, the mass of adopters is too low, in any neighborhood, for diffusion to take place[14],[15]. Intuitively, the initial adoption level cannot trigger diffusion if entropy is high enough; the number of adopters at $t = 0$ is not sufficient to render soil variance irrelevant. This assumption is unessential for the main results; it is made for the sake of simplicity and is in line with the under-adoption issue discussed in the previous sections.

Notice that this diffusion process cannot be reduced to a contagion model: It is not enough to have adopters in the neighborhood. Social learning demands more: in the presence of operational differences in the use of the new technology among different soils, it is necessary to incur into a cost to adjust it. This cost is by construction lower when previous adopters operate under similar conditions as non-adopters.[16] In terms of the discrete counterpart, a higher share of adopters in a given neighborhood means that the expected distance to the closest adopter decreases.

Decisions in period t induce a (possibly changed) end-of-period distribution of adopters with associated mass $M\left(N_A^t\left(\theta_i\right)\right)$. We are implicitly assuming that farmers need at least one

[14]This assumption is trivially satisfied if the support of types is unbounded.

[15]If $\theta \in \mathbb{R}$, this condition boils down to $\overline{M} > 2R\alpha$.

[16]It is possible to rewrite the model in terms of learning about profits instead of how to operate the technology.

period to learn the new technology (intuitively, they have to observe the whole growing cycle). Notice that $M\left(N_A^t(\theta_i)\right) \geq M\left(N_A^{t-1}(\theta_i)\right)$ as the set of adopters never decreases.

An allocation is a vector of adoption decisions $\{a_i\}_i^t$. Define an equilibrium (path) in this economy as follows:

Definition 1. For a given vector θ and initial distribution $\{a_{i0}\}_i$, an equilibrium profile $\{a_{it}^*\}_{it}$ is such that for all i and for all $t \geq 1$, $a_{it}^* = 1$ if and only if $\Delta\pi \geq c\left(M\left(N_A^{t-1}(\theta_i)\right)\right) - F_t$ or $a_{it-1} = 1$.

In the long run, this path will necessarily converge to a constant distribution $\{a_i^*\}_i$ as it is a monotone and bounded sequence. Define the set of adopters by Θ_A^t and the corresponding share of adopters by A^t.

Intuitively, the expected level of A^t should depend on σ^2 for any given t: if farmers are too disperse, it will be less likely to find enough adopters within a neighborhood such that learning is profitable.[17] However, the impact of σ^2 on A^t depends itself on the adoption level A^t, as the following proposition establishes. In what follows, we assume without loss of generality, and only for ease of notation, that the derivative $\dot{A}^t\left(\sigma^2\right) \equiv \frac{dA^t\left(\sigma^2\right)}{\sigma^2}$ exists.[18]

Proposition 1. *For any t, the aggregate adoption level A^t is constant in σ^2 if $A^t \in \{0,1\}$ and decreasing for some $A^t \in (0,1)$.*

Proof. Consider first an initial situation in which $a_i = 0$ for all i; then assumption 1 implies that it is not profitable for any agent to adopt the new technology no matter the value of σ^2: Social learning cannot take place in the absence of previous adopters in the neighborhood. Then $A^t\left(\sigma^2\right) = \dot{A}^t\left(\sigma^2\right) = 0$ for any t. Reasoning is similar if $a_i = 1$ for all i - or, more generally, for any profile $\{a_i\}_i$ such that $M\left(N_A(\theta_i)\right) > m$ for all i: non-adopters will find optimal to switch to the new technology due to assumption 2. In this case, every farmer will choose the new technology in at most one period and again $\dot{A}^t\left(\sigma^2\right) = 0$. For the last point, it suffices to show a higher variance will lead to lower adoption in one period ($t = 1$) - it then follows that the share of adopters will be smaller in every period afterward as non-adopters will have a lower number of previous adopters to learn from. Since G is single-peaked and $\overline{M} > M^U$, the set of types such that adoption is profitable necessarily decreases when σ^2 increases, completing the argument.[19]

□

Intuition is straightforward. When adoption levels are too low, there is no one to learn from: Diffusion cannot take place for any level of σ^2. It follows that the impact of heterogeneity

[17] The time subscript will be dropped to ease notation.

[18] It is straightforward to rewrite the argument for a non-differentiable function A^t.

[19] One can show that if G is not single-peaked, A^t decreases non-monotonically in σ^2.

on adoption should be zero. When adoption levels are high enough, the cost of learning eventually becomes lower than the benefit: Adoption will be so widespread that farmers will be able to learn no matter how different their soils are. Intuitively, when there are many adopters, some of them will have a type of soil similar to θ_i for any i.[20] However, at intermediate levels, eventually an increase in heterogeneity must reduce adoption: The level of adopters in any given neighborhood goes below the minimum necessary to allow learning.

Without further structure on the distribution G, one cannot derive additional properties of $\dot{A}^t$. For illustration purposes, assume from now on that $A^t\left(\sigma^2\right)$ is continuously differentiable and has only only local minimum - labeled A^c. These assumptions are non-essential but will facilitate the interpretation of the empirical results. The following corollary is then immediate.

Corollary 1. *The derivative $\dot{A}^t\left(\sigma^2\right)$ is decreasing for $A^t \in (0, A^c)$ and decreasing for $A^t \in (A^c, 1)$.*

We turn now to the relationship between social learning and other diffusion methods.

Corollary 2. *An increase in the use of the formal channel F_t may either crowd out the learning channel ($|\dot{A}^t\left(\sigma^2\right)| \downarrow$) or reinforce it ($|\dot{A}^t\left(\sigma^2\right)| \uparrow$).*

These institutions can either weaken or strengthen the relationship between soil heterogeneity and adoption of the Direct Planting System. The formal channel causes the learning cost to decrease and thus corresponds to an exogenous increase in the share of adopters in any given period: A^t rises. Since the impact of heterogeneity on adoption is non-monotonic, the new level of adoption may be associated either to a higher impact or to a lower one. In the former case, technical assistance and farmers' associations can substitute social learning and thus weaken this relationship. In the latter, they are complements: they help regions to reach adoption rates in which soil heterogeneity hinders social learning and hence are complements.

Notice further that this result does not rely on any assumption of the cross-derivative $\frac{\partial^2 c(\sigma^2)}{\partial M_t \partial F_t}$ - which is zero in the present setup. Were it positive (negative), the region where F_t and social learning were substitutes would be larger (smaller), but with no qualitative change in the results.

The empirical counterpart of the economy described above is a municipality. Formally, an economy is defined by $\left(\sigma^2, \alpha, R, G\right)$. The model then predicts that municipalities with higher soil heterogeneity σ^2 should have, on average, and for any given t, lower rates of adoption of the new technology. However, this impact should be zero when these rates are either too low (A^t close to zero) or too high (A^t close to one). Moreover, social learning and the formal channel may be either complements or substitutes: The reduction of the learning cost by F

[20] We are implicitly using the fact that, due to assumption 2, there are no "isolated types". The argument may be extended to include such cases.

is equivalent to an exogenous increase in the set of adopters. *Ex-ante* it is not possible to tell whether this will increase or decrease the derivative $\dot{A}^t$. If it increases (decreases), the channels are complements (substitutes). In short, the impact of soil heterogeneity on adoption levels should have a specific format if social learning is the actual channel; social learning can then be identified indirectly. Notice lastly that the model's predictions hold at an aggregate level which allows us to use only data at the municipality level to test it.

4 Data

4.1 Soil Heterogeneity

Our empirical approach relies on measures of soil heterogeneity. We build them using detailed GIS information from the Brazilian soil map developed by EMBRAPA, the Brazilian Agricultural Research Corporation (EMBRAPA 2011). The map is based on the most recent classification system for Brazilian soils (Santos 2006), which uses a hierarchical taxonomy: a hypothetical soil 'Aa1' belongs to order 'A', suborder 'a', group '1'. 'Order' is the first and more general classification level, and the following ones are subdivisions. Although the classification system allows for finer levels up to a sixth layer, the map does not report information beyond the third level. It provides information for geographical units at scale 1:5.000.000 for each level.

The classification system is based on the physicochemical composition of soil, which is a major determinant of the physical properties of each type of soil. Physical properties, in their turn, define the suitability of different agricultural methods. For example, higher soil temperature may call for a thicker layer of residue on the surface in order to decrease exposure to sunlight so as to avoid excessive heat. Hence, a different type of soil calls for some adjustment (a micro-innovation) in order to apply the DPS. Lastly, this classification system is "smooth" in the sense that the difference in physical properties between two types of soil is roughly the same for any pair of types.

The baseline empirical exercise considers only the most general level (order). The most general level cannot be changed by the agricultural method in 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. Hence, any measure built on this classification system can be safely assumed not to depend on adoption levels of the DPS. We show in the robustness section that results are unchanged when one considers the more refined levels (a natural result since correlation between alternative soil heterogeneity measures is quite high).

There are thirty five different orders. We merge the soil map with the municipalities map of Brazil[21] to build a measure of the share of each municipality covered by these orders. We

[21] Obtained from IBGE (Brazilian Institute for Geography and Statistics) which is the institution responsible for the official maps of the country.

use the same procedure to build measures for the other levels. We then use these shares to build a Herfindahl index (HHI) of soil orders for each municipality. The index varies from zero to one with a higher value denoting more homogeneity.

Soil heterogeneity (S) is defined as the inverse of its Herfindahl index ($1/HHI$). We interpret it as a measure of the effective number of soils in the municipality (in line with the industrial organization literature). S is a variance measure and is a direct empirical counterpart of the variance of soils defined in the theoretical model presented in Section 3.

We expect a higher S to reduce adoption of the DPS. We also expect the impact of S on technology adoption to be non-monotonic and higher at intermediary adoption rates. The intuition is that neighbours' experiences are less informative in more heterogeneous municipalities: the adaptation cost is higher, decreasing technology adoption. As discussed in Section 2, this is an artificial variable in agricultural terms: it has no direct impact on production (i.e., it does not enter the production function of farmers). In particular, it does not affect the suitability of other inputs, such as tillage machinery. It follows that heterogeneity cannot affect adoption levels by making traditional farming more costly.

Table 3 presents summary statistics to the main soil heterogeneity measure. We trim the upper one percent tail of the heterogeneity distribution as S increases too rapidly after this threshold. The average value of S is 1.67 with variance 0.64. This means that the average municipality is covered by 1.67 orders.

It is important to note that our approach to measure heterogeneity in growing conditions contrasts with Munshi (2004) learning study. He classifies regions as more or less heterogeneous using information on the crops cultivated in each of them. He argues that rice growing regions present more geographic heterogeneity than wheat growing ones and that this pattern influences technology diffusion.

Our approach uses direct geographic information and is more similar to the ones used by Michalopoulos (2012) and Fenske (2012), who apply different geographic heterogeneity measures to historical and institutional development frameworks. The use of direct geographic information is an important improvement compared to Munshi (2004) study.

4.2 Agricultural Outcomes

Agricultural outcomes come from the Brazilian agricultural census collected in 2006. The main agricultural outcome used in our empirical estimates is the Direct Planting System adoption rate. We define it as the share of farms which use the DPS.

The theoretical model connects soil heterogeneity and technology adoption through social learning; it predicts that there should be no impact when adoption is either too low or too high. However, most municipalities have quite low adoption levels - configuring precisely the under-adoption problem under study. These municipalities add significant noise to the empirical exercise. To avoid this problem, we consider in the baseline estimates only municipalities with adoption levels above 5% and present similar results including municipalities below this threshold as a robustness exercise. We also drop the upper one percent tail of the soil heterogeneity as described above. We have a final sample of 1,708 municipalities.

Table 4 reports the distribution of adoption rates in the restricted sample. The average adoption rate is 30%, with a standard deviation of 26.5%. Adoption rates are above 40% in the states in the South of Brazil (*Rio Grande do Sul*, *Santa Catarina* and *Paraná*) and approximately 20% in the states in the Center-West (*Goiás*, *Mato Grosso do Sul* and *Mato Grosso*). These are the states that concentrate most soybean production, which is the crop under which adoption rates are reportedly higher. Adoption rates are typically around 10% in the other states.

It is important to highlight that adoption rates of the Direct Planting System actually capture technology diffusion. It is generally difficult to separate incomplete technology adoption from input underuse (Foster and Rosenzweig 2010). As mentioned in Section 2, the adoption of the DPS is a precise example of technology diffusion as farmers can use similar inputs and achieve higher output.[22]

Other agricultural controls include number of farms, average farm revenues, schooling measures, access to government technical assistance, number of tractors, association to cooperatives, use of credit, and land distribution measures. Table 2 reports summary statistics of these variables.

4.3 Other Variables

Our baseline estimates also control for municipality measures of rainfall, temperature, land gradient, latitude, longitude and altitude. We calculate average seasonal rainfall and temperature for the period 1970 to 2010 for each municipality using gridded data on rainfall and temperature obtained from the Terrestrial Air Temperature and Precipitation Version 3.01. Land gradient is computed using raster maps of elevation of Brazil and the Zonal Statistics tool in ArcMAP 10.1. The land gradient measure is the log of the average gradient in pixels calculated for each municipality. Latitude, longitude and altitude were obtained through the IPEADATA website.

We also control for the distance from each municipality to the nearest municipality where a diffusion center (CAT) is located. We compute this distance between municipality centroids. This measure is used both in the baseline estimates and in the heterogeneity analysis. Finally, we use information on the location of bank branches to control for different access to credit in some robustness exercises. Table 2 reports summary statistics for these variables.

5 Results

5.1 Baseline Estimates

We start investigating the relationship between soil heterogeneity and technology adoption

[22] The optimal choice of inputs generally changes under a new technology. However, this is different from change of inputs *given* a technology such as, for example, when credit constraints are lowered.

by estimating the following equation using Ordinary Least Squares (OLS):

$$A_{m,s} = \beta S_{m,s} + \mathbf{X}_{m,s}\Gamma + \psi_s + \varepsilon_{m,s}$$

where $A_{m,s}$ is the proportion of farmers that adopted the Direct Planting System and $S_{m,s}$ is the Herfindahl index of soil heterogeneity in municipality m and state s. $\mathbf{X}_{m,s}$ is a vector of controls that includes geographic characteristics and other relevant determinants of technology adoption in agriculture which are discussed below. The OLS approach is justified since the predicted relationship between heterogeneity and adoption holds for any given t.

The central identification assumption is that soil heterogeneity is orthogonal to $\varepsilon_{m,s}$. The identification assumption requires three conditions to hold. First, soil heterogeneity must not be determined by technology use. Second, soil heterogeneity must not determine municipalities boundaries. Third, heterogeneity must not correlated to unobserved factors that affect technology adoption.

The first and second conditions are consistent with the soil classification used to build the heterogeneity measure. This classification is neither affected by land use nor is associated with geographical accidents that often determine boundaries between municipalities. The third condition is more sensitive. Soil heterogeneity may be correlated with geographic characteristics that are associated with agricultural productivity and technology adoption. We include several geographic characteristics in the vector $\mathbf{X}_{m,s}$to mitigate the concern that geographical characteristics are driving the results.

Our interpretation is also based on the assumption that soil heterogeneity does not affect technology adoption through channels other than social learning. We include several socioeconomic characteristics in the vector $\mathbf{X}_{m,s}$to mitigate the concern that socioeconomic characteristics correlated both with soil heterogeneity and technology adoption are driving the result.[23]

Table 4 presents the OLS estimates. Column 1 reports the coefficient of a bivariate regression of the DPS adoption rate on soil heterogeneity. Column 2 includes controls for the share of the municipality covered by more than thirty different soil types, historical temperature and rainfall in each season, latitude, longitude, and the log of land gradient as additional controls. Column 3 includes state fixed effects as controls. Column 4 further includes farm characteristics (log of the number of farms, log of farm revenues, farmers' human capital, access to government provided technical assistance and log of the number of tractors) as controls to capture for other potential determinants of adoption rates. Column 5 additionally includes controls for the presence of formal learning channels (cooperatives and diffusion centers).

The results provide support to the idea that soil heterogeneity decreases adoption rates. There is a negative and statistically significant relationship between these variables in all

[23]Notice that causal inference on the parameter β is unaffected by the inclusion of socioeconomic characteristics in $\mathbf{X_{m,s}}$as soil heterogeneity is invariant to socioeconomic characteristics. Th inclusion of socioeconomic characteristics in $\mathbf{X_{m,s}}$aims to test the whether the impact of soil heterogeneity on technology adoption is driven by social learning or by some other socioeconomic characteristic that may be affected by soil heterogeneity.

specifications. The coefficient estimated in Column 1 suggest that the impact of soil heterogeneity on adoption is quite large. One standard deviation in soil heterogeneity decreases DPS adoption by five percentage points. However, the inclusion of geographic characteristics in Column 2 decreases the estimated coefficient in almost 80%. The result suggest that soil heterogeneity is associated with geographic characteristics, which in their turn are associated with lower DPS adoption.

The coefficient on soil heterogeneity changes little with the inclusion of additional controls in Columns 3 to 5. The coefficients from Columns 2 to 5 imply that a one standard deviation increase in soil heterogeneity decreases DPS adoption by 1 to 1.3 percentage points even when we control for several geographic and socioeconomic characteristics. The negative coefficients are statistically different from zero either at the 5% or at the 1% levels. We consider the specification in Column 4 the most adequate since the control variables included in Column 5 may respond to technology adoption and artificially bias our coefficient downward.[24] One standard deviation increase in soil heterogeneity decreases DPS adoption in 1.3 percentage points in the preferred specification and is significant at the 1% level.[25] The results are consistent with our theoretical framework that suggest that soil heterogeneity decreases technology adoption by deterring social learning.

5.2 Quantile Regressions

The OLS estimates provide evidence that soil heterogeneity decreases technology adoption as predicted by the theoretical framework presented in Section 3. However, a complete test of the social learning mechanism outlined in the theoretical framework should take into consideration the prediction that the impact of soil heterogeneity is non-monotonic: higher at intermediate adoption rates than at either high or low adoption rates.

We examine whether this prediction holds in our data using the unconditional quantile estimator proposed by Firpo et al. (2009). The authors propose a regression method to evaluate changes in explanatory variables in the unconditional distribution of the outcome variable. Their method departs from the traditional quantile regression literature which evaluates the impact of changes in explanatory variables in the conditional distribution of the outcome variable.[26] The unconditional quantile regression is adequate to our empirical setting as our

[24] In particular, farmers may choose to join a cooperative to learn about the DPS.

[25] A common problem in inference when using data on quite small spatial units is the presence of spatial correlation in the error term. That usually makes standard errors as the ones reported in Table 4 inconsistent. Therefore, we also estimate the standard errors using the method proposed by Conley (1999). The method allows estimation of consistent standard errors in the presence of spatial correlation by imposing some structure to the correlation of the error term across spatial units using their relative distance. A key feature of the method is deciding a cutoff above which the correlation falls to zero. We calculate standard errors allowing for spatial correlation of the error term using three different cutoffs for the distance between municipality centroids: 50 kilometers, 100 kilometers and 150 kilometers. Standard errors from the soil heterogeneity coefficient in Columns 2 to 5 increase about 15% when the 50 kilometers cutoff. It increases about 33% and 65% when the 100 and the 150 kilometers cutoffs are used. Estimates from the preferred specification in Column 4 are significant at the 5% level when the first and second cutoffs are used and at the 10% level when the third cutoff is used.

[26] Koenker and Basset (1978) provides the seminal treatment to quantile regression.

theoretical framework predicts that the relationship between soil heterogeneity and technology adoption should change with different adoption levels and not with different adoption levels conditional on a set of covariates. The method proposed by Firpo et al. (2009) can be computed using regression methods on a Recentered Influence Function (RIF) discussed at length by the authors.[27]

We reestimate the specification in Column 4 of Table 4 across different adoption rates using this estimator.[28] Results are reported in Figure 2. The relationship between soil heterogeneity and technology adoption is U-shaped as predicted by the theoretical framework. The impact of soil heterogeneity on DPS adoption is small or zero either at small or high adoption rates. However, soil heterogeneity is found to have an important impact at intermediate adoption rates. The estimated coefficient is statistically different from zero and above the average impact estimated throguh OLS when DPS adoption rate are between 18 and 50% (these adoption rates correspond to the percentiles 50 to 75 in our sample).

The relationship between soil heterogeneity and DPS adoption peaks at the adoption rate of 40% (which correspond to the percentile 70). One standard deviation increase in soil heterogeneity decreases DPS adoption in 5.8 percentage points in this adoption rate. The maximum impact is about four times larger than the average impact which highlights the non-monotonicity in the relationship between soil heterogeneity and technology adoption.

Results in Figure 2 support the interpretation that soil heterogeneity decreases DPS adoption by deterring social learning. The presence of social learning is identified indirectly from the distinctive footprint it leaves on the relationship between soil heterogeneity and technology adoption. Soil heterogeneity does not affect technology adoption either at low adoption rates (when the social learning channel is essentially closed) either at high adoption rates (when social learning is possible regardless of soil heterogeneity). It hinders social learning at intermediate levels, when it increases the cost of learning and hence reduces technology adoption.

5.3 Formal Learning

The theoretical model predicts that other learning channels such as cooperatives or diffusion centers can either increase or decrease the impact of soil heterogeneity on adoption rates. The intuition for this result is straightforward. The presence of a formal channel decreases learning costs and corresponds to an exogenous increase in the share of adopters. Since the impact of heterogeneity on adoption is non-monotonic, the new level of adoption may be associated either to a higher impact or to a lower one.

We investigate the issue empirically using information on the presence or proximity of

[27] 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 using the RIF-OLS are quite similar to the ones using RIF-Logit (which considers this distribution to be logistic) or RIF-NP (which is non-parametric).

[28] Results are qualitatively similar when we implement the quantile regression using different specifications.

producers' associations and diffusion centers. Let the presence of a formal learning channel in a municipality m in state s be denoted by $F_{m,s}$. We test whether the effect of soil heterogeneity on technology adoption is different when formal learning channels are present by estimating the following equation by OLS:

$$A_{m,s} = \beta_1 S_{m,s} + \beta_2 (S_{m,s} x F_{m,s}) + \beta_3 F_{m,s} + \mathbf{X}_{m,s}\Gamma + \psi_s + \varepsilon_{m,s}$$

We start discussing the role of cooperatives. Farmers' cooperatives are an important institution in rural Brazil. Cooperatives help farmers to acquire inputs and sell their products. They also help farmers in experimenting with different crop varieties and fertilizers (Jepson 2006). An average of 49% of the farmers are associated with cooperatives in the sample municipalities. We examine whether cooperatives are complements or substitutes to soil heterogeneity including a binary variable of whether the share of producers associated to a cooperative is above the sample median as the formal learning channel.

Results are reported in Column 1 of Table 5. Adoption rates in municipalities with high presence of cooperatives are 17.8 percentage points larger than municipalities below the median. The presence of cooperatives is also associated with a higher impact of soil heterogeneity on adoption rates. The relationship between soil heterogeneity and adoption rates is essentially zero for municipalities with low presence of cooperatives but is negative and statistically significant in municipalities with high presence of cooperatives. The estimated coefficient on the interaction of soil heterogeneity and technology adoption is also economically important. One standard deviation increase in soil heterogeneity decreases DPS adoption in 3.4 percentage points in municipalities with high presence of cooperatives

We then investigate the role of diffusion centers. Section 2 discusses the important role of the diffusion centers known as CAT in the dissemination of the Direct Planting System in Brazil. The CATs were related to FEBRAPDP, the main DPS federation in the country. There were 56 CATs distributed over the whole country in 2006. The main task of CATs was to spread knowledge about the Direct Planting System and adapt it whenever necessary. We expect the presence of these clubs near a municipality to increase its adoption rate. The average distance of a municipality to a diffusion center is 340 kilometers. We compute the distance from each municipality to the nearest CAT and create a binary variable which is one in municipalities below the median distance to a CAT.

Column 2 in Table 5 presents the results. Municipalities close to diffusion centers have adoption rates 11.8 percentage points higher than more distant (above the median) ones. The proximity is also associated with a higher impact of soil heterogeneity on adoption rates. The relationship between soil heterogeneity and DPS adoption is negative both for municipalities close or far from diffusion centers. However, the coefficient on the interaction term provides evidence that soil heterogeneity is more important in municipalities close to diffusion centers. One standard deviation increase in soil heterogeneity decreases DPS adoption by 5 percentage points in municipalities close to diffusion centers.[29]

[29] It is possible to include "distance to the initial adopting region" (i.e., the original innovator) in this exercise

Including all formal learning channels together in Column 3 in Table 5 gives qualitatively similar results. Soil heterogeneity and DPS adoption are negatively related only in municipalities where either cooperatives are important or diffusion centers are located nearby. Figures 3 and 4 provide evidence that the U-shaped relationship between soil heterogeneity and adoption rates is present only in municipalities where either cooperatives are important or diffusion centers are located nearby. Figures 3 and 4 are consistent with the idea that cooperatives and diffusion centers increase the relationship between soil heterogeneity and adoption mainly because they increase adoption rates toward levels where social learning becomes viable and more relevant.

6 Robustness

6.1 Alternative Measures of Soil Heterogeneity and Alternative Samples

This subsection considers the robustness of the OLS results to alternative soil heterogeneity measures and to alternative samples. We start considering alternative soil heterogeneity measures. The measure used so far was constructed at the municipality level and used the most general level of the EMBRAPA (2011) soil map.

We consider alternative measures based on different soil classifications and on another geographic classification. The first alternative measure is built with more refined information from the soil map. The main pitfall of this alternative measure is that more detailed components of the soil can be affected by land use. However, it can be used to assess the robustness of the baseline results to a soil heterogeneity measure built using a more comprising soil classification.

The correlation between the original soil heterogeneity index and the measure defined above is 0.83. Column 1 in Table 6 reestimates the preferred OLS specification (Column 4 from Table 4) using this alternative soil heterogeneity measure. The estimated coefficient on soil heterogeneity changes little (-1.845) in comparison to the coefficient estimated using the original measure (-1.991).

The second alternative measure of soil heterogeneity is built using information on soil heterogeneity not only from the municipality itself but also from neighboring municipalities. The measure is the weighted average of the soil heterogeneity from the municipality and its neighbors. The observations are weighted by the area of the spatial units. The main pitfall of this alternative measure is that it creates correlation between the soil heterogeneity measures of different municipalities. Therefore, the computed standard errors should be interpreted with caution. However, this alternative measure overcomes the fact the the original measure limits the relevant heterogeneity to each municipality.

The correlation between the original soil heterogeneity measure and the measure defined above is 0.62. Column 2 in Table 6 reestimates the preferred OLS specification (Column 4

- results are unaffected. This accommodates the alternative view of 'gravitational' diffusion of knowledge (a recent study is Keller and Yeaple (2013)). We interpret the original innovator as another diffusion center.

from Table 4) using this alternative soil heterogeneity measure. The estimated coefficient on soil heterogeneity increases significantly in absolute value (-5.140) in comparison to the coefficient estimated using the original measure[30]. This estimate suggests that the original measure probably understates the relevant soil heterogeneity and ends up attenuating the impact of soil heterogeneity on technology adoption. Therefore, we can consider the evidence based on the original measure as a lower bound of the impact of soil heterogeneity on DPS adoption.

Another potential concern with the OLS estimates is sample selection. Our estimates exclude municipalities with low adoption rates from the sample as the theoretical mechanism we highlight is closed when adoption is nonexistent or too low. We examine whether the baseline results are sensitive to sample selection considering alternative samples including either all Brazilian municipalities with information on the relevant variables or all Brazilian municipalities in which DPS adoption is positive.

Column 3 in Table 3 reestimates the preferred OLS specification (Column 4 in Table 4) using the full sample. The number of observations rises to 5,060. The coefficient of soil heterogeneity is negative and statistically significant as in the baseline OLS estimates. Its magnitude is smaller than the coefficient from the baseline exercise. A smaller coefficient is consistent with the theoretical framework, suggesting that social learning does not exist and, therefore, soil heterogeneity is not relevant in the observations included. The results are unchanged when we reestimate the preferred OLS specification (Column 4 in Table 4) using all municipalities with positive DPS adoption. Column 4 in Table 3 presents the estimated coefficient on soil heterogeneity. The coefficient is quite similar to the one estimated for the full sample.

6.2 Additional Controls

This subsection considers the robustness of the OLS results to the inclusion of additional controls. We perform several robustness exercises including measures of land distribution and access to credit and to markets as additional controls. These controls are included to examine whether the relationship between soil heterogeneity and DPS adoption is driven not by social learning but by the correlation between soil heterogeneity and some socioeconomic characteristics.[31]

A potential concern to the baseline estimates is that it is easier for larger farms to incur in the learning costs necessary to adopt the DPS. To the extent that soil heterogeneity and farm size are correlated, the baseline OLS results can reflect the correlation between farm size and DPS adoption (instead of social learning). We test for this possibility by including measures of land distribution (share of farmland covered by farms of different sizes) as additional controls.

[30] We calculated standard errors adjusting for the existence of spatial correlation of the error term as we did with the baseline estimates. The estimated coefficient is statistically different from zero at the 1% level whichever distance cutoff we choose.

[31] Notice that the preferred OLS specification (Column 4 in Table 4) already accounts for some socioeconomic characteristics related to technology adoption (number of farms, farm size and human capital).

The results presented in Column 1 in Table 7 provide evidence that land distribution is not driving the OLS estimates from Table 4. The soil heterogeneity coefficient (-1.734) is quite similar to the one estimated in the preferred OLS specification (-1.991).

Another potential concern is that farmers with more access to financial services may incur more easily in the learning costs necessary to adopt the DPS. To the extent that soil heterogeneity and financial access are correlated, the baseline OLS results can reflect the correlation between financial access and DPS adoption (instead of social learning). We do not expect differentiated access to financial access in municipalities with more soil heterogeneity to be a major concern since DPS adoption does not involve upfront costs, and reduces production risk. However, it is important to account for this possibility as the literature on technology adoption highlights its importance.[32]

We include different measures of financial access in the preferred OLS specification. Column 2 in Table 7 includes the number of bank branches in the municipality as an additional control. We account separately for the number of Banco do Brasil bank branches and for the number of other bank branches since Banco do Brasil is the main provider of agricultural credit in the country. Column 3 in Table 7 additionally includes the average value of farm debt as another measure of financial access. The soil heterogeneity coefficient estimated in both Columns (-2.026 and -1.912, respectively) is quite similar to the coefficient from the preferred OLS specification (-1.991).

A final concern with the baseline estimates is that DPS adoption may lead to changes in the cultivated products and both adoption and these changes may be prevented by lack of access to markets. To the extent that soil heterogeneity and market access are correlated, the baseline OLS results can reflect the correlation between market access and both land use and DPS adoption (instead of social learning). We test for this possibility by estimating the impact of soil heterogeneity on technology adoption conditional on land use. While the included controls are endogenous and will probably drive the estimates downwards, it is useful to examine whether soil heterogeneity negatively affects DPS adoption when land use is held constant to mitigate any concern that market access drives the baseline results. Column 4 in Table 7 reports the results and provides evidence that soil heterogeneity is negatively related to DPS adoption even when we control for land use. The coefficient (-1.667) is about 15% smaller than the one from the preferred OLS specification (-1.991) and similar to the other OLS estimates in Table 4. The robustness of the baseline OLS results to additional controls reinforces the interpretation that social learning is the mechanism that connects soil heterogeneity and DPS adoption.

6.3 Falsification Tests

A potential concern with the interpretation of the results presented in the last section is that soil heterogeneity may be capturing some unobserved geographic or socioeconomic characteristic that are correlated with soil heterogeneity and DPS adoption. This subsection performs

[32] See Karlan et al. (2012) for evidence on the importance of financial access to technology adoption.

two falsification tests that reinforce the interpretation that soil heterogeneity reduces DPS adoption by limiting social learning about agricultural practices.

We first estimate the unconditional quantile relationship between soil heterogeneity and the share of farms with access to electricity. Since soil heterogeneity limits social learning in agriculture, it should have no impact on access to electricity (or in any other non-agricultural technology). The results presented in Figure 5 provide evidence that soil heterogeneity is unrelated to access to electricity. The estimated coefficient of soil heterogeneity using access to electricity as the dependent variable is neither statistically different from zero nor is higher at intermediate adoption levels.

We then estimate the unconditional quantile relationship between soil heterogeneity and the share of farms that use a harvester. Since soil heterogeneity limits social learning about the DPS, it should have no impact on harvester use since harvesting methods are unchanged with DPS adoption. The results presented in Figure 6 provide evidence that soil heterogeneity is unrelated to use of harvester. The estimated coefficient of soil heterogeneity with harvester use as the dependent variable is neither statistically different from zero nor is higher at intermediate adoption levels.

Overall, the falsification tests reinforce the interpretation that soil heterogeneity reduces DPS adoption by limiting social learning. Alternative explanations based on the correlation between soil heterogeneity and some omitted factors that limit technology adoption or agricultural development do not seem to play a role. Neither soil heterogeneity is related to the use of a non-agricultural technology nor it is related to the use of agricultural technologies that are unaffected by DPS adoption.

7 Conclusion

Technology adoption is the object of extensive research in economics due to its importance to economic development. Existing evidence points out that social learning plays an important role in inducing technology adoption. However, social learning can be deterred by the existence of large geographic differences across potential adopters. We examine whether geographic differences deter social learning and reduce technology adoption using evidence from the adoption of the Direct Planting System (DPS) in Brazil.

The DPS is particularly relevant for several reasons. It is a production technique with both public and private gains: Greenhouse gas emissions are lower and productivity is higher. It is also a production technique with no upfront costs and little change in input use. The main constraint to adoption is the nneed to learn how to operate the system - a knowledge that disseminates mostly through learning-from-peers, since extension services and underdeveloped in Brazil. Therefore, the context in which DPS adoption takes place is unique in the sense that the correlation between geographic heterogeneity and under-adoption can be traced to learning costs.

We present a simple theoretical model that formalizes the intuition that social learning is weaker when soil heterogeneity is large. The model predicts that adoption rates will be lower when heterogeneity is high. The model also predicts the impact of soil heterogeneity on adoption to be zero when adoption rates are too low (and social learning cannot take place) or when adoption is widespread (and social learning will develop in spite of different geographic characteristics). The impact is predicted to be higher for intermediate adoption rates (when social learning is present but feeble).

The empirical results support the model predictions. Our index of soil heterogeneity decreases DPS adoption and the impact is higher at intermediate adoption rates. The result holds even when we include as controls an exhaustive set of alternative determinants of technology adoption stressed in the literature. Robustness exercises provide further support to the relationship using alternative heterogeneity indexes and samples. We interpret our results as evidence that geographic diversity reduces technology adoption by deterring social learning. We also provide evidence that other learning channels do not mitigate the impact of soil heterogeneity on adoption but rather increase it by rising DPS adoption to levels where the relationship between soil heterogeneity and technology adoption is more important.

The paper contributes to the social learning literature. It provides evidence that social learning can be deterred by heterogeneity across adopters as suggested theoretically by Ellison and Fudenberg (1993) and empirically by Munshi (2004). It uses a methodological approach based on the distinctive footprint that social learning leaves on the relationship between soil heterogeneity and adoption to identify its presence. The methodology can be used to identify social learning even when data on social networks is unavailable.

The findings have important implications for policies aimed at promoting technology adoption. Providing temporary learning facilities to farmers may induce substantial diffusion through social networks in homogeneous areas. However, information provision should be sustained for longer periods in heterogeneous areas as social learning can be substantially weaker.

References

Acemoglu, Johnson, Robinson, 2002. Reversal of fortune: geography and institutions in the making of the modern world income distribution. The Quarterly Journal of Economics.

Alsan, 2012. The impact of the tsetse flight on african development, working Paper.

Alvarenga, Cruz, Hernani, Novotny, Pereira, Filho, P., Santana, 2006. Sistema plantio direto, working Paper.

Bandiera, Rasul, 2006. Social networks and technology adoption in northern mozambique. Economic Journal 116.514, 869–902.

Camargo, Junior, M., Wendling, 2011. Sistema de plantio direto na conservação do solo e água e recuperação de áreas degradadas, working Paper.

Comin, Ferrer, 2013. If technology has arrived everywhere, why has income diverged? Nber Working Paper Series.

Conley, Udry, 2010. Learning about a new technology: pineapple in ghana. American Economic Review 100.1, 35–69.

Derpsch, 1997. Historical review of no-tillage cultivation of crops, working Paper.

Derpsch, 1999. Frontier in conservation tillage and advances in conservation practice, working Paper.

Derpsch, Friedrich, Kassam, 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.

Derpsch, Moriy, 1998. Implications of no-tillage versus soil preparation on sustainability of agricultural production, working Paper.

Diamond, J., 1997. Guns, Germs, and Steel: The Fates of Human Societies. W. W. Norton and Company.

Durante, 2010. Risk, cooperation and the economic origins of social trust: an empirical investigation, working Paper.

Ellison, G., Fudenberg, D., 1993. Rules of thumb for social learning. Journal of Political Economy, 612–643.

EMBRAPA, 2011. O novo mapa de solos do brasil. MAPA.

Fenske, 2012. Ecology, trade and states in pre-colonial africa, working Paper.

Firpo, Fortin, Lemieux, 2009. Unconditional quantile regressions. Econometrica.

Foster, Rosenzweig, 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. The Journal of Political Economy, 1176–1209.

Foster, Rosenzweig, 2010. Microeconomics of technology adoption, working Paper.

Inoue, 2003. Sistema de preparo do solo e o plantio direto no brasil. Agropecuária Técnica.

Jackson, M., 2008. 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 (3), 289–316.

Karlan, Osei, Osei-Akoto, Udry, 2012. Agricultural decisions after relaxing credit and risk constraints, working Paper.

Keller, Yeaple, 2013. The gravity of knowledge. American Economic Review 103(4), 1414–1444.

Koenker, Basset, 1978. Regression quantiles. Econometrica, 33–50.

Landers, 2005. Plantio direto. histórico, características e benefícios do plantio direto, working Paper.

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.

Santos, 2006. Sistema Brasileiro de Classificação de Solos. EMBRAPA.

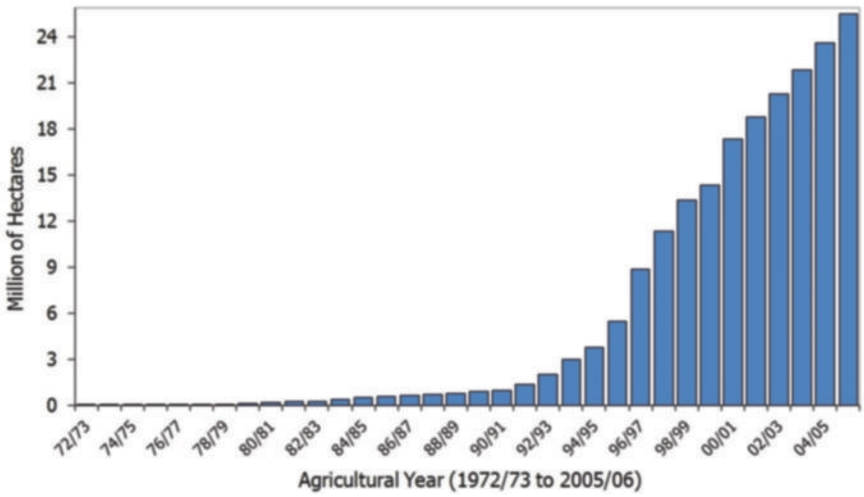
Sorrenson, Portillo, 1997. Paraguay soil conservation project. economic of no-tillage and crop rotations policy and investment implications, working Paper.

Udry, 2010. The economics of agriculture in africa: Notes on a research program. African Journal of Agricultural and Resource Economics.

UFRPE, G., 2009. Inovação tecnológica na agricultura: o caso do plantio direto, working Paper.

Young, 2009. Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning. The American Economic Review 99.5, 1899–1924.

FIGURE 1: Diffusion of the Direct Planting System



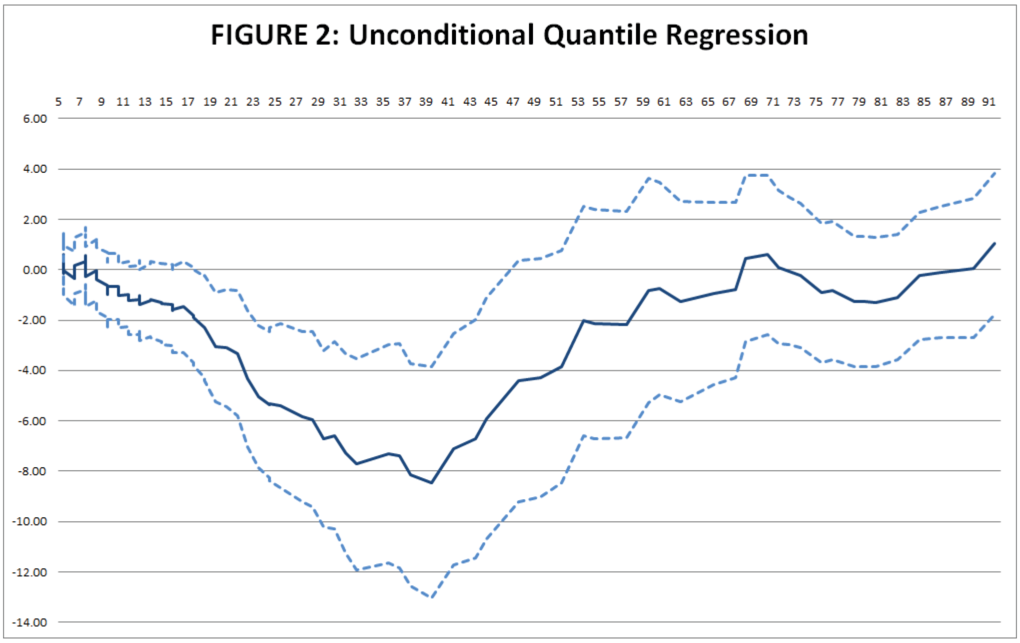


Figure 2. Unconditional Quantile Regression

The solid line reports the estimated coefficients for the soil heterogeneity variable for different adoption levels and the dashed lines report the confidence intervals. The regressions are estimated using the unconditional quantile regression method proposed by Firpo et al (2009) and the included controls and the sample are the same from Table 4, Column 4.

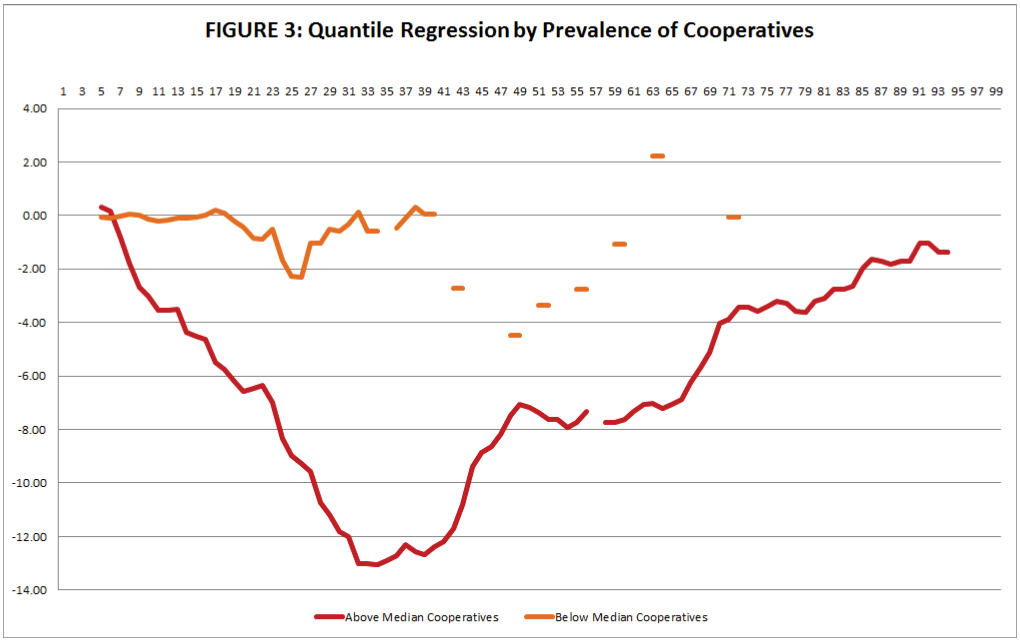


Figure 3. Quantile Regression by Prevalence of Cooperatives

The solid lines report the estimated coefficients for the soil heterogeneity variable for different adoption levels using the same method and specifications used in Figure 2. "Below Median Associations" (orange line) refers to a subsample of municipalities in which the share of farmers associated with a cooperative is below the sample median. "Above Median Associations" (red line) refers to a subsample of municipalities in which the share of farmers associated with a cooperative is equal or above the sample median.

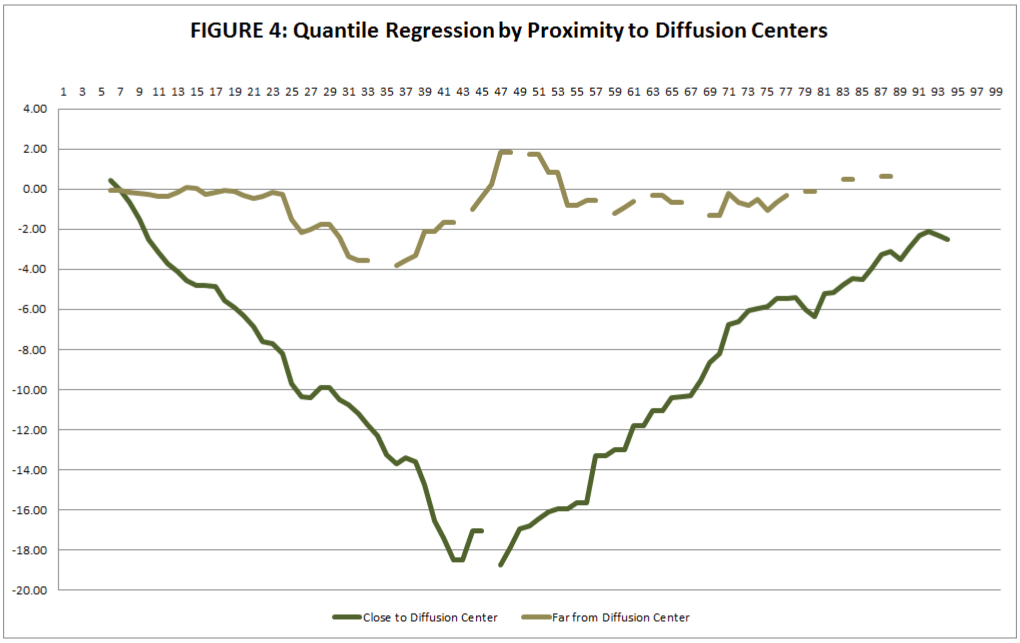


Figure 4. Quantile Regression by Proximity of Diffusion Centers

The solid lines report the estimated coefficients for the soil heterogeneity variable for different adoption levels using the same method and specifications used in Figure 2. "Far from Diffusion Centers" (light green line) refers to a subsample of municipalities which are located more than 246 kilometers from a diffusion center. "Close to Diffusion Centers" (dark green line) refers to a subsample of municipalities which are located at 246 or less kilometers from a diffusion center.

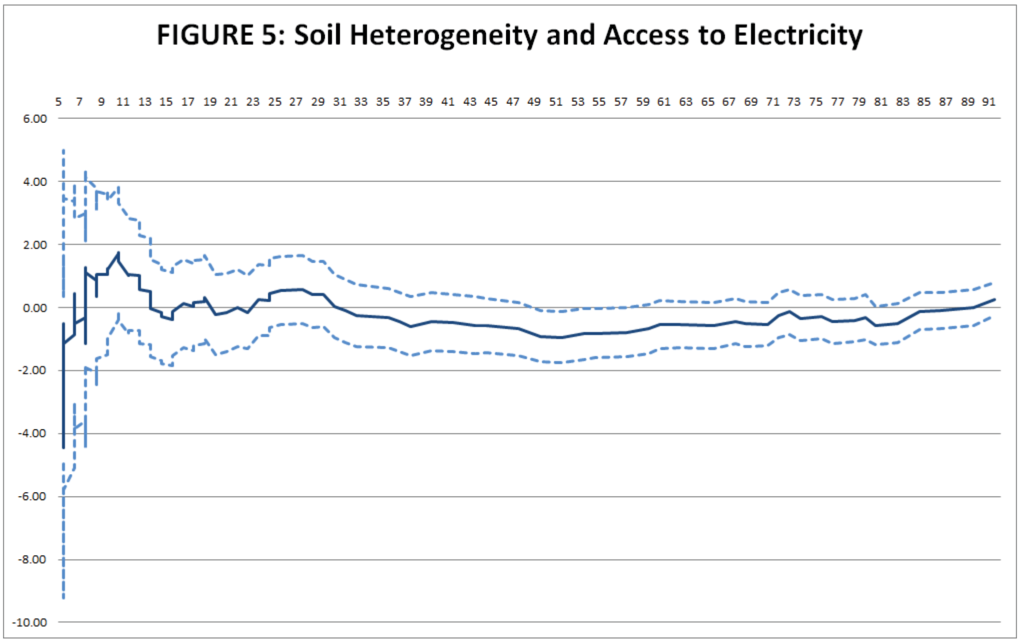


Figure 5. Soil Heterogeneity and Electricity Use

The solid line reports the estimated coefficients for the soil heterogeneity variable for different quantiles of electricity use and the dashed lines report the confidence intervals. The regressions are estimated using the unconditional quantile regression method proposed by Firpo et al (2009) and the included controls and the sample are the same from Table 4, Column 4.

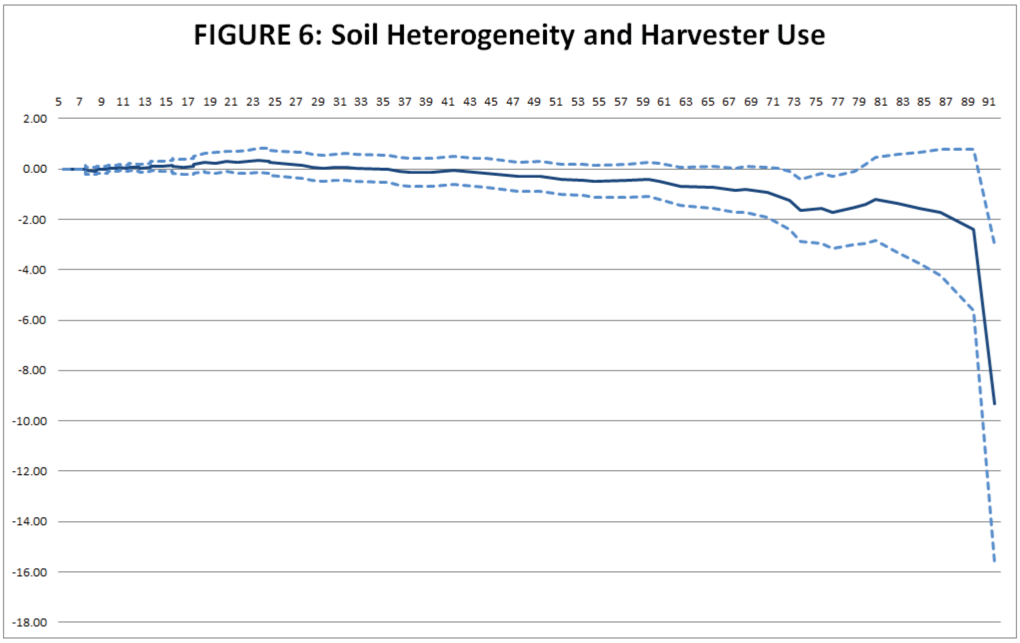


Figure 6. Soil Heterogeneity and Harvester Use

The solid line reports the estimated coefficients for the soil heterogeneity variable for different quantiles of harvester use and the dashed lines report the confidence intervals. The regressions are estimated using the unconditional quantile regression method proposed by Firpo et al (2009) and the included controls and the sample are the same from Table 4, Column 4.

Table 1: Costs and Benefits from the Direct Planting System

	Costs	Benefits
PANEL A: Public		
Agricultural / Environmental		Lower carbon emission to the atmosphere Increase of carbon and nitrogen stocks Increased biodiversity Reduction in environmental contamination
PANEL B: Private		
Economic	Increased cost of herbicides	Lower fuel Consumption Agricultural Machinery lasts longer Lower fertilizer consumption
Agricultural / Environmental	Lower germinative capacity of plants	Lower evaporation and lower soil temperature Roots of seeds reach greater depths Time reduction of soil preparation Smaller water loss through evaporation Increased soil organic matter Less water and soil shedding Lower thermal ad hydraulic amplitude Reduction of erosion losses Increase of life in soil (maily earthworms) Soil protection against solar radiation Reduction of time between harvest and sowing

Table 2: Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Panel A: Main variable					
Soil Heterogeneity	1714	1,69	0,69	1,00	7,89
Panel B: Geographic Controls					
Average monthly rainfall in the summer	1714	175,34	55,35	36,51	471,10
Average monthly rainfall in the autumn	1714	119,51	57,28	14,49	456,12
Average monthly rainfall during the winter	1714	84,91	53,21	3,31	222,74
Average monthly rainfall during the spring	1714	140,71	54,22	6,86	383,66
Average temperature in the summer	1714	23,51	1,89	18,10	28,42
Average temperature in the autumn	1714	19,54	3,99	12,68	27,69
Average temperature in the winter	1714	18,90	4,59	11,14	28,69
Average temperature in the spring	1714	22,59	2,91	16,17	29,19
Log of average gradient	1714	12,61	0,66	9,90	14,35
Panel B: Farm Characteristics					
Log of number of farms	1714	6,56	0,90	0,69	9,20
Log of average revenues	1713	2,97	1,46	-1,60	8,38
Log of revenues per hectare	1713	-0,76	1,43	-6,86	4,15
Eight or more years of schooling	1714	24,16	14,47	1,59	86,49
Eleven or more years of schooling	1714	13,32	10,07	0,00	69,57
Access to government provided technical assistance	1714	15,03	15,20	0,00	87,12
Log of the number of tractors	1628	4,77	1,41	1,10	7,86
Panel C: Other Learning Mechanisms					
Producers' Associations	1714	48,58	22,45	0,00	96,08
Distance to Diffusion Center (in 100km)	1714	346,40	307,09	0,00	1977,76

Notes: Calculations exclude observations in which less than 5% of the farms adopts the direct planting system. It also excludes observations with extreme values of soil heterogeity. Rainfall and temperature variables are averages for the period 1971-2010.

Table 3: Adoption Rates per State

State	Direct Planting System Adoption					
	Restricted Sample (adoption equal or above 5%)			Full Sample (all municipalities)		
	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations
Rondônia	7,23	2,38	14	3,60	2,88	52
Acre	15,09	6,07	11	8,28	8,21	22
Amazonas	11,48	6,15	7	1,98	4,09	62
Roraima	8,90	4,29	4	3,21	4,27	15
Pará	13,67	11,18	41	4,94	8,26	142
Amapá	14,90	5,35	3	3,09	6,21	16
Tocantins	11,96	6,31	25	2,83	5,14	139
Maranhão	13,46	8,34	75	5,56	7,62	217
Piauí	14,16	8,33	66	5,05	7,56	221
Ceará	11,84	7,39	49	4,03	6,15	184
Rio Grande do Norte	11,87	5,90	8	1,00	2,87	165
Paraíba	11,90	11,58	34	2,45	6,15	220
Pernambuco	12,62	8,39	36	3,15	6,06	182
Alagoas	12,10	6,11	18	2,89	5,15	101
Sergipe	9,39	4,95	3	0,91	2,13	72
Bahia	9,87	4,78	71	2,50	4,04	414
Minas Gerais	12,86	10,52	193	3,93	7,08	845
Espírito Santo	6,42	1,24	3	1,29	1,59	77
Rio de Janeiro	6,04	1,16	2	1,00	1,42	90
São Paulo	17,24	15,58	83	3,02	7,89	643
Paraná	41,48	23,31	306	32,27	26,47	398
Santa Catarina	42,85	26,11	214	32,11	28,88	289
Rio Grande do Sul	52,88	30,00	341	39,12	34,29	466
Mato Grosso do Sul	19,99	16,79	28	8,06	13,66	76
Mato Grosso	22,49	19,16	34	6,88	13,74	126
Goiás	17,58	14,30	44	3,95	8,91	241
Federal District	13,48	-	1	13,48	-	1
BRAZIL	30,14	26,48	1714	10,17	20,06	5476

Notes: Percentage of farms which adopts the direct planting system in each state. Calculations exclude observations in which soil heterogeneity is higher than ten.

Table 4: OLS Regressions

Dependent Variable	Direct Planting System Adoption Rate				
	Bivariate Relationship	Geographic Controls	State FE	Farm Characteristics	Learning Mechanisms
	(1)	(2)	(3)	(4)	(5)
Soil Heterogeneity	-7.282***	-1.538**	-1.802***	-1.991***	-1.524**
	(0.796)	(0.686)	(0.659)	(0.699)	(0.685)
Log of land gradient		-2.136**	-1.903**	-0.830	-1.427
		(0.979)	(0.915)	(0.963)	(0.938)
Altitude		-0.005*	0.005*	0.005	0.006*
		(0.003)	(0.003)	(0.003)	(0.003)
Latitude		0.006	1.820***	2.380***	1.827***
		(0.368)	(0.474)	(0.497)	(0.508)
Longitude		-0.382***	-0.560*	-0.641*	-0.215
		(0.147)	(0.324)	(0.346)	(0.327)
Log of number of farms				-3.890***	-4.534***
				(0.886)	(0.883)
Log of average revenues				-0.374	-0.443
				(0.587)	(0.567)
Eight or more years of schooling				0.139	0.114
				(0.120)	(0.115)
Eleven or more years of schooling				-0.305*	-0.307*
				(0.172)	(0.161)
Access to government provided technical assistance				-0.009	-0.029
				(0.038)	(0.037)
Log of number of tractors				3.788***	3.594***
				(0.706)	(0.694)
Share of farmers associated to a co-op					0.289***
					(0.026)
Distance to diffusion center (in 100 kilometers)					-0.006
					(0.175)
Soil Types	N	Y	Y	Y	Y
Rainfall and Temperature	N	Y	Y	Y	Y
State FE	N	N	Y	Y	Y
Observations	1.714	1.714	1.714	1.628	1.628
R-squared	0,036	0,594	0,651	0,671	0,698

Notes: Sample includes all municipalities for which adoption rates are above 5% and for which soil heterogeneity does not take extreme values. Robust standard errors in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 5: Learning Mechanisms

Dependent Variable	Direct Planting System Adoption Rate		
	Cooperatives	Diffusion Centers	All
	(1)	(2)	(3)
Soil Heterogeneity	0.4601	-1.8519***	0.6130
	(0.7356)	(0.7092)	(0.7441)
Prevalence of producers' association	17.8206***		17.8463***
	(2.2814)		(2.2746)
Prevalence of producers' associations x Soil Heterogeneity	-5.0966***		-5.0971***
	(1.1359)		(1.1348)
Close to Diffusion Center		11.7941**	12.9629**
		(5.9396)	(5.2276)
Close to Diffusion Center x Soil Heterogeneity		-6.3716**	-6.9551**
		(3.1081)	(2.7341)
Geographic Characteristics	Y	Y	Y
State FE	Y	Y	Y
Farm Characteristics	Y	Y	Y
Observations	1.628	1.628	1.628
R-squared	0,693	0,671	0,693

Notes: Sample includes all municipalities for which adoption rates are above 5% and for which soil heterogeneity does not take extreme values. Prevalence of producers' assocations is a dummy variable which takes value one when the share of producers who belong to a producers' assocation is above the sample median. Close to Diffusion Center is a dummy variable which takes value one when the distance from the municipality to the nearest diffusion center is below the sample median. Robust standard errors in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 6: Alternative Heterogeneity Measures and Alternative Samples

Dependent Variable	Direct Planting System Adoption Rate			
	Alternative Soil Heterogeneity		Alternative Samples	
	More detailed soil classification	Including heterogeneity in neighbouring municipalities	Full Sample	Positive Adoption
	(1)	(2)	(3)	(4)
Soil Heterogeneity	-1.845***	-5.140***	-0.965***	-1.010***
	(0.500)	(1.085)	(0.259)	(0.296)
Geographic Controls	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Farm Characteristics	Y	Y	Y	Y
Observations	1.628	1.628	5.060	4.308
R-squared	0,671	0,674	0,671	0,674

Notes: Sample includes all municipalities for which adoption rates are above 5% and for which soil heterogeneity does not take extreme values. Neighbours' Soil Heterogeneity I is the mean value of the neighbouring municipalities soil heterogeneity weighted by each municipality area. Neighbours' Soil Heterogeneity II is also the mean value of the neighbouring municipalities soil heterogeneity but now weighted by the length of the frontier between the municipality and its neighbours. Robust standard errors in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 7: Land Distribution, Credit and Access to Markets

Dependent Variable	Direct Planting System Adoption Rate			
	Land Distribution	Bank Branches	Total debt	Access to Markets
	(1)	(2)	(3)	(4)
Soil Heterogeneity	-1.734**	-2.026***	-1.912***	-1.667***
	(0.689)	(0.702)	(0.698)	(0.574)
Banco do Brasil Bank Branches		1.230	1.160	0.170
		(0.825)	(0.803)	(0.678)
Other Bank Branches		-0.178	-0.165	-0.012
		(0.131)	(0.127)	(0.108)
Log of average farm debts			3.574***	2.383***
			(0.518)	(0.485)
Share of farmland cultivated with soy				0.513***
				(0.072)
Share of farmland cultivated with maize				0.112***
				(0.041)
Share of farmland cultivated with sugarcane				-0.036
				(0.039)
Share of farmland cultivated with rice				-0.096
				(0.149)
Share of farmland cultivated with beans				-0.249***
				(0.050)
Share of farmland cultivated with cotton				-0.423
				(0.279)
Geographic Characteristics	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Farm Characteristics	Y	Y	Y	Y
Land Distribution Controls	Y	N	N	N
Observations	1.628	1.628	1.619	1.619
R-squared	0,693	0,671	0,684	0,764

Notes: Sample excludes municipalities for which soil heterogeneity does not take extreme values. Robust standard errors in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.