*Land Economics* 95(4), November 2019
"Geographic Heterogeneity and Technology Adoption: Evidence from Brazil,"
by Juliano Assunção, Arthur Bragança, and Pedro Hemsley

# Appendix

## A.1 Adoption Rates per State

In this section, we further discuss the distribution of DPS adoption across the country. Table A2 reports the DPS adoption rates per state in the group of municipalities used in the regressions presented in the text (adoption rate above 5%) and in all municipalities. The mean DPS adoption is 30% in the former group and 10% in the latter.

The DPS is more disseminated in the states of Rio Grande do Sul, Paraná and Santa Catarina (in the South of Brazil). The DPS adoption rate is higher than 5% in approximately three quarters of the municipalities located in these states. The average DPS adoption ranges between 40-50% in the municipalities used in the regressions and 30-40% in all municipalities. The diffusion of the DPS in these states is expected since the DPS was originally developed to help farmers from the South of Brazil to cope with soil erosion.

This technology is much less disseminated in other states of Brazil. In the group of municipalities used in the regressions, the average DPS adoption rate ranges between 6-22%. Adoption is higher in the crop producing areas in the states of São Paulo (in the Southeast of Brazil) and Goiás, Mato Grosso do Sul and Mato Grosso (in the Center-West of Brazil) and lower in the states of Espírito Santo and Rio de Janeiro (in the Southeast of Brazil) and Sergipe (in the Northeast of Brazil).

It is important to note that there is more than one municipality included in the regressions in all states but the Federal District (which is not divided in municipalities as the other states). This implies our empirical design is using information from all states even when we include state fixed effects in the regressions.

## A.2 Selection on Observables vs. Selection on Unobservables

In this section, we use Oster (2017)'s method to evaluate the likelihood that the correlation between heterogeneity and (unobserved) geographic determinants of technology adoption drives the results discussed in the text. Let $\beta^S$ be the coefficient on soil heterogeneity of a "short" regression including a restricted set of geographic controls and $\beta^L$ the coefficient on soil heterogeneity of a "long" regression including the full set of geographic controls and $R^S$ and $R^L$ the R-Squared from these regressions.

Following Oster(2017), we can approximate the true effect of soil heterogeneity by

$$\beta \sim \beta^L - \delta(R_{max} - R^L)\left(\frac{\beta^L - \beta^S}{R^S - R^L}\right)$$

in which $\delta$ is the relative importance of selection on unobservables to selection on observables and $R_{max}$ is the R-Squared of a hypothetical of regression of adoption on soil heterogeneity controlling for all observed and unobserved geographic characteristics correlated with soil heterogeneity.

The expression above indicates how the ratio of the differences between coefficients and R-Squared from "short" and "long" regressions is informative about the relative size of the two types of selection needed for the effect of soil heterogeneity to be zero. It also indicates this ratio might be used to compute bounds on the coefficient on soil heterogeneityunder different assumptions on $\delta$.

Oster (2017) shows that the exact relationship between the bias and the relative importance of the different types of selection can be derived combining the coefficients and R-Squared from "short" and "long" regressions with information about the variances and covariances of the dependent variable, the variable of interest and the controls.

Table A3 uses this exact relationship to compute the relative size of the two types of selection needed for the effect of soil heterogeneity to be zero under different hypothesis on $R_{max}$. The specification from Table 2, column 1 is used as the "short" regression and the specification from Table 2, column 5 as the "long" regression. Column 1 reports results obtained under the hypothesis $R_{max} = 1$; column 2 under the hypothesis $R_{max} = 1.5 \times R^L$; column 3 under the hypothesis $R_{max} = 1.4 \times R^L$; and column 4 under the hypothesis $R_{max} = 1.3 \times R^L$.[1]

We find that selection on unobservables would need to be between 2.87 to 4.97 times the size of the selection on observables to drive the effect of heterogeneity to zero. Hence, it is unlikely that the effects discussed in the text are driven by (unobserved) geographic determinants of technology adoption that are correlated with soil heterogeneity.

Table A4 uses this relationship to compute bias-adjusted coefficients of interest for $\delta = 1$. Columns 1-4 report results obtained using the same assumptions on the maximum R-Squared used in Table A3. Again, the specification from Table 2, column 1 is used as the "short" regression and the specification from Table 2, column 5 as the "long" regression. The coefficients on soil heterogeneity are remain negative in all columns. Their magnitude ranges between 1.73 and 1.94 depending on the value of $R_{max}$. This implies that allowing for selection on unobservables of equal importance than selection on observables reduces the effect of soil heterogeneity on DPS adoption in less than 20%. We interpret these estimates as lower bounds of the effect of soil heterogeneity on DPS adoption.

## A.3 Mechanisms

Figure 3 provides evidence that the effect of soil heterogeneity is not mediated by other common economic determinants of technology adoption like farm size, mechanization, training, technical assistance or credit. Table A5 presents the numerical estimates of the conditional direct effects reported in this figure. The effects are statistically significant and their sizes are comparable to the size of the total effect reported in Table 2.

Nevertheless, as discussed in section 5, the sequential g-estimator of the conditional direct effects used to identify the importance of different mechanisms is consistent only under the stringent hypothesis of "sequential unconfoundedness". Thus, we examine the sensitivity of the results to deviations from this hypothesis. Acharya et al.(2016) shows the bias of the sequential g-estimator is a function of observed quantities and the correlation between the error terms of the following structural equations:

$$A_i = \alpha_0 + \alpha_1 S_i + \gamma_1 M_i + \gamma_2' \boldsymbol{X}_i + \gamma_3' \boldsymbol{W}_i + \epsilon_i$$

$$M_i = \beta_0 + \beta_1 S_i + \delta_1' \boldsymbol{X}_i + \delta_2' \boldsymbol{W}_i + \nu_i$$

Denote the correlation between $\epsilon_i$ and $\nu_i$ by $\rho$. If $\rho = 0$, "sequential unconfoundedness" is not violated. However, if $\rho \neq 0$, "sequential unconfoundedness" is violated and the sequential g-estimator of the conditional direct effects has an asymptotic bias proportional to this correlation. This implies it is possible to test the sensitivity of the results reported in the text to different values of $\rho$.

Figures A1, A2, A3 report the results of sensitivity analysis of the conditional direct effects. For seven of the nine mediators considered, the results from Figure 3 are robust to arbitrary values for $\rho$. For the number of farms (Figure A1, Panel A), the conditional effect of soil heterogeneity goes to zero if the correlation between unobserved determinants of DPS use and of the number of farms is higher than 0.10. For technical assistance (Figure A2, Panel B), the conditional effect of soil heterogeneity goes to zero if the correlation between unobserved determinants of DPS use and of technical assistance is lower than -0.25. In these cases, these variables will drive the relationship between heterogeneity and technology use we document.

However, we believe it is unlikely these correlations are in the range required for this to occur. On the one hand, the number of farms is extremely persistent and unlikely to be connected to technology use other than through geographic factors (which are observed). On the other hand, the correlation between unobserved determinants of technology use and technical assistance is probably positive and not negative.

## A.4 Robustness to Spatial Correlation and Weighting Procedures

Section 5 shows that the results are robust to changes in the definition of soil heterogeneity and changes in the sample selection. In this section, we provide further evidence of the robustness of the results to the existence of spatial correlation in the error term and to the use of weights in the regressions.

**Standard Errors**. Table A6 re-estimates the specifications from Table2using the method proposed by Conley(1999) to consistently estimate standard errors in the presence of spatial correlation in the error term. This method is built on the hypothesis that the correlation in the error term of two units is inversely related to their distance. This enables the construction of a spatial weights matrix that can be used to compute consistent standard errors. To build this matrix, we must define distance cutoffs. These cutoffs determine the maximum distance between units for the correlation between their error terms be different from zero. We calculate standard errors allowing for spatial correlation of the error term using 50, 100, and 150 kilometers cutoffs. The results continue significant at the usual statistical levels regardless the cutoff used.

**Weights**. Table A7 re-estimates the specifications from Table 2 weighting observations using measures of municipality size. Panel A weights observations using the municipality area, while Panel B using the municipality farmland. Regardless the choice of weights, the coefficients on soil heterogeneity continue negative and statistically significant at the usual levels. The magnitude of the coefficients increases between 10% and 80% depending on the specification.

## A.5 Theoretical Framework

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

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

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

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

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

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

$$N(\theta_i) = \{\theta_j : d(\theta_i, \theta_j) < R\} \qquad (A.1)$$

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

$$N_A(\theta_i) = \{\theta_j : d(\theta_i, \theta_j) < R \text{ and } a_j = 1\} \qquad (A.2)$$

This set has mass $M(N_A(\theta_i)) = \int_{N_A(\theta_i)} g(\theta_i) d(\theta_i)$. We can thus define the adaptation costs for non-adopters as $c\left(M(N_A(\theta_i))\right)$, a decreasing function of this mass. This cost is equal to zero for adopters. It should be noted that adopters will never switch from the new technology to the traditional one because the adoption cost is paid once and $\Delta\pi > 0$. This model's feature implies that the set of adopters never decreases, distinguishing our adoption environment from other environments in which adoption costs are paid in all periods and changes in these costs induce switching behavior.[3]

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

We can therefore describe adoption choices using the following rule:

$$a_i = 1 \Leftrightarrow \Delta\pi > c\left(M(N_A(\theta_i))\right) \qquad (A.3)$$

Equation A.3 enables us to characterize the model's equilibrium and its comparatives statistics. We introduce additional assumptions that will facilitate the equilibrium characterization. First, we introduce an assumption on the adoption distribution. Define $\overline{M} = c^{-1}(\Delta\pi)$ as the lowest mass of adopters that enables diffusion and define $\overline{M}^U =$

$M\left(N_A^0(\theta_i)\right)$ as the initial mass of adopters under the uniform distribution in the same neighborhood.[4] We assume that $\overline{M} > \overline{M}^U$, which implies that the initial adoption rate cannot trigger diffusion when the distribution is flat. Therefore, the diffusion process cannot be reduced to a contagion model because it is not enough to have adopters in the neighborhood. Second, we introduce restrictions on the cost function. We assume that $c(0) > \Delta\pi$ and that $c(m) < \Delta\pi$ for some $m < 1$. The former condition ensures we are modeling technology diffusion, whereas the latter ensures the technology is viable.

Let an allocation be a vector of adoption choices $\{a_i\}_i$. The model's equilibrium is the set of allocations $\{a_i^*\}_i$ for which equation A.3 is valid.

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

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

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

The model also predicts that soil heterogeneity will not affect adoption when adoption rates are either too low or too high. In the former case, adoption is so limited that there will not exist enough adopters to learn from at all levels of soil heterogeneity. In the latter, the opposite situation occurs, and there will exist enough adopters to learn from regardless soil heterogeneity. For intermediate adoption levels, the impact of soil dissimilarities will be the highest.[5] The following proposition establishes this result:

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

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

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

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

It is worth highlighting a more general interpretation of the model above. Adaptation costs may depend on previous adoption or, more generally, on the existing stock of knowledge about the new technology. Previous adoption adds to this stock, but it is not the only possibility: agronomic research may develop an adaptation to a specific soil even in the absence of any adopters. Again, the results above go essentially unchanged as long as one interprets "mass of adopters" as "mass of types of soil for which the new technology has been adapted for".[6]

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

## A.6 Heterogeneous Effects across Adoption Rates

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

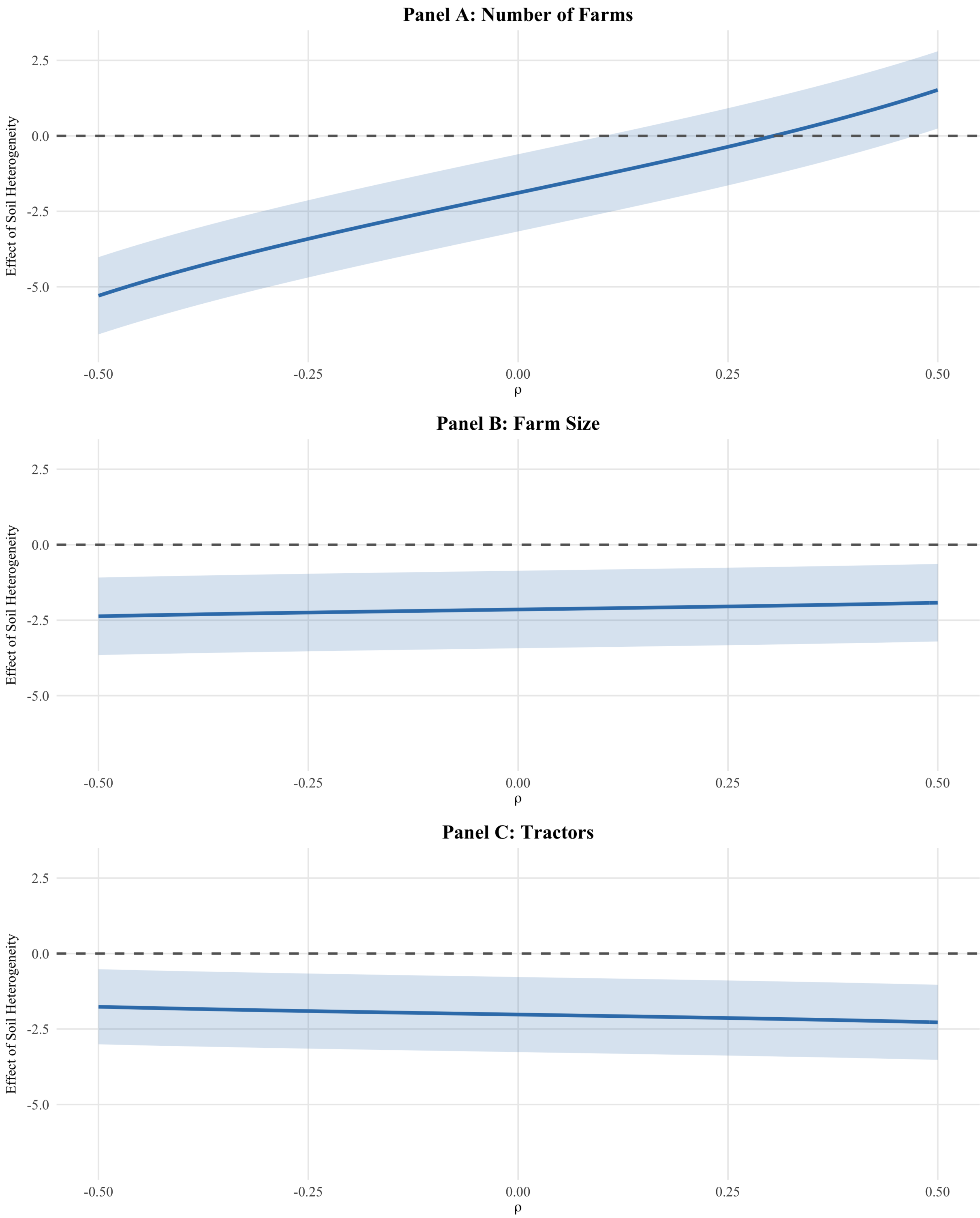
In this section, we address this issue using the estimator developed by Firpo et al. (2009). The authors use a simple estimation method that involves OLS estimation to compute unconditional quantile effects of a regressor on the dependent variable. This estimator is based on the concept of influence function. The influence function $IF(A, \nu, F_A)$ of a distributional statistic $\nu(F_A)$ is the influence of an individual observation on that statistic. The IF can be used to compute the Re-centered Influence Function (RIF) can be de- fined as $RIF(A, \nu, F_A) = \nu(F_A) + IF(A, \nu, F_A)$ for a general distributional statistic and as $RIF(A, q_\tau, F_A) = q_\tau + IF(A, q_\tau, F_A)$ for the $\tau$th quantile of the distribution of the dependent variable.

Firpo et al.(2009) prove that the marginal effect of a change in the distribution of co-variates on the unconditional quantile of the distribution of the dependent variable is the coefficient from a regression of $RIF(A, q_\tau, F_A)$ on the covariates. Therefore, we can estimate the impact of soil heterogeneity on technology adoption on the $\tau$th quantile of the distribution of DPS adoption by regressing $RIF(A, q_\tau, F_A)$ on soil heterogeneity and other covariates.[7]

We use this estimator to test whether the impact of soil heterogeneity on DPS adoption is U-shaped. We use the same specification from Table 2, column 5. Figure A4 reports the results and the 95% confidence intervals. The results are consistent with the theoretical model. The impact is zero or small at either low or high adoption rates and negative at intermediate adoption rates. The coefficients are significant and above the average effect for adoption rates ranging from 20 to 50% in the sample (percentiles 50 to 75). The impact of soil heterogeneity on DPS adoption reaches its maximum at the adoption rate of 40%. An increase of one standard deviation in soil heterogeneity decreases DPS adoption by 6.0 percentage points in this quantile. This impact is four times the average impact estimated in the previous section.

Figures A5 report the effect of soil heterogeneity on the adoption of our placebo technologies – electricity and harvester use. For both technologies, we there is no relationship between soil heterogeneity and adoption of these technologies across all quantiles. Together, these results provide further support for the adaptation costs mechanism discussed in the text.

**Figure A1: Sensitivity Analysis (1)**




Notes: The figure reports the sensitivity of the direct effects of soil heterogeneity conditional on the log of the number of farms (Panel A), the log of farm size (Panel B) and the share of farms which owns a tractor (Panel C) to violations of the 'sequential unconfoundedness' assumption. The solid lines plot the coefficients while the light blue area the 95% confidence intervals.

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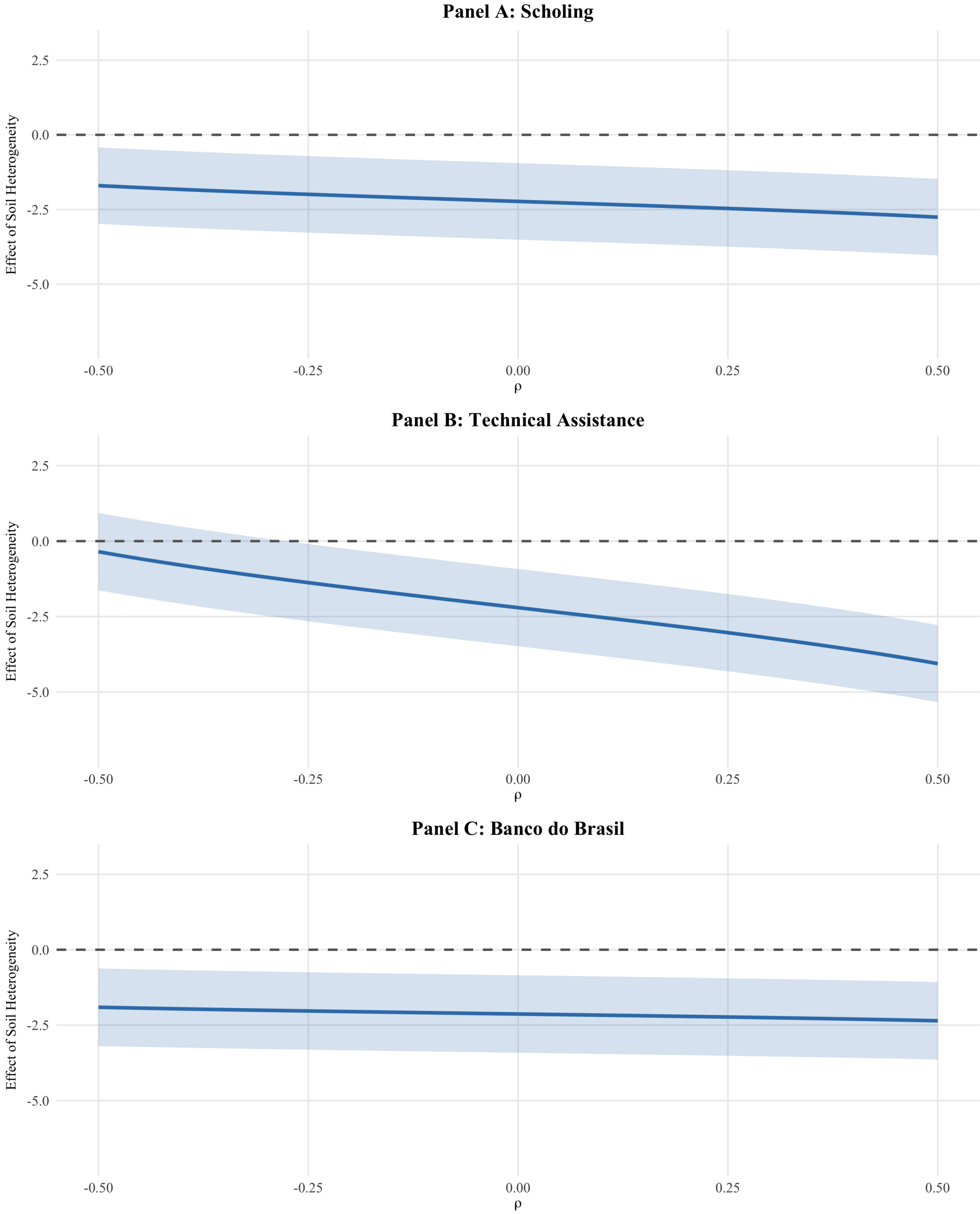
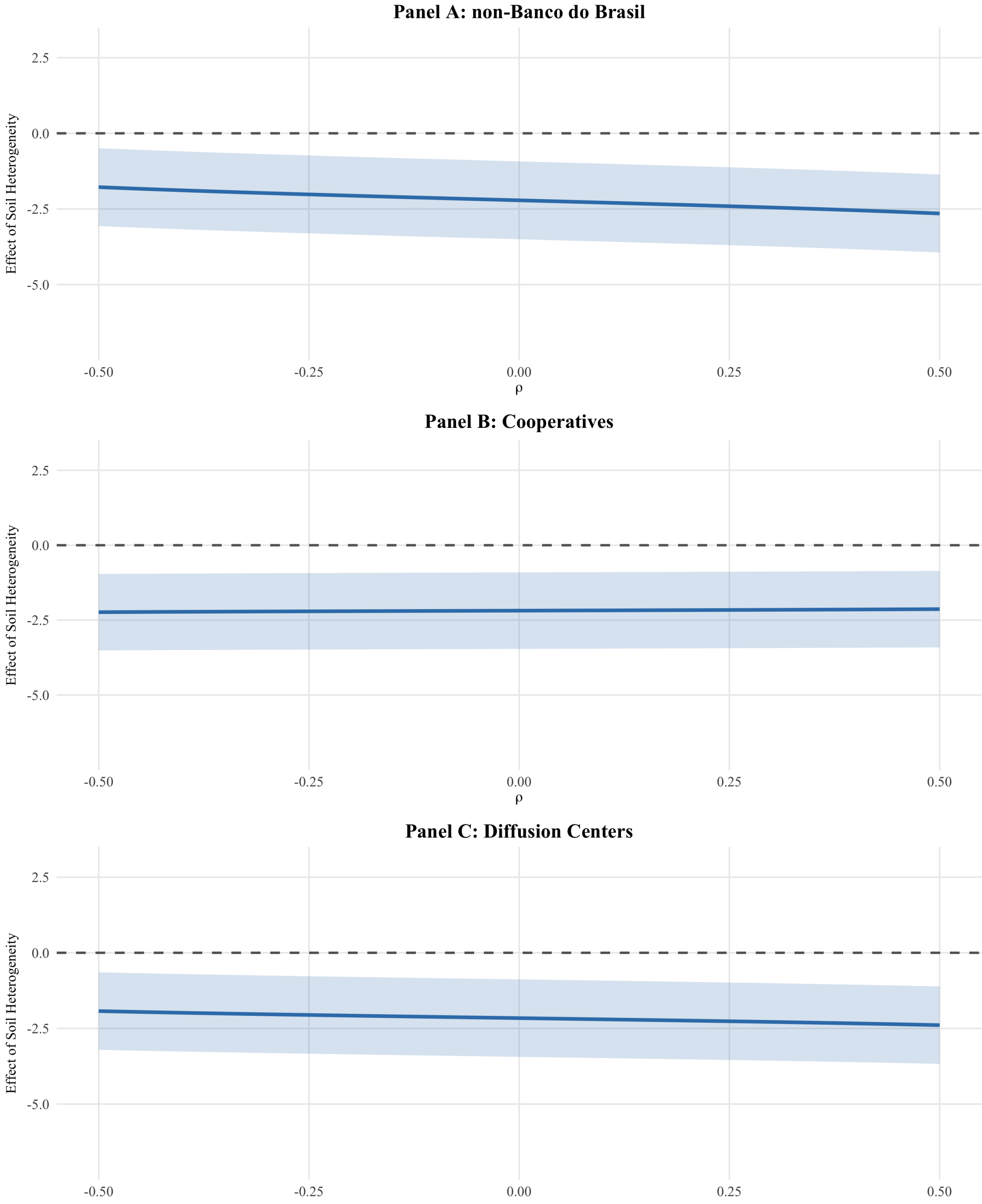
**Figure A2: Sensitivity Analysis (2)**



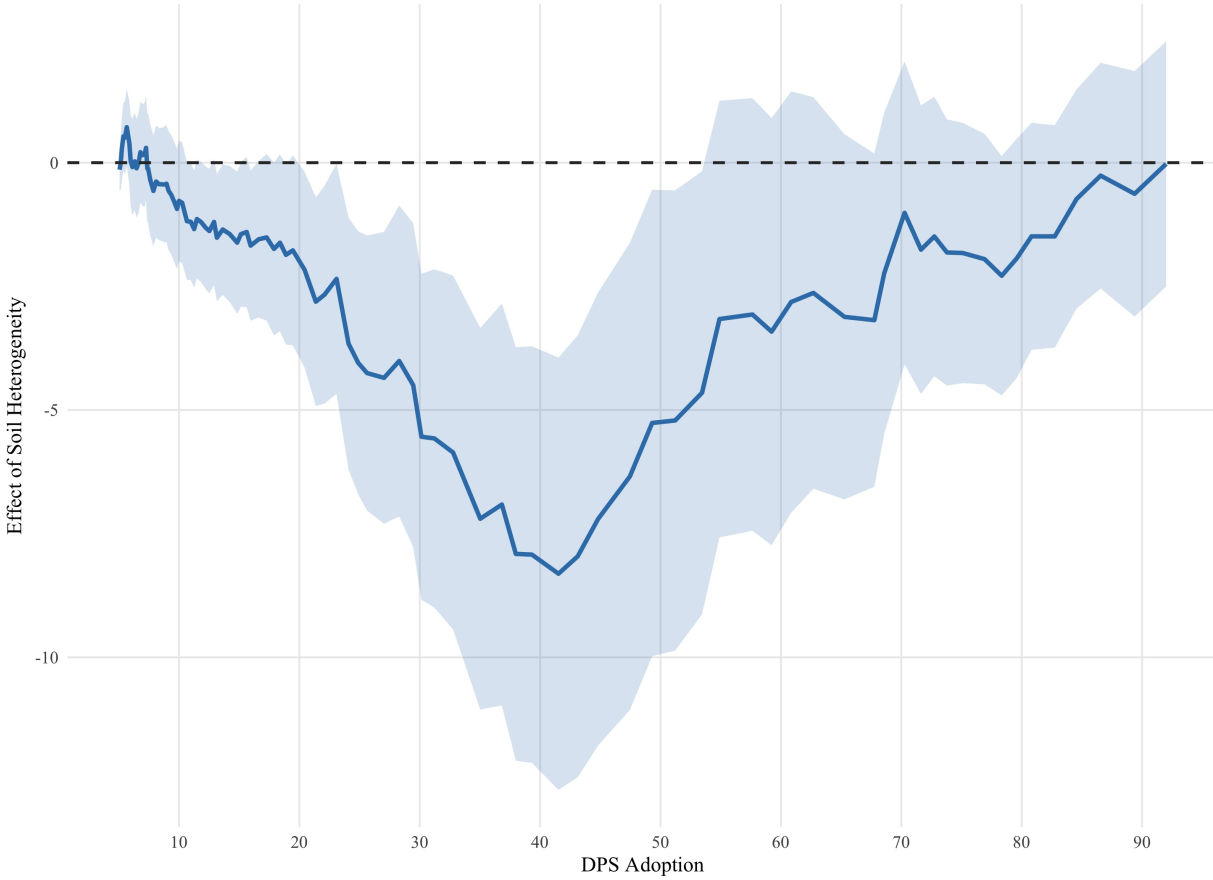

Notes: The figure reports the sensitivity of the direct effects of soil heterogeneity conditional on the share of farmers with 11+ years of schooling (Panel A), the share of farms with access to technical assistance (Panel B) and the number of Banco do Brasil bank branches (Panel C) to violations of the 'sequential unconfoundedness' assumption. The solid lines plot the coefficients while the light blue area the 95% confidence intervals.

**Figure A3: Sensitivity Analysis (3)**



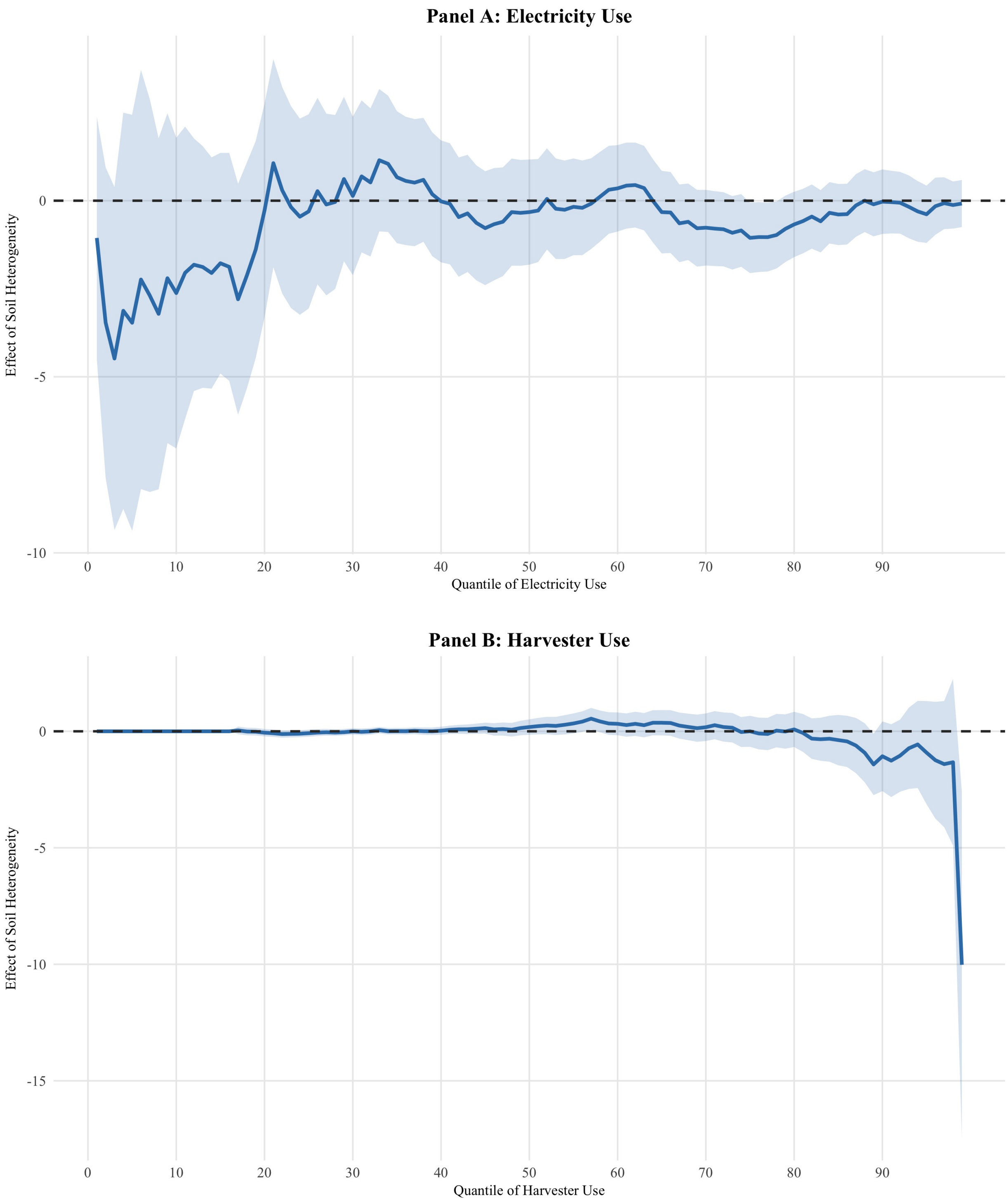

Notes: The figure reports the sensitivity of the direct effects of soil heterogeneity conditional on the number of *non*-Banco do Brasil bank branches (Panel A), the share of farms which belongs to a cooperative (Panel B) and the distance to diffusion centers (Panel C) to violations of the 'sequential unconfoundedness' assumption. The solid lines plot the coefficients while the light blue area the 95% confidence intervals.

**Figure A4: Quantile Effects of Soil Heterogeneity on DPS Adoption**




Notes: The figure reports the effect of soil heterogeneity on DPS adoption for different adoption levels. The blue line plots the coefficients while the light blue area the 95% confidence intervals. The estimates are constructed using the RIF-OLS estimator proposed by Firpo et al. (2009).

**Figure A5: Quantile Effects of Soil Heterogeneity on Placebo Technologies**




Notes: The figure reports the effect of soil heterogeneity on electricity use and harvester use for different adoption levels. The blue line plots the coefficients while the light blue area the 95% confidence intervals. The estimates are constructed using the RIF-OLS estimator proposed by Firpo et al.(2009).

**Table A1: Costs and Benefits from DPS Adoption**

| **Panel A: Public** | Costs | Benefits |
|---|---|---|
| Environmental | | Lower carbon emission<br>Increase in carbon and nitrogen stocks<br>Less contamination |

| **Panel B: Private** | Costs | Benefits |
|---|---|---|
| Economic | Higher herbicide use | Lower fuel consumption<br>Lower fertilizer use<br>Increase in machinery durability<br>Time reduction in soil preparation<br>Time reduction between harvest and sowing |
| Environmental | Lower germinative capacity of plants | Lower evaporation<br>Lower soil temperature<br>Deeper roots<br>Reduction in soil preparation<br>Smaller water loss<br>Increase in organic matter Lower<br>water and soil shedding<br>Lower thermal and hydraulic amplitude<br>Erosion Reduction<br>Soil protection from solar radiation |

**Table A2: Adoption Rate per State**

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

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

**Table A3: Comparing Different Types of Selection**

| | | Size of Selection | | | |
|---|---|---|---|---|---|
| Short | Long | (1) | (2) | (3) | (4) |
| Table 2, column 1 | Table 2, column 5 | 2.86 | 2.95 | 3.73 | 5.07 |
| Maximum R-Squared | | 1.00 | 0.99 | 0.92 | 0.85 |

Notes: The table reports the relative importance of selection on unobservables to selection on observables required to zero the effects from column 5 in Table 2.

**Table A4: Comparing Different Types of Selection**

| | | Effect of Soil Heterogeneity for $\delta = 1$ | | | |
|---|---|---|---|---|---|
| Short | Long | (1) | (2) | (3) | (4) |
| Table 2, column 1 | Table 2, column 5 | -1.73 | -1.74 | -1.85 | -1.94 |
| Maximum R-Squared | | 1.00 | 0.99 | 0.92 | 0.85 |

Notes: The table reports the relative importance of selection on unobservables to selection on observables required to zero the effects from column 5 in Table 2.

**Table A5: Mechanisms**

| | Dep. Var.: DPS adoption | |
|---|---|---|
| | Coef. | S.E. |
| *Effect of soil heterogeneity net of the effect operating through:* | | |
| Number of Farms | -1.739** | (0.794) |
| Farm Size | -2.194*** | (0.795) |
| Tractors | -2.024*** | (0.772) |
| Schooling | -2.128*** | (0.796) |
| Technical Assistance | -2.156*** | (0.795) |
| Bando do Brasil | -2.158*** | (0.794) |
| non-Banco do Brasil | -2.151*** | (0.794) |
| Cooperatives | -2.186*** | (0.795) |
| Diffusion Centers | -2.156*** | (0.795) |

Notes: The table reports the effects of soil heterogeneity on DPS adoption conditional on nine different mediators. All coefficients are computed using the method proposed by Acharya et al.(2016). *** p<0.01; ** p<0.05; * p<0.10

**Table A6: Soil Heterogeneity and Technology Adoption**

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

Notes: The table reports the results from estimating equation (3). The specifications are the same from Table 2. Standard errors allowing for spatial correlation in the error term computed using Conley(1999) are reported in parentheses (50km cutoff), brackets (100km cutoff), and braces (150km cutoff). *** $p<0.01$; ** $p<0.05$; * $p<0.10$

**Table A7: Soil Heterogeneity and Technology Adoption**

| | Dependent Variable: DPS Adoption | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A: Area** | | | | | |
| Soil Heterogeneity | -3.710*** | -2.787*** | -2.578*** | -3.010*** | -2.346** |
| | (0.775) | (0.814) | (0.975) | (1.072) | (1.024) |
| R2 | 0.370 | 0.436 | 0.480 | 0.485 | 0.533 |
| N | 1681 | 1681 | 1681 | 1681 | 1681 |
| **Panel B: Farmland** | | | | | |
| Soil Heterogeneity | -4.311*** | -3.443*** | -3.393*** | -3.458*** | -2.711** |
| | (0.924) | (0.909) | (0.975) | (1.012) | (0.959) |
| R2 | 0.370 | 0.473 | 0.541 | 0.542 | 0.589 |
| N | 1681 | 1681 | 1681 | 1681 | 1681 |
| Soil Types | Yes | Yes | Yes | Yes | Yes |
| Gradient and Altitude | Yes | Yes | Yes | Yes | Yes |
| Agronomic Potential | No | Yes | Yes | Yes | Yes |
| Temperature and Rainfall | No | No | Yes | Yes | Yes |
| Latitude and Longitude | No | No | No | Yes | Yes |
| State FE | No | No | No | No | Yes |

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

[1] We chose these different values of $R_{max}$ to encompass the values used both in the work of Altonji et al. (2005) ($R_{max} = 1$) and the work of Oster (2017) ($R_{max} = 1.3 \times R^L$).

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

[3] See Suri (2011) for one example.

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

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

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

[7] 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 consistent if the distribution of the dependent variable is linear in the explanatory variables. Firpo et al. (2009) provides evidence that estimates obtained using the RIF-OLS are quite similar to those obtained using RIF-Logit (which considers this distribution to be logistic) or RIF-NP (which is non-parametric).