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Arthur Amorim Bragança

Three Essays on Rural Development in Brazil

Tese de Doutorado

Thesis presented to the Postgraduate Program in Economics of the Departamento de Economia, PUC-Rio as a partial fulfillment of the requirements for the degree of Doutor em Economia

Advisor: Prof. Juliano Assunção
Co-advisor: Prof. Claudio Ferraz

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Prof. Juliano Assunção
Advisor
Departamento de Economia - PUC-Rio

Prof. Claudio Ferraz
Co-advisor
Departamento de Economia - PUC-Rio

Prof. Gustavo Gonzaga
Departamento de Economia - PUC-Rio

Prof. Leonardo Rezende
Departamento de Economia - PUC-Rio

Prof. Bernardo Mueller
Departamento de Economia - UnB

Prof. Rodrigo Soares
EESP/FGV

Prof. Mônica Herz
Coordinator of the Centro de Ciências Sociais - PUC-Rio

Rio de Janeiro, August 18, 2014

Arthur Amorim Bragança

Arthur Bragança holds a B.A. in Economics from the Federal University of Minas Gerais (UFMG) and a Ph.D. in Economics from the Catholic University of Rio de Janeiro (PUC-Rio). During his Ph.D. studies, he was a visiting scholar in the Department of Economics at Harvard University for a period of one year. The primary focus of his research has been development, agriculture, environmental and resource economics, and political economics.

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Abstract

Bragança, Arthur; Assunção, Juliano (advisor); Ferraz, Claudio (co-advisor). **Three Essays on Rural Development in Brazil.** Rio de Janeiro, 2014. 155p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

This thesis is composed of three articles on rural development in Brazil. The first article studies the impact on labor selection of the technological innovations implemented in the 1970s that allowed soybean cultivation in Central Brazil. It combines the timing of these innovations with variation on agronomic potential to cultivate the crop to evaluate the effect of the technological innovations. Results indicate that the innovations changes agricultural practices with increases in the use of modern inputs. The changes in agricultural practices affected the demand for skill in agriculture and induced selection into agriculture of individuals with higher educational attainment and selection out of agriculture of individuals with lower educational attainment. Suggestive evidence indicates that the impact of the technological innovations on output would be one third lower in the absence of labor selection. The second article examines whether geographic heterogeneity affects technology adoption. We develop a simple model in which geographic heterogeneity affects adoption by influencing adaptation costs. The model predicts the impact of geographic heterogeneity on technology adoption to be negative and non-monotonic. We test the model predictions using data on soil heterogeneity and the adoption of the Direct Planting System in Brazil. This technology increases revenues and decreases costs and its adoption neither requires large costs nor increases risk. However, the direct planting system must be adapted to specific site conditions, making adoption costly when geographic heterogeneity is large. We use detailed data on soil characteristics to show that geographic heterogeneity negatively impacts adoption in a pattern consistent to the theoretical model. The results indicate that geographic heterogeneity can be an important barrier to the diffusion of agricultural technologies. The third article studies the connection between special interests and government policies in the context of conservation policies in the Brazilian Amazon. Industries like agriculture or logging often oppose stringent conservation policies and the paper examines whether these industries are able to influence conservation policies. I construct a measure of connection to agricultural interests of the local politicians and use a regression discontinuity design to provide evidence that municipalities with mayors connected to agriculture have higher deforestation rates in election years. The timing of the effect indicates that special interests (as opposed to ideological preferences) drive the result. Estimates also suggest that the effect is higher when the politicians have reelection incentives and is related to changes in enforcement of environmental regulations. The results provide evidence that politicians distort policies near elections to benefit special interest groups connected to them. The first article is co-authored with Juliano Assunção and Claudio Ferraz while the second article is co-authored with Juliano Assunção and Pedro Hemsley.

Keywords

Agricultural Development; Technological Change; Technology Adoption; Migration; Political Economics; Deforestation

Resumo

Bragança, Arthur; Assunção, Juliano (orientador); Ferraz, Claudio (coorientador). **Three Essays on Rural Development in Brazil.** Rio de Janeiro, 2014. 155p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Essa tese é composta de três artigos sobre desenvolvimento rural no Brasil. O primeiro artigo analisa o impacto das inovações tecnológicas que, na década de 1970, adaptaram a soja para o Brasil Central sobre seleção de trabalhadores. O artigo combina o momento das inovações tecnológicas com variação agronômica no potencial para cultivo de soja para estimar os efeitos dessas inovações. Os resultados indicam que as inovações tecnológicas ocasionaram mudanças nas práticas agrícolas com aumento do uso de insumos modernos. Essas mudanças nas práticas agrícolas afetaram a demanda por capital humano e induziram imigração de trabalhadores qualificados e emigração de trabalhadores desqualificados. A evidência também sugere que o impacto das inovações tecnológicas sobre a produção agrícola seria um terço menor na ausência de fluxos de trabalhadores. O segundo artigo examina se heterogeneidade geográfica afeta adoção de tecnologia. O artigo desenvolve um modelo teórico simples em que heterogeneidade geográfica afeta adoção de novas práticas através de sua influência sobre custos de adaptação. O modelo prediz uma relação negativa e não monotônica entre heterogeneidade geográfica e adoção de tecnologia. Essa predição é testada utilizando dados de heterogeneidade de solos e adoção do Plantio Direto na Palha na agricultura brasileira. Essa tecnologia aumenta lucros e sua adoção não requer investimentos fixos e não aumenta riscos. Todavia, o Plantio Direto na Palha precisa ser adaptado para condições locais, tornando sua adoção custosa quando a heterogeneidade dos solos é alta. Os resultados empíricos mostram que a heterogeneidade de solos reduz adoção do Plantio Direto na Palha de maneira consistente com o modelo teórico. Essa evidência sugere que heterogeneidade geográfica pode ser uma importante barreira para a difusão de práticas agrícolas modernas. O terceiro artigo analisa a relação entre grupos de interesse e políticas públicas no contexto de políticas de combate ao desmatamento na Amazônia brasileira. Representantes da agropecuária e da indústria madeireira se opõem a

essas políticas devido ao seu efeito negativo sobre suas atividades e o artigo investiga se esses grupos de interesse utilizam seu poder político para influenciar políticas de combate ao desmatamento. O artigo constrói uma medida de conexão dos políticos aos interesses da agropecuária e utiliza um desenho de regressão com descontinuidade para mostrar que municípios governados por políticos ligados à agropecuária apresentam maior taxa de desmatamento em anos eleitorais. Os resultados também sugerem que o efeito é mais forte em municípios onde o prefeito tem incentivos de reeleição e está conectado a mudanças na fiscalização ambiental. Essa evidência indica que políticos distorcem políticas públicas para beneficiar grupos de interesse conectados a eles. O primeiro artigo é co-autorado com Juliano Assunção e Claudio Ferraz e o segundo com Juliano Assunção e Pedro Hemsley.

Palavras-chave

Desenvolvimento Rural; Mudança Tecnológica; Adoção de Tecnologia; Migração; Economia Política; Desmatamento

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1 Technological Change and Labor Selection in Agriculture: Evidence from the Brazilian Soybean Revolution

1.1. Introduction

Technological innovations are essential to promote agricultural development. An extensive literature argues that improvements in crops and fertilizers and the development of tractors and harvesters were critical to promote agricultural growth throughout the past centuries both in developed and developing countries.[1]

Adjustments to technological innovations can lead to substantial labor reallocation to and from agriculture. The theoretical literature suggests that technological change in agriculture can affect both the size and composition of the agricultural labor force (Schultz, 1953; Matsuyama, 1992; Ngai and Pissarides, 2007; Lagakos and Waugh, 2013; Young, 2013). Existing empirical studies document the effects of technological innovations on the size of the rural labor force but are silent on the impact of these changes on the composition of the agricultural labor force (Caselli and Coleman II, 2001; Foster and Rozenzweig, 2008; Nunn and Qian, 2011; Bustos et al., 2014; Hornbeck and Keskin, *Forthcoming*). Assessing the consequences of technological innovations for labor selection in agriculture is essential to understand the incidence of these innovations. It is also important to explain important phenomena such as the income differences between agricultural and non-agricultural activities (Gollin et al., 2014).

This paper uses the historical experience from agriculture in Central Brazil to provide causal evidence on the connection between technological innovations and labor selection in agriculture. It explores exogenous variation coming from technological innovations that adapted soybeans for the agro-climatic

[1] See Griliches (1958), Olmstead and Rhode (2001, 2008) and Evenson and Gollin (2003) for evidence of the importance of technological innovations to agricultural development in different contexts.

characteristics from Central Brazil to understand whether it influenced the composition of the agricultural labor force.

Soybean adaptation was the result of biological innovations implemented during the 1970s that enabled its cultivation in Central Brazil. Technological innovations adapted soybeans for the poor and acid soils from the region and reshaped agriculture in this agricultural frontier. Adaptation allowed farmers to move from extensive cattle grazing using almost no modern inputs to intensive crop cultivation using modern inputs and machines (Klink and Moreira, 2002).

Historical accounts suggest that the shift from pasture to crop cultivation affected human capital demand as crop cultivation is more skill-intensive than cattle grazing.[2] In particular, soybean cultivation required use of modern inputs and experimentation with seeds and fertilizers. Historical accounts indicate that these activities are intensive in human capital.[3]

We organize the analysis in two different parts. First, we investigate the effects of the technological innovations on land use and agricultural practices in Central Brazil. Second, we assess the impact of these innovations on migration rates and the composition of the agricultural labor force. In particular, we investigate whether the technological innovations affected educational attainment both of migrants and natives to understand its impact on labor selection in agriculture.

Our empirical design combines the timing of the technological change with variation in agronomic potential for soybean cultivation using modern technologies to estimate the impact of the technological innovations. Following Nunn and Qian (2011) and Bustos et al. (2014), we use FAO/GAEZ data to construct a measure of agronomic potential for soybean cultivation using modern technologies.[4] We use this measure to estimate whether outcomes increased faster in municipalities with higher soybean potential when compared to municipalities with lower soybean potential. Baseline specifications include geographic and

[2] See Strauss et al. (1991) for some evidence of the importance of human capital to the adoption of modern technologies in Central Brazil.

[3] See Welch (1970) for a discussion of the importance of skills to foster experimentation in agriculture. See also Foster and Rosenzweig (1996) for evidence on the complementarities between modern agricultural inputs and skills.

[4] Nunn and Qian (2011) are the first paper which used FAO/GAEZ data in economics while Bustos et al. (2014) propose the measure of agronomic potential used in this paper.

baseline municipal characteristics as controls to mitigate the concern that differential trends in the outcomes drive the estimates.

We document that the technological innovations had a sizable effect on land use. Following the technological innovations, crop cultivation increased in municipalities more suitable for soybean cultivation using modern technologies. The increase in crop cultivation is associated with a rise in the use of modern inputs such as liming and tractors.[5] The effects on the adoption of these inputs are substantial and point out that the technological innovations induced intensification of the agricultural practices.

We also find that the changes in land use and agricultural practices did not increase the use of labor in agriculture. However, the results indicate that migration rates increased, suggesting that the technological innovations induced significant labor movements. This reallocation affected characteristics of the agricultural labor force as educational attainment increased both among migrants and natives. Human capital accumulation does not explain the results as the findings are robust to restricting the sample to cohorts outside school when the innovations took place. These findings suggest that the technological innovations stimulated immigration of individuals with higher-than-average human capital to municipalities more suitable for soybean cultivation and emigration of individuals with lower-than-average human capital from these localities. A conservative calculation suggests that such selection pattern account for about half of the increase in educational attainment in these municipalities.

We interpret this result as evidence that the technological innovations increased human capital demand in agriculture. This interpretation is consistent with the results on agricultural practices and the literature documenting that modern technologies and human capital are complements in agriculture (Foster and Rosenzweig, 1996). Further evidence supporting this interpretation comes from occupational choices. Results point out that the technological innovations increased the share of the agricultural labor working in occupations intensive in human capital (such as driving tractors, preparing soils, applying fertilizers etc.).

[5] Liming is the most important fertilizer to crop cultivation in central Brazil as it is needed to reduce soil acidity. See Rezende (2002) for a discussion of the importance of investments in liming to agricultural production in Central Brazil.

The labor movements can increase the effects of the technological innovations on agricultural output, facilitating adjustment in land use and farming practices.[6] To provide evidence on this mechanism, we estimate the impact of the technological innovations on agricultural output both excluding and including measures of schooling and occupational structure as controls. The effects of the technological innovations decrease in 30 to 35% when these covariates are included. This result provides suggestive evidence that selection was essential to enable agriculture to adapt and benefit from the technological innovations.

The results survive to a number of robustness exercises. We use data from pre-treatment periods to provide evidence that the trends in agricultural outcomes before the technological innovations were similar in municipalities with different levels of agronomic potential. We also construct a price index to show that the results are robust to controlling for changes in prices. We also provide evidence that the results are robust to the inclusion controls for access to credit and land tenure. This robustness check mitigates concerns that other policies drive the estimates.

Our results contribute to different streams of the literature. Earlier literature documented that technological change in agriculture affects the size of the rural labor force (Caselli and Coleman II, 2001; Foster and Rosenzweig, 2008; Nunn and Qian, 2011; Bustos et al., 2014; Hornbeck and Keskin, *Forthcoming*). We complement this literature showing that agricultural development also affects the composition of the rural labor force. This evidence is important to understand different phenomena such as the income differences between agricultural and non-agricultural activities (Lagakos and Waugh, 2013; Young, 2013; Gollin et al., 2014). In particular, our results complement the evidence from Bustos et al. (2014). These authors document that technological innovations in the Brazilian agriculture are associated with labor movements from agriculture to other industries. Our evidence uses a different historical experiment to document that technological innovations in the Brazilian agriculture also associated with changes in labor selection. Both studies highlight that technological innovations in agriculture have significant consequences for labor movements.

[6] Existing empirical studies suggest that farmers face difficulties to adjust agricultural practices to different growing conditions (Olmstead and Rhode, 2008; Hornbeck, 2012; Bazzi et al., 2014).

This paper also provides novel evidence on the connection between technological innovations and educational attainment in agriculture. Foster and Rosenzweig (1996) document that the Green Revolution increased human capital demand in agriculture and induced its accumulation in India. The technological innovations studied in this paper also increased the human capital demand in agriculture. However, our results point out that labor selection explains a substantial share of the increase in educational attainment. Hence, this paper brings attention to the importance of migration in the adjustment to changes in production possibilities in agriculture.

Moreover, our results contribute to the literature investigating the causes and consequences of the expansion of the Brazilian agricultural frontier during the last decades (Gasques et al., 2004; Rada and Buccola, 2012; Rada, 2013). It provides causal evidence on the role of technological innovations in affecting the composition of the labor force in the agricultural frontier.

The remaining of the paper is organized as follows. Section 2 provides background information on technological innovations and agricultural development in central Brazil. Section 3 describes the data. Section 4 presents the empirical design used in the estimates. Section 5 presents the results on agricultural outcomes. Section 6 presents the results on labor selection. Section 7 presents the robustness exercises. Section 8 concludes.

1.2. Historical Background

1.2.1. Agricultural Development in Central Brazil before 1970

Central Brazil covers about one fifth of Brazil and is composed of four states (*Goiás*, *Mato Grosso*, *Mato Grosso do Sul* and *Tocantins*). It is mostly located in the Cerrado biome although some of its lands are in other biomes. The main characteristics of this biome are the prevalence of savannah vegetation and the tropical climate with a rainy summer and a dry winter. The region's soils are infertile due to a combination of soil acidity, aluminum prevalence, and nutrient scarcity.[7] These features limited occupation and agricultural development in Central Brazil until recent decades. High transportation costs to the main Brazilian cities and ports exacerbated the region's natural disadvantages and further limited

[7] Detailed information on the Cerrado can be found in Oliveira and Marquis (2002).

its occupation and agricultural development (Guimarães e Leme, 2002; Klink and Moreira, 2002).

Industrialization and urbanization of neighboring states increased the demand for meat and promoted extensive cattle ranching in the region after 1920. Cattle ranching benefited from the native pastures that cover a substantial share of Central Brazil's land area. However, its impact on occupation and agricultural development was limited since it used little labor or modern inputs (Klink and Moreira, 2002).

Promoting occupation and agricultural development in the region became an objective of several Brazilian governments after 1940 (Guimarães and Leme, 2002). The Brazilian government aimed to promote crop cultivation in central Brazil in order to meet the growing food demand created due to a combination of urbanization and population growth (Klink and Moreira, 2002). Expanding agricultural production was considered important to ease the pressures on food prices and avoid inflation.

The government also sought to expand the agricultural frontier to foster industrialization through higher demand for farm inputs. It believed that the expansion of the agricultural frontier would increase the demand for tractors and fertilizers and help these industries to develop in Brazil. Finally, the expansion of the agricultural frontier was considered important to reduce pressures on land reform in other regions. In particular, the conservative modernization proposed after the 1964 coup sought to relieve these pressures through population movements to the agricultural frontier rather than through land reform (Salim, 1986; Helfand, 1999; Houtzager and Kurtz, 2000).

Incentives for agricultural production along the agricultural frontier after 1940 included both subsidies and investments in infrastructure (Klink and Moreira, 2002). The government subsidized credit and provided agricultural credit lines with negative interest rates. It also established minimum price programs to reduce risks that farmers faced when operating on the agricultural frontier. In addition, the government invested in road building and electrification.

Colonization projects concentrated subsidies and investments in infrastructure (Santos et al., 2012). Colonization projects were either public or private depending on the region. These projects provided farmers with land rights and some basic infrastructure which facilitated migration and induced farmers to move to the agricultural frontier (Jepson, 2002). The first colonization projects were created in the 1940s in the municipalities of Ceres (in the state of *Goiás*) and Dourados (in the state of *Mato Grosso do Sul*).[8] Subsequent projects were established in the region until the 1980s.

Government policies induced the occupation of Central Brazil after 1940. Rural population increased 3% per year from less than 1 million in 1940 to 2.6 million in 1970 despite the substantial urbanization experienced during that period in Brazil as a whole. However, the evolution of rural development was less impressive. Income per inhabitant increased 1.7% per year in the same period. Historical accounts emphasize that limited agricultural development was a consequence of the increased cultivation of the region's acid and nutrient poor soils (Sanders and Bein, 1976). Crop cultivation was an intermediate stage between deforestation and cattle grazing since it helped the soil to retain nutrients. For this reason, investments in fertilizers and tractors remain limited (Klink and Moreira, 2002).

1.2.2. Technological Change and the Adaptation of Soybeans for Central Brazil

Adverse agro-climatic characteristics were an important constraint to agricultural development in Central Brazil. These characteristics limited cultivation of agricultural products – such as soybeans and cotton – cultivated with success in other Brazilian regions. Government investments in agricultural research started in the 1960s aiming to overcome the geographic constraints that agricultural production faced in Central Brazil (Klink and Moreira, 2002). These investments were inspired by the Green Revolution in other developing countries.[9] The adaptation of soybeans to the growing conditions found in Central Brazil is a case of success of these public investments in agricultural research.[10]

Investments focused in engineering soybean varieties adapted to the tropical climate and the Cerrado biome started in the 1950s in the *Instituto Agronômico de Campinas* and expanded in the 1960s with the establishment of a national

[8] The *Colônia Nacional Agrícola de Goiás (CANG)* was founded in Ceres in 1942 while the *Colônia Nacional Agrícola de Dourados (CAND)* was founded in 1944.

[9] Cabral (2005) describes the importance of the Green Revolution in other developing countries in inducing the Brazilian government to invest in agricultural research.

[10] It is unclear in the literature what motivated the Brazilian government to invest in soybean research and not in other crops.

program that coordinated and promoted research on this crop. These investments continued to increase fast in the subsequent decade with the creation of Embrapa, the national agricultural research corporation (Spehar, 1994; Cabral, 2005; Kiihl and Calvo, 2008).

Soybean adaptation was essential for its cultivation in Central Brazil. Yields from traditional varieties in Central Brazil were lower than 1 ton per hectare (compared to yields higher than 2 tons per hectare in southern Brazil). The central issue to plant development in the region was the reduced sunlight exposition in tropical areas compared to temperate areas from which the crop originates. Another important issue was the abundance of aluminum, which is toxic to plants, in the region's soils (Spehar 1994). Both issues impaired plant development and negatively affected the yields obtained using traditional varieties.

The investments in soybean research succeeded both in developing varieties resistant to aluminum and adapted to the tropical climate. Varieties adapted to the agro-climatic characteristics from Central Brazil were developed following the experiences of the Green Revolution elsewhere. The first varieties that could be cultivated in some Central Brazil areas were launched in 1965 and 1967. These varieties were adapted to latitudes lower than 20 degrees, enabling soybean cultivation in southern localities of the region along the states of *Goiás* and *Mato Grosso do Sul*. These varieties achieved experimental yields higher than 2 tons per hectare. Varieties more resistant to aluminum were developed in 1969 and 1973. A significant development came in 1975 with the development of the *Cristalina* cultivar, which achieved experimental yields higher than 3 tons per hectare and could be cultivated in more localities from Central Brazil. Later developments generated in Embrapa research centers created varieties quite resistant to high aluminum levels and adapted to latitudes below 10 degrees (Spehar, 1994; de Almeida et al., 1999). These developments complete the adaptation process.

1.2.3. Agricultural Development in Central Brazil after 1970

Historical accounts suggest that the technological innovations led to a considerable expansion of soybean cultivation in Central Brazil after 1970 (Klink and Moreira, 2002). Cultivation at the beginning of the 1970s was concentrated in the region's southernmost areas as the varieties introduced in the late 1960s could not be cultivated in latitudes smaller than 10 degrees. Technological developments induced settlement and cultivation in northern Central Brazil by the end of the 1970s despite the reduction in international prices.[11] Soybean cultivated area reached more than 2.5 million hectares in 1985. Yields more than doubled in the period.

The expansion of soybean cultivation induced substantial changes in agricultural practices. Rezende (2002) argues that technological innovations were essential to turn intensive agriculture viable in Central Brazil. Nevertheless, the author also argues that the expansion of crop cultivation also required significant investments in land preparation as liming and other fertilizers must be used in large amounts to fertilize soils. His calculation indicates that expenditures with liming and other fertilizers represent 42.5% of the total investments needed to prepare land for intensive agriculture. As a comparison, land acquisition represents 25% while land clearing represents 17.5% of these investments.

Investments in tractors are also required to intensive agriculture in Central Brazil. The prolonged droughts common in the region turn the use animal traction impossible as soils become too compact during the dry season (Sanders and Bein, 1976). Plowing using animal traction must begin after the end of this season. Such timing reduces water absorption as soils are still compact when it starts raining. It also pushes plowing to a period when mules and other animals are debilitated. Tractors remove these constraints with farmers being able to prepare soils during the drought. Technical assistance also became more important as farmers must experiment with distinct crop varieties never tested in that environment (Jepson, 2006*a, b*).

The changes in agricultural practices needed to soybean cultivation seem to have increased human capital demand and induced migration. The literature suggests that migration was important to promote the adoption of modern agricultural technologies in Central Brazil (Kiihl and Calvo, 2008). Migrants benefited from previous experience with crop agriculture and modern farming inputs (de Carli, 2005; Monteiro et al., 2012). Settlement was concentrated in areas in which government investments and public or private colonization projects had provided land rights and some infrastructure (Jepson, 2002; Santos et al.,

[11] The increase in international prices increased soybean cultivation in the 1970s in subtropical areas as well. However, cultivated area remained constant in these areas following the fall in prices in the second half of the decade while it continued to expand in Central Brazil.

2012). Settlers started cultivating rice as aluminum-resistant varieties were available (Monteiro et al., 2012). Soybean cultivation started later as farmers needed time to experiment with different varieties (Macêdo, 1998; Jepson, 2006*a*, *b*). Existing research suggest that human capital was critical to induce experimentation and soybean adoption (Strauss et al., 1991).

1.3. Data

1.3.1. Data on Soybean Potential

Evaluating the impact of technological innovations in agriculture is often difficult since the time series correlation between innovations and agricultural outcomes might be spurious and capture unobserved determinants of these variables. For this reason, it is important to build a credible empirical design to investigate the effects of the technological innovations that adapted soybeans to Central Brazil.

Our empirical design explores variation in the municipalities that benefited more from the technological innovations to investigate its effect on agricultural and socioeconomic outcomes. We measure the gain from the technological innovations with data from the Food and Agriculture Organization (FAO) Global Agro-Ecological Zones (GAEZ) database. The database uses an agronomic model that combines geographical and climatic information to predict potential yields for several crops under different levels of input use. Levels of input use range from low (corresponding to traditional agricultural practices) to high (corresponding to commercial agriculture using machinery and chemicals). The data is reported in 0.5 degrees by 0.5 degrees grid cells.[12]

Following Bustos et al. (2014), we define the agronomic potential for cultivating soybeans using modern technologies as the difference between the potential soybean yield under the high and the low input level. The measure captures the potential gain that a farmer could obtain shifting land use to soybean

[12] The FAO/GAEZ dataset was introduced in the economics literature by Nunn and Qian (2011) who investigate the effect of the introduction of potatoes in urbanization in Europe. This dataset was subsequently used in a number of papers such as Costinot et al. (*Forthcoming*) who investigate the impact of climate change in agriculture, Bustos et al. (2014) who investigate the impact of Genetically Engineered (GE) crops on agriculture and industrialization in Brazil and Marden (2013) who investigate the impact of agricultural reforms on agriculture and industrialization in China.

after its adaptation to Central Brazil. A limitation of the measure used is that the agronomic model that underlies the FAO/GAEZ data uses contemporaneous (as opposed to historical) information on technologies to measure agricultural potential for each crop. Hence, we are assuming that technological change after the period analyzed did not change the comparative advantage to cultivate soybeans across Central Brazil.[13] This restrictive assumption can be validated using data on soybean adoption. We should not observe a positive correlation between soybean adoption and agronomic potential if technological change after the sample period affected comparative advantage. We return to this issue in the discussion of the results.

We measure soybean potential measure at the municipality level that is the administrative division for which data on the Agricultural Census is available. It is also the smallest administrative division for which we observe the location of individuals in the Population Census. Several municipalities were created in the region and some other municipalities change their borders in the period analyzed. We account for this using a definition of minimum comparable areas of the Brazilian Institute of Applied Economic Research (IPEA) that make spatial units consistent over time. The main results are estimated using a minimum comparable areas definition that makes spatial units consistent with the existing municipalities and borders from 1970. That leaves 254 spatial units that can be compared through time.[14] We refer to these minimum comparable areas as municipalities throughout the paper.

Soybean potential is constructed in three steps using the ArcMap 10.1 software. First, we superimpose the map on potential soybean yields under different input regimes and the map on municipalities. Second, we calculate the average potential soybean yield of all cells falling within a municipality both for the under the low input and the high input regimes. Third, we calculate the soybean potential as the difference between the average soybean potential yields in each input level.

Figure 1.1 presents a map of agronomic potential for cultivating soybeans using modern technologies in Central Brazil. Darker municipalities have the

[13] A similar assumption is made in Costinot and Donaldson (2011).

[14] There were 303 municipalities in central Brazil in 1970 and 366 municipalities in central Brazil in 1985. The minimum comparable areas from IPEA are constructed in a conservative fashion that aims to make borders compatible through time.

higher agronomic potential, while lighter municipalities have the lower agronomic potential. Average agronomic potential is 2.15 (with a standard deviation 0.58) and it ranges from 0.67 tons per hectare to 3.3 tons per hectare. Most variation in this measure comes from variation in potential yields under the high input regime as potential yields in the low input regime are close to zero.[15] Results are robust to defining agronomic potential as the potential yield in the high input regime.

1.3.2. Data on Agricultural Outcomes

The empirical analysis uses data of agricultural outcomes from the Brazilian Agricultural Census. The main results use data from the rounds that occurred in 1970, 1975, 1980 and 1985. The data from 1970 represents agricultural outcomes before the technological innovations. The data from 1975 and 1980 represent agricultural outcomes during the technological innovations while the data from 1985 represents agricultural outcomes after the technological innovations. The data is reported at the municipality-level and was obtained from the original microdata. We also use data from the 1960 Agricultural Census in robustness exercises. This data was digitized from the original publication.

The main outcomes obtained from the Agricultural Census are used to measure soybean adoption, land use, input use, and agricultural output. Soybean adoption is measured using different outcomes. The first is the number of hectares of soybean per each 1000 hectares of farmland. The second is the soybean production in tons per each 1000 hectares of farmland. The third is the share of farms cultivating the crop.

Land use is measured using three different variables: cropland, pastures, and forests. All variables are reported as a percentage of total farmland. Input use is also measured using three different variables: labor use per each 1000 hectares of farmland, the number of tractors per 1000 hectares of farmland, and the share of farms using liming.

Agricultural output is measured as the natural logarithm of the value of agricultural production either per labor unit or hectare. The former is a measure of labor productivity and the latter a measure of yields. We divide the value of agricultural production in the value of crop and the value of animal production

[15] The average potential soybean yield under the low input regime is 0.25 and ranges from 0.08 and 0.57.

(milk, meat, and eggs). Output data is deflated to 2010 using the deflators proposed in Corseuil and Foguel (2002). The census deflator is used for 1970 and 1980 and the PNAD deflator is used for 1975 and 1985.[16] Table 1.1 presents the descriptive statistics of the variables described above.

1.3.3. Data on Socioeconomic Outcomes

The empirical analysis also uses data on socioeconomic outcomes from the Population Census. The main results use data from the rounds that occurred in 1970, 1980 and 1991. The data from 1970 represents outcomes before the technological innovations. The data from 1980 represents outcomes during the technological innovations while the data from 1991 represents outcomes after the technological innovations. All data is available at the individual level.

The main outcomes obtained from the Population Census data are migration status, educational attainment, and occupational choices. We restrict the sample to individuals from 15 to 64 years who live in rural areas and are either working or looking for a job. We focus on rural areas since we are interested in labor selection in agriculture. We assume that all working individuals living in rural areas work in occupations related to agriculture.[17]

The preferred measure of migration status is an indicator equal to one if the individual was not born in the state and zero otherwise. We also use an indicator equal to one if the individual was not born in the municipality and zero otherwise as an alternative migration measure. The variable based on the state of birth is the preferred migration measure as it captures long distance migration and not short distance migration across adjacent municipalities. This ensures that spillovers across municipalities do not drive the estimates. It also guarantees that the

[16] The series containing the PNAD deflator starts in 1976. We use the consumer price index from the Brazilian Census Bureau to calculate the deflator for 1975. This price index is the same used in the methodology proposed in Corseuil and Foguel (2002) to construct the deflator for other years. It should be noted that the choice of deflator is irrelevant for the estimates since we use year fixed effects.

[17] An alternative would be to focus on a sample of individuals who report working in agricultural activities. That would ensure that there are no individuals in our sample that are not employed in farms. We choose to focus on a sample of individuals who live in rural areas because there might be some individuals whose occupations are not classified as agricultural, but that are working in farms. Since technological change can also affect these occupations, we focus on a sample of individuals living in rural areas and assume that individuals with non-agricultural occupations living in rural areas are also working in activities related to farming. This distinction does not seem to be relevant in the data and results are similar for the sample of individuals who report working in agricultural activities.

creation of municipalities does not affect whether an individual is coded as migrant.

The measure of educational attainment is an indicator equal to one when the individual has completed four years of schooling and zero otherwise. Educational attainment was quite low in Central Brazil in the period. About 8.7% of the rural labor force had four years or more of schooling in 1970. This number increases to 25% and 40.9% in 1980 and 1991. Hence, this variable seems to capture whether a person is skilled or not in the period. In addition, this variable can be constructed directly from the census data as opposed to the variable years of schooling that is built using approximations.[18] Nevertheless, the results are robust to using different educational attainment measures.

The measures of occupational choice are obtained using the classification developed by Chein (2006). We define three occupational groups: skilled agricultural workers, unskilled agricultural workers, and proprietors or managers. Skilled workers are either agricultural technicians or employees that handle machines and soil preparation. Unskilled workers are all other individuals working in other agricultural occupations. Proprietors or managers are individuals who either are owners or manage an establishment. Table 1.2 presents the descriptive statistics of the variables described above.

1.4. Identification Strategy

This section presents the identification strategy used to investigate the effect of the technological innovations that adapted soybeans to Central Brazil. The first step of the empirical analysis is to estimate the impact of the technological innovations on agricultural outcomes using data aggregated at the municipality level from the Agricultural Census from 1970 to 1985. We use a research design that resembles a differences-in-differences and estimate year-specific changes between municipalities suitable and unsuitable to soybean production using modern technologies relative to the baseline. The estimating equation is:

[18] It is important to highlight that the census bureau does not provide direct information on years of schooling in the Population Censuses from 1970 and 1980. This can be constructed using procedures described in the literature (see Rigotti et al. (2004) for an example).

$$Y_{mst} = \alpha_m + \delta_{st} + \sum_{v=1975}^{1985} \gamma_v \, (Soybean\ Potential_m * I_v) + \sum_{v=1975}^{1985} (\boldsymbol{X}_m * I_v) \, \boldsymbol{\Gamma}_v + u_{mst} \qquad (1.1)$$

where Y_{mst} is an agricultural outcome in municipality m in the state s in the period t; α_m is a municipality fixed effect; δ_{st} is a state-time fixed effect; $Soybean\ Potential_m$ is the agronomic potential to cultivate soybeans using modern technologies; I_v is a year indicator; $\boldsymbol{X}_m$ is a vector of geographic and initial characteristics; and u_{mst} is an error term. We cluster standard errors at the municipality level in all specifications. The coefficients of interest are the three γ_v which represent the impact of the technological innovations in the different sample periods. We allow the coefficients to change through time to differentiate the impact of the technological innovations on agricultural outcomes during different phases of the adaptation process.

The municipality fixed effects control for time invariant characteristics of municipalities that might be correlated with soybean potential. The state-time fixed effects controls for shocks specific to each of the four states included in the sample. These shocks might either reflect different policies or different trends.[19] Therefore, the identification assumption is that, within a state and in the absence of the technological innovations, agricultural outcomes would have changed similarly in municipalities with higher and lower potential to cultivate soybeans. This is the equivalent of the parallel trends assumption from differences-in-differences models. The difference is that it must hold *within* municipalities located in each state and not *across* municipalities located in different states.

We include the controls $\boldsymbol{X}_m$ to allow trends in agricultural outcomes differ according to some observed municipal characteristics and relax the parallel trends assumption. The controls can be divided in two groups. The first group corresponds to geographic characteristics. The characteristics included are natural logarithm of the distance to the coast and the distance to the federal capital. These controls allow municipalities with different locations to benefit differentially from the investments in infrastructure and in colonization made during the period. The

[19] It is important to note that there were only two states in central Brazil in the beginning of the period under analysis. *Mato Grosso* and *Mato Grosso do Sul* split in 1975 and *Goiás* and *Tocantins* split in 1989. However, I include state-year fixed effects considering the four states that exist in current days on the assumption that the important differences that exist across these states were already relevant in the earlier period.

second group corresponds to baseline characteristics. The characteristics included are the share of available land, log of the total farmland, log of the number of farms, number of state-owned bank branches, number of private-owned bank branches, and initial value of the dependent variable. These variables allow municipalities with different characteristics to have different trends. Furthermore, the inclusion of the initial value of the dependent variable as an additional control controls for convergence in the outcomes.

The robustness exercises further test whether the parallel trends assumption holds. We use data from the 1960 Agricultural Census to investigate whether changes agricultural outcomes before the technological change were related to soybean potential. The limit of the 1960 Agricultural Census data is that we do not observe all outcomes observed in later periods and the robustness exercise can be performed just for a subset of the outcomes used in the main estimates.

Another concern of the estimates is whether changes in international prices are driving the results. We construct a price index combining data on crop output in the baseline and soybean prices and show that the estimates are robust to its inclusion. Other robustness exercises include controls for access to credit and land tenure to mitigate concerns that changes in these variables that can be correlated with soybean potential drive the estimates. These controls are not included in the main estimates since the included variables are endogenous as technological innovations can influence them. The main estimates are robust to the inclusion of these additional covariates.

The second step of the empirical analysis is to estimate the impact of the technological innovations on migration status and educational attainment using individual level from the Population Census from 1970 to 1991. The empirical design is the same used for agricultural outcomes with the difference that outcomes are now observed at the individual level and that there are just three sample periods. The estimating equation using individual data is:

$$Y_{imst} = \alpha_m + \delta_{st} + \sum_{v=1980}^{1991} \gamma_v \, (Soybean\ Potential_m * I_v) + \sum_{v=1980}^{1991} (\boldsymbol{X}_m * I_v)\, \boldsymbol{\Gamma}_v + \beta \boldsymbol{Z}_{imst} + u_{imst} \quad (1.2)$$

where Y_{imst} is the outcome of interest from individual i in municipality m, state s and period t and $\boldsymbol{Z}_{imst}$ is a vector of individual level controls. The individual controls included are dummies for sex and for five-year age groups.

The other variables are the same variables included in equation (1.1). It is not possible to include the initial value of the dependent variable as a control since there is no panel data on individuals. Nevertheless, we do include the initial value of the dependent variable in the municipality as a control.

The coefficients of interest are the γ_v estimated for 1980 and 1991. These coefficients enable us to investigate the impact of technological innovations on labor selection during different phases of the adaptation process. The identification assumption needed for causal inference on these coefficients is the same parallel trends assumption discussed above for the coefficients estimated in equation (1.1). We cluster standard errors at the municipality-level in all specifications estimated using equation (1.2).

1.5. Technological Change and Agricultural Modernization

1.5.1. Land Use

Table 1.3 presents the estimates of the impact of the technological innovations on soybean adoption. The table aims to validate the measure of agronomic potential and investigate whether municipalities more suitable for soybean cultivation experienced faster increases in cultivation and production of this crop. The table reports estimates of equation (1.1) for three different outcomes: soybean cultivation per 1000 hectares, soybean production per 1000 hectares and the share of farms cultivating the crop.

Column 1 reports the effect of technological change on soybean cultivation conditional on municipal and state-year fixed effects. Column 2 includes geographic characteristics as controls while column 3 includes baseline characteristics as controls. These columns provide evidence that municipalities more suitable to soybean cultivation using modern technologies experienced larger increases in soybean cultivation than municipalities less suitable for it in the period 1970 to 1985. This finding validates the agronomic potential measure and suggests that the comparative advantage to cultivate soybeans in Central Brazil did not change after the sample period.

Columns 1 to 3 also show that the impact of the technological innovations on soybean adoption grows over time. This result is consistent with the idea that adaptation was a gradual process that allowed cultivation to occur in more areas.

It is also consistent with the idea that takes time for farmers to change agricultural practices to adopt different crops and agricultural practices. The increases in the coefficients suggest that the estimates are not capturing the impact of changes in soybean prices, which increased at the beginning of the 1970s and decreased at the end of this decade.

It is important to note that the addition of baseline controls reduces the size of the estimated impact of the technological innovations. That suggests that the inclusion of baseline characteristics is essential for the empirical design. The magnitude of the estimated impact of the technological innovations is substantial. One standard deviation increase in agronomic potential is associated with a relative increase in 14.2 to 17.5 hectares in soybean cultivation per thousand hectares of farmland from 1970 to 1985. The results provide evidence that the agronomic potential measure is a useful indicator of the gain that technological innovations brought to farmers in Central Brazil.

Columns 4 to 6 report the effects of technological innovations on soybean production using the same specifications used in columns 1 to 3. The results are similar to the ones discussed above. Production increased faster in municipalities more suitable to soybean cultivation. The estimated increases are larger in later periods and are reduced with the inclusion of controls. The magnitude of the estimated impact is also substantial. One standard deviation increase in agronomic potential is associated with a relative increase in 24.6 to 34.5 tons in soybean production per thousand hectares of farmland from 1970 to 1985. A back of the envelope calculation comparing estimates in columns 1-3 with estimates in columns 4-6 from the same table suggest that the technological innovations increased yields by about 80%.

Columns 7 to 9 report the effect of the technological innovations on the share of farms cultivating the crop. The results point out that the technological change had a significant impact on the share of farms producing the crop both in 1980 and 1985. The effects estimated in 1975 are not significant across specifications (despite the point estimates being positive in all columns). This result suggests that expansion of crop cultivation was not restricted to the intensive margin.

An important question is whether the technological innovations affected land use in general. To answer this question, Table 1.4 reports estimates of the impact of technological change on land use. The table reports estimates equation (1.1) for three different outcomes: the share of cropland, the share of pastures and the share of forests. Columns 1, 4 and 7 report the estimates obtained conditional on municipal and state-year fixed effects. Columns 2, 5 and 8 report the estimates obtained conditional also on geographic characteristics. Columns 3, 6 and 9 report the estimates obtained conditional also on baseline agricultural characteristics.

In columns 1 to 3 we find that the technological innovations increased the share of cropland both in 1980 and 1985. The effects are significant in all three specifications. Their magnitudes suggest that one standard deviation increase in agronomic potential is associated with a rise in 1.3 to 2.2 percentage points in the share of cropland from 1970 to 1980 and 1.9 to 2.7 percentage points in this variable from 1970 to 1985. These magnitudes are substantial since cropland represented just 6% of the total farmland in the baseline. This result evidences that soybean cultivation did not expand replacing other crops. Indeed, the total estimated increase cropland is even larger than the estimated increased in soybean cultivation, which is consistent with the idea that the technological innovations had positive spillovers to the production of other crops.[20]

The evidence from the remaining columns suggests that cropland expanded over pastures (columns 4 to 6) and not over forests (columns 7 to 9). On the one hand, the share of pastures declines in more suitable municipalities in all specifications. The relative decline in pastures from 1970 to 1985 is significant at the 10% level in column 4, at the 5% level in column 5, and not significant in column 6. On the other hand, the changes in forests have no clear pattern. The coefficients switch from being positive to negative across different periods and specifications. These findings suggest that technological innovations inducing farmers to invest in agricultural intensification rather than in land clearing.

1.5.2. Input Use

The results from Tables 1.3 and 1.4 provide evidence that soybean adaptation shifted land use from pasture to crop cultivation. We argued before that crop cultivation requires agricultural practices quite different from the ones used

[20] There are several reasons that indicate that such spillovers exist. Investments in machines might enable production of other crops in areas not suited to soybean cultivation. Moreover, there might be agronomic benefits from rotating land across different crops.

in cattle grazing. Therefore, it is expected that the technological innovations affected the use of inputs.

Table 1.5 presents evidence consistent with this idea. It reports estimates of the impact of technological change obtained using equation (1.1) on labor use, tractor use and liming use. We choose liming as the measure of fertilizer use since it is recognized to be the main fertilizers needed to cultivate crops in Cerrado lands (Spehar, 1996; Rezende, 2002). Estimates from columns 1 to 3 report the results for labor use, estimates from columns 4 to 6 report the results for tractor use and estimates from columns 7 to 9 report the results for liming use. The specifications are the same used before.

Columns 1 to 3 point out that the technological innovations had no effect on the total labor use in agriculture. In the period 1970 to 1985, total labor use increased at similar rates in municipalities more and less suitable for soybean cultivation using modern technologies. More productive agriculture neither increased total labor force in agriculture as in Foster and Rosenzweig (2008) and Hornbeck and Keskin (*Forthcoming*) nor decreased it as in Bustos et al. (2014).

The remaining columns present evidence that technological innovations increased the use or modern inputs in agriculture. Columns 4 to 6 show that the technological innovations induced farmers to adopt machines. Following the technological innovations, the number of tractors increased faster in municipalities more suitable for soybean cultivation. The effects are significant in all specifications and indicate that one standard deviation increase in the potential measure led to a growth in .33 to .41 in the number of tractors per thousand hectares from 1970 to 1985. Columns 7 to 9 report that the technological innovations also induced farmers to adopt fertilizers. The effects are also significant in all three specifications and suggest that one standard deviation increase in agronomic potential is associated with a rise in 1.9 to 2.9 percentage points in the share of farms using liming from 1970 to 1985. These impacts are consistent with the idea that crop cultivation in Central Brazil required mechanization and fertilizers to be feasible.

It is important to notice that the effect of the technological innovations on liming use decline from 1980 to 1985. This result is inconsistent with previous findings that indicate that the impacts of the innovations increase over time. The expansion of the use of this fertilizer on pastures might explain this result.[21] Data on the total expenditure on fertilizers and pesticides suggests that this might be the case. We find that the effects of technological innovations on these expenditures are positive and increase over time (these estimates are available upon request).

1.5.3. Agricultural Output

Table 1.6 reports estimates of the impact of the technological innovations on agricultural output. The table reports estimates of equation (1.1) for the following outcomes: the log of the value of agricultural production per hectare and the log of the value of agricultural production per worker. Panel A report estimates using the value of crop production as the outcome while Panel B reports estimates using the value of animal production as the outcome. The specifications include the same controls used in the previous tables.

Panel A shows that technological innovations increased crop output. Columns 1 to 3 indicate that the log of crop output per worker increased faster in municipalities more suitable for soybean cultivation using modern technologies. Estimates are significant in all specifications for the period of 1985. The significance for the previous periods varies, but the point estimates are positive in all specifications. The magnitude of the coefficients estimated in column 3 suggests that an increase in one standard deviation in the potential measure is associated with a 32% increase in crop output per labor unit.

Increases in output per labor unit in agriculture can come either from increases in output per hectare or in the number hectares per labor unit. Biological innovations such as the one studied are often associated with increases in production per area (Hayami and Ruttan, 1970). Columns 4 to 6 investigate whether this is the case. The results provide evidence that the log of crop output per hectare increased faster in municipalities more suitable for soybean cultivation. The point estimates are similar to the point estimates from columns 1 to 3, indicating that the increase in crop output per labor unit can be attributed to increases in output per hectare.

Panel B repeats the same estimations using data from the farm output from animal products. The results from columns 1 to 6 indicate that the technological

[21] See Junior and Vilela (2002) for a discussion of the role of liming in increasing the quality of pastures and, therefore, productivity in livestock production.

change did not affect the log of the value of animal production neither per labor unit nor area. These findings point out that the reduction in pastures did not decrease output from animal products. Either the marginal product of the land converted from pasture to crops was close to zero or that spillovers from better agricultural practices offset the reduction in pastures.

These results reinforce the interpretation that the estimates capture the impact of the technological innovations in crop cultivation (as opposed to general improvements in agricultural practices). In addition, these suggest that general equilibrium considerations arising from the displacement of cattle grazing from areas that benefited from the technological innovations to areas that did not benefit from it do not seem to be relevant.

1.6. Technological Change and Labor Selection

1.6.1. Migration Status

Table 1.7 reports estimates of the impact of the technological innovations on migration status. It reports estimates of equation (1.2) in which the outcome of interest is an indicator equal to one if the individual is a migrant. Estimates consider the full sample described in the data section. Columns 1 to 3 define migrants as individuals not born in the state. Columns 4 to 6 define migrants as individuals not born in the municipality.

In columns 1 to 3 we estimate that the share of migrants in the labor force increased faster in municipalities more suitable for soybean cultivation. The estimates are not significant at the usual statistical levels in column 1 but are significant in columns 2 and 3. The impact of the technological innovations increases over time with the coefficients estimated in 1991 being larger than the coefficients estimated in 1980. The magnitude of the impact of the technological innovations is substantial: an increase in one standard deviation in agronomic potential is associated with an increase in 1.9 percentage points in the likelihood that an individual was not born in the state from 1970 to 1980 and an increase in 3.6 percentage points from 1970 to 1991.

It should be noted that the definition of migration used in the estimates from columns 1 to 3 is a conservative measure of migration. It underestimates total migration as it does not consider individuals who migrate within a state. We use this variable as the preferred migration measure because it is less affected by measurement error. Columns 4 to 6 provide evidence that the results are robust to using an alternative migration definition. Technological innovations increase the migration rate in all specifications and point estimates are even larger than the ones obtained using the preferred migration measure.

These results provide evidence that migration increased in response to the technological innovations. Since the total labor force remained constant, the rise in the share of migrants indicates that both immigration and emigration increased. More individuals sort into and out of the rural sector in municipalities which benefit from the technological innovations.

1.6.2. Educational Attainment

One interpretation for the increase in migration rates documented in the previous subsection is that population movements are responding to changes in the demand for human capital in agriculture. This interpretation suggests that technological innovations should affect the educational attainment of the rural labor force. Table 1.8 investigates whether this is the case. It reports estimates of the impact of technological innovations on schooling using equation (1.2). The outcome of interest is an indicator equal to one if the individual completed four years of more of formal schooling. Columns 1 to 3 report estimates for the full sample. Columns 4 to 6 report estimates for a subsample of individuals born in the state (*natives*). Columns 7 to 9 report estimates for a subsample of individuals born in another state (*migrants*).

Columns 1 to 3 point out that educational attainment increased faster in municipalities more suitable for soybean cultivation. The effects of the innovations are significant at the usual statistical levels across all specifications. These impacts increases over time with the coefficients estimated for 1991 being twice the size of the coefficients estimated for 1980. The magnitudes of these coefficients suggest that an increase in one standard deviation in agronomic potential is associated with an increase in 1.9 percentage points in the likelihood that an individual has four or more years of schooling from 1970 to 1980 and an increase in 3.3 percentage points in this likelihood from 1970 to 1991. These effects are large since just 8.7% of the agricultural labor force had four years or more of schooling in the baseline.

The results described above are consistent with technological innovations affecting either selective migration or investments in skill acquisition. We divide the sample between individuals who were born in the state (*natives*) and individuals who were born in another state (*migrants*) to separate these channels. An increase in educational attainment among natives can reflect both selection and skill acquisition. Nevertheless, an increase in educational attainment among migrants reflects selection.[22] Columns 4 to 6 present estimates for the sample of natives while columns 7 to 9 present estimates for the sample of migrants.

The results point out that technological change increased educational attainment both among natives and migrants. The estimated impacts are significant in all specifications in the natives subsample (columns 4 to 6) and the specifications including controls in the migrants subsample (columns 8 and 9). The estimates in the more saturated specifications in columns 6 and 9 from Table 1.8 are larger in magnitude in the subsample of migrants. The results on migrants provide evidence that labor selection helps to drive the rise in educational attainment.

To assess the importance of the selection mechanism, we can perform a calculation assuming that selection accounts for all the increase in educational attainment among migrants while skill acquisition accounts for all the increase among natives. Given the size of the migrant cohort, our estimates suggest that about half of the increase in educational attainment can be attributed to labor selection.

Table 1.9 reports estimates of the impact of technological change on educational attainment for cohorts born from 1930 to 1955. These cohorts were at least 15 years old in 1970, which implies that the technological innovations did not affect their schooling choices during school age. While individuals can return to school later, this is rare and the effects of the technological innovations on educational attainment among these cohorts are expected to reflect selection rather than skill acquisition. Columns 1 to 9 report estimates including the same controls included in columns 1 to 9 from Table 1.8.

The results from Table 1.9 are similar to the ones from the previous table. These findings provide evidence that selection can be even more important to

[22] We are assuming that there are no general equilibrium impacts of the technological change that increase the return to skill in all locations.

explain the rise in educational attainment than the calculation performed above suggested. However, it is important to note that the magnitude of the estimates is smaller in most specifications. That is suggestive that skill acquisition explains at least some of the increase in educational attainment documented in Table 1.8.

Older individuals are thought to have more specific human capital and higher moving costs than younger ones. This fact suggests that the effects of technological innovations on the composition of the labor force might be more intense among some cohorts. We estimate cohort-specific impacts of the technological innovations to investigate whether their effect is heterogeneous across cohorts. Estimates include individuals born from 1930 to 1955 and are obtained estimating the following equation:

$$Y_{imst} = \alpha_m + \delta_{st} + \sum_{v=1980}^{1991} \sum_{c=1930}^{1955} \gamma_{vc} \left(Soybean\ Potential_m * I_v * I_c \right) + \sum_{v=1980}^{1991} \boldsymbol{\theta}_v \left(\boldsymbol{X}_m * I_v \right) + \beta \boldsymbol{Z}_{imst} + u_{imst} \quad (1.3)$$

where I_c is an indicator that takes value one when the individual belongs to cohort c. The parameters γ_{vc} estimate whether educational attainment of each cohort increased faster in municipalities with higher agronomic potential compared to municipalities with lower agronomic potential during the period 1970 to 1991. The identification assumption on these parameters is that educational attainment of each cohort would have evolved in a similar fashion in municipalities with different levels of agronomic potential in the absence of the technological innovations that adapted soybean to Central Brazil.

Figure 1.2 reports the results. It plots the cohort-specific effects of the technological innovations on educational attainment. Panel A presents the estimates of γ_{1980c} for different cohorts of natives. Panel B presents the estimates of γ_{1991c} for different cohorts of natives. Panel C presents the estimates of γ_{1980c} for different cohorts of migrants. Panel D presents the estimates of γ_{1991c} for different cohorts of migrants. The reported estimates included state-year fixed effects, cohort fixed effects, sex dummies and geographic and baseline characteristics as controls.

The estimates plotted in all four panels indicate that the increases in educational attainment are concentrated among younger cohorts. In the natives subsample, the effect of technological innovations on educational attainment is concentrated among cohorts born after 1950 in the first treatment period (Panel A) and after 1945 in the second treatment period (Panel B). In the migrants subsample, these effects are concentrated among cohorts born after 1940 in the first treatment period (Panel C) and after 1945 in the second treatment period (Panel D). The comparison of the cohort-specific impact of the technological change on educational attainment among migrants (Panels C and D) and natives (Panels A and B) reveals that the effect in the former group is higher than in the latter. There are also more cohorts of migrants which are affected than there are cohorts of natives.

Overall the results from this subsection suggest that technological innovations induced immigration of skilled individuals to municipalities that benefited more from it. The findings also suggest that the innovations induced emigration of unskilled individuals from these municipalities. Both movements are concentrated among cohorts facing lower migration costs and result in an increase in the overall educational attainment of the rural labor force.

1.6.3.Occupational Choices

Table 1.10 reports estimates of the impact of technological change on occupational choices. It reports estimates of equation (1.2) for the following outcomes of interest: an indicator equal to one if the individual works in a skilled occupation in agriculture; an indicator equal to one if the individual works in an unskilled occupation in agriculture and; an indicator equal to one in the individual is either a manager or a proprietor. Columns 1 to 3 report estimates in which the outcome is whether the individual works in a skilled occupation in agriculture. Columns 4 to 6 report estimates in which the outcome is whether the individual works in an unskilled occupation in agriculture. Columns 7 to 9 in which the outcome is whether the individual is a manager or a proprietor.

Columns 1 to 3 point out that the share of labor working in skilled agricultural occupations increased faster in municipalities more suitable for soybean cultivation. The estimated impacts are significant and robust across specifications. This finding suggests that the technological innovations might have affected migration and the composition of the rural labor force through changes in the jobs available in the sector. Crop cultivation and the adoption of modern agricultural practices created employment opportunities for individuals with higher-than-average human capital and induced their migration to municipalities in which crop cultivation and agricultural intensification were happening.

The impact of the technological change increases over time with the coefficients estimated in 1991 being about 2.2 times the coefficients estimated in 1980. The estimated magnitudes suggest that an increase in one standard deviation in soybean potential is associated with an increase in .5 percentage points in the likelihood that an individual works in a skilled occupation from 1970 to 1980 and an increase in 1.2 percentage points in the same measure from 1970 to in 1991.

Columns 4 to 6 indicate that the share of labor working in unskilled agricultural occupations declined faster in municipalities more suitable for soybean cultivation. This result provides evidence that the technological change induced farms to replace unskilled labor for skilled labor. Fewer job opportunities for individuals with lower-than-average human capital stimulated their emigration from municipalities that benefited from the technological innovations. Columns 7 to 9 provide evidence that the share of the labor force working as managers or proprietors did not increase faster in more suitable municipalities. That suggests that the technological change did not induce changes in the use of managerial capital in agriculture.

1.6.4. Selection and Agricultural Output

Table 1.11 re-estimates the impact of the technological innovations on agricultural output including aggregate measures of schooling and occupational choices as controls. These estimations aim to provide tentative evidence on the quantitative importance of the selection pattern documented above on aggregate output. It is expected that the inclusion of these controls will reduce the impact of the technological change on agricultural output whenever labor selection is important to drive the increase in agricultural production.

We first re-estimate the specification from columns 3 and 6 from Table 1.6 using data either for 1970 and 1980 or 1970 and 1985. The results from these specifications are presented in columns 1, 3, 5 and 7 from Table 1.11. We then include the average educational attainment and the share of the agricultural labor force in skilled occupations as controls in columns 2, 4, 6 and 8. Columns 2 and 4 uses data from the Population Census from 1980 to construct these measures while columns 6 and 8 uses data from the Population Census from 1991 to construct these measures.

The results from the odd columns are quite similar to the results estimated in columns 3 and 6 from Table 1.6. The technological innovations have a large and significant impact on crop output measured either as the log of the value of crop production per labor unit (columns 1 and 3) or the log of the value of crop production per hectare (columns 5 and 7). These effects can reflect either the direct impact of technological change on agricultural output or its indirect impact through labor selection.

The results from the even columns indicate that a substantial percentage of the impact is due to labor selection and the changes in the agricultural labor force it induces. The inclusion of controls for the average educational attainment and the share of the agricultural labor force in skilled occupations reduce the estimated coefficients of the technological change in 30 to 35%. The impact is similar across specifications. It is important to note that these estimates are suggestive since we do not have exogenous variation in migration costs. However, these results provide tentative evidence on the importance of selection and are consistent with a recent literature which suggests that labor selection amplifies the impact of improvements in agricultural technologies (Lagakos and Waugh, 2013; Young, 2013).

1.7. Robustness Checks

1.7.1. Parallel Trends

The identification assumption which underlies the empirical design is that – within a state and in the absence of the technological innovations – the changes in agricultural outcomes would have been the same in municipalities with higher and lower soybean potential. This is the equivalent of the parallel trends assumption from differences-in-differences strategies with difference is that it does not need to hold *across* municipalities located in different states due to the inclusion of state-year fixed effects. Also, trends can be different on some observable variables included in the vector $\boldsymbol{X}_m$.

We provide suggestive evidence that the parallel trends assumption holds before the innovations occurred. We examine whether changes agricultural outcomes before the technological innovations were related to agronomic potential using these modern technologies. This provides evidence that trends were similar before the technological innovations.

A limitation of this robustness test is that we lack data before 1970 for several outcomes. Therefore, the exercise is performed only for some outcomes presented in the previous estimates. To implement the robustness test we also have to account for the creation of municipalities and border changes in the period 1960 to 1970. The total sample has 193 municipalities. The results are presented in Table 1.12 and indicate that changes in agricultural outcomes were similar across municipalities with different agronomic potential before the innovations occurred. We report estimates including geographic controls. Results available upon request provide evidence that the results are similar either excluding geographic controls or including initial characteristics.

1.7.2. Agricultural Prices

One important concern is that changes in agricultural prices drive the estimates. Some accounts suggest that the expansion of soybean cultivation during the 1970s was led by increases in soybean prices (Kiihl and Calvo, 2008). Indeed, the data from the agricultural censuses indicates that prices received by farmers rose between 1970 and 1975 as fish flour production in Peru collapsed.[23] Prices fell from 1975 to 1980 and remain stable afterwards.

The pattern of the coefficients suggests that changes in prices do not seem to drive the results. Impacts are much higher in later periods when prices were falling. We provide further evidence that prices are not driving the results including a control for soybean prices in the estimates. The control is denominated is the product of value of crop production as a share of total agricultural production in the baseline period and the average farm gate soybean price in the municipalities in the sample. The intuition of this variable is that municipalities in which crop production is more important benefit more from increases in soybean prices.

The results from estimates including this variable as a control are presented in Tables 1.13 and 1.14. Columns 1 to 3 from Table 1.13 present the results for

[23] Fish flour is another important source of animal protein.

agricultural outcomes while columns 1 and 2 from Table 1.14 present estimates for socioeconomic outcomes. In this and in the following robustness tests, we focus in three agricultural outcomes (share of crops, tractor use and crop output) and two socioeconomic outcomes (educational attainment and occupational choice). The results from both tables indicate that prices increases do not drive the estimates presented in the previous sections.

1.7.3. Land Tenure

Another concern is that colonization projects induced changes in land tenure that drive the main results. Public and private colonization projects are a characteristic of the expansion of the Brazilian agricultural frontier in the period (Alston et al., 1996; Jepson, 2002). To the extent that these colonization projects and the changes in land tenure associated with them are correlated with the agronomic potential measure, the results might confound the impact of the technological innovations and the impact of land tenure. This might be relevant since the literature indicates that land tenure is an important determinant of investments among farmers (Banerjee et al., 2002; Goldstein and Udry, 2008).

We include the share of the farmland cultivated by tenants and by occupants to examine whether the main results are driven by the expansion of bank branches. It is important to note that these controls are endogenous as technological change can affect the demand for land titling. However, including these controls in the estimates is useful to examine the robustness of the main results. The results from these estimates are presented in Tables 1.13 and 1.14. Columns 4 to 6 from Table 1.13 present the results for agricultural outcomes while columns 3 and 4 from Table 1.14 present estimates for socioeconomic outcomes. The results from both tables indicate that the estimates are robust to changes in land tenure that happened in the period.

1.7.4. Access to Credit

A final concern is that the expansion in agricultural credit drives the main results. A large expansion in the number of bank branches in the period (Graham et al., 1987). The existing literature suggests that changes in the number of bank branches can be important to agricultural development in environments in which credit constraints are pervasive (Burgess and Pande, 2005).

The expansion in bank branches could affect more municipalities more suitable for soybean cultivation using modern technologies under the assumption that credit constraints are more important constraints to the expansion of crop agriculture than to other agricultural activities. Therefore, the main results might confound the impact of the technological change with the impact of the expansion in the number of bank branches.

We control for the number of bank branches (both private and state-owned) to examine whether the main results are sensitive to the addition of these covariates. These controls are endogenous as technological innovations can affect total credit demand and – through this channel – the number of bank branches. Nevertheless, the estimates are important to examine the robustness of the main results. The results from these estimates are presented in Tables 1.13 and 1.14. Columns 7 to 9 from Table 1.13 present the results for agricultural outcomes while columns 5 and 6 from Table 1.14 present estimates for socioeconomic outcomes. The results from both tables indicate that the estimates are robust to changes in the number of bank branches that happened in the period.

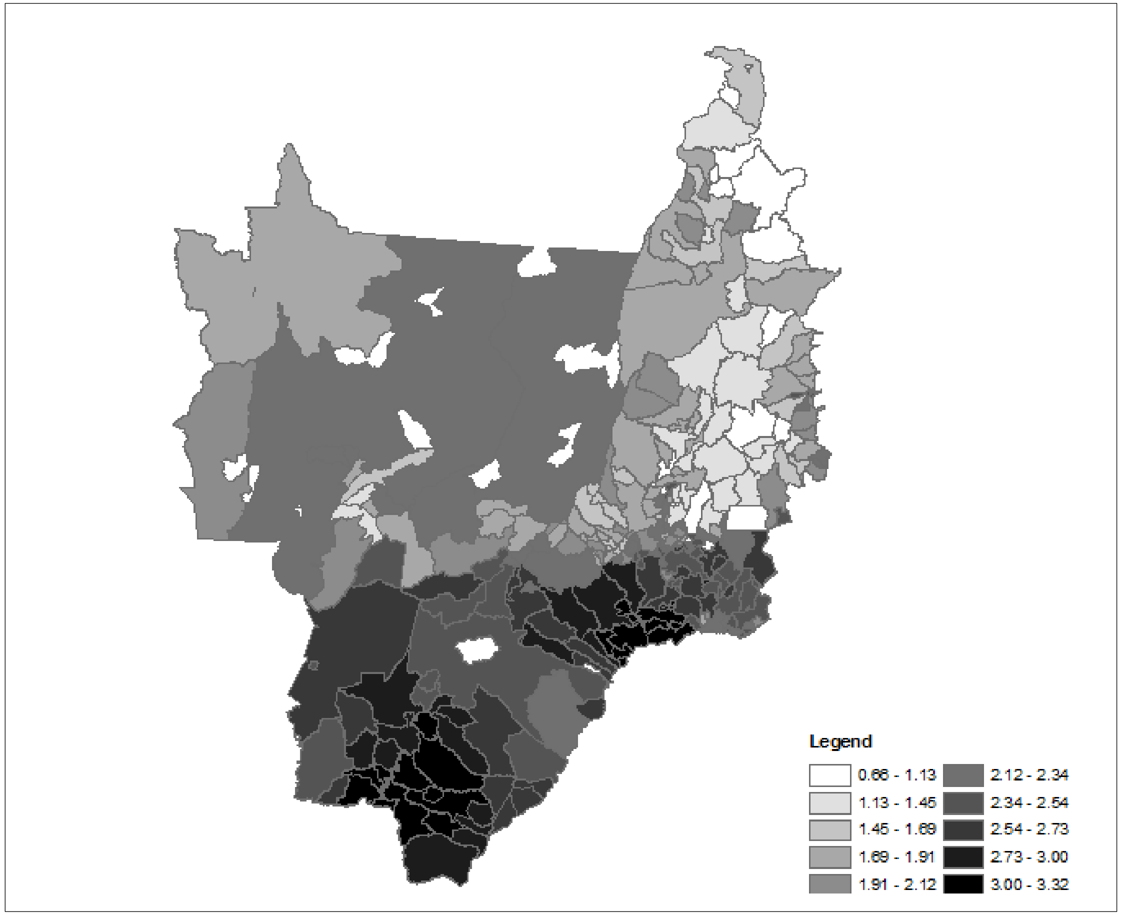
1.8. Conclusion

In this paper, we use detailed data on agricultural potential to estimate the causal impact of technological innovations that adapted soybeans for Central Brazil. We estimate that these innovations induced farmers to convert pasture into crops and to adopt modern inputs such as tractors and fertilizers. We also estimate that innovations led to selection of unskilled labor out of agriculture and selection of skilled labor into this sector.

These results illustrate the connection between technological innovations and the composition of the rural labor force and complement earlier empirical evidence on the connection of technological innovations and the size of the rural labor force (Caselli and Coleman II, 2001; Foster and Rosenzweig, 2008; Nunn and Qian, 2011; Bustos et al., 2014; Hornbeck and Keskin, *Forthcoming*). This historical episode suggests that changes in production possibilities in agriculture have different impacts across the various groups of workers. This finding can have significant implications for the debate on agricultural policies and adjustment to climatic change.

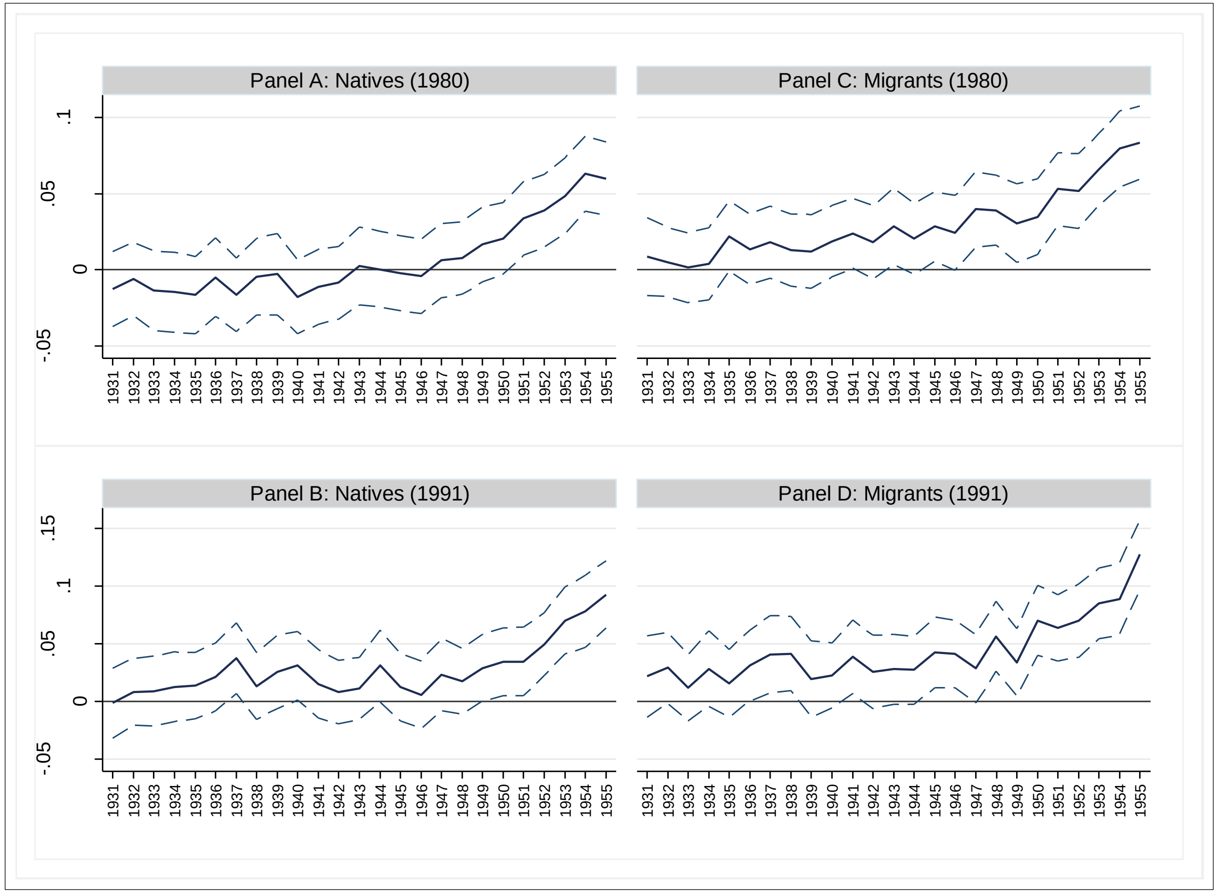
This episode also provides evidence that complementarities between human capital and modern agricultural technologies induce substantial changes in the composition of the rural labor force in response to technological innovations. These responses are similar to the ones predicted by the models presented in Lagakos and Waugh (2013) and Young (2013). Hence, we provide evidence that the labor selection mechanism emphasized in these papers has empirical relevance and might account for the observed differentials in income between agricultural and non-agricultural activities.

Figure 1.1 – Soybean Potential in Central Brazil



Notes: Data source is FAO-GAEZ. Soybean potential is the difference in potential soybean yields under the high and the low input regime.

Figure 1.2 – Technological Change and Educational Attainment across Cohorts



Notes: The solid lines report the effect of the technological change on educational attainment across cohorts. Estimates are obtained estimating equation (1.3) in the main text for subsamples of migrants and natives. Sample includes individuals born from 1930 to 1955 either employed or looking for a job living in municipalities in the states of Goiás, Mato Grosso, Mato Grosso do Sul and Tocantins. Controls used are age of birth, sex, state-year fixed effects and geographic and baseline characteristics interacted with time dummies. Dashed lines represent 95% confidence intervals obtained estimating standard errors clustered at the municipality level.

Table 1.1: Descriptive Statistics – Agricultural Censuses

	1970		1975		1980		1985	
Panel A: Soybeans								
Cultivation per 1000 hectares	0.415	(0.105)	2.282	(0.618)	7.688	(1.842)	15.686	(2.575)
Production per 1000 hectares	0.362	(0.099)	3.243	(0.956)	13.587	(3.411)	29.655	(5.024)
Share of Farms	0.714	(0.228)	1.299	(0.394)	2.065	(0.467)	3.272	(0.527)
Panel B: Land Use								
Share of Cropland	6.077	(0.455)	7.626	(0.515)	8.163	(0.476)	8.755	(0.510)
Share of Pasture	67.525	(1.068)	68.579	(0.998)	67.428	(0.865)	69.192	(0.769)
Share of Forests	14.046	(0.829)	13.435	(0.873)	13.027	(0.733)	11.478	(0.586)
Panel C: Input Use								
Labor Use	21.842	(1.333)	23.105	(1.292)	22.805	(1.220)	24.652	(1.289)
Tractor Use	0.246	(0.025)	0.498	(0.044)	0.848	(0.053)	1.083	(0.065)
Liming Use	0.319	(0.047)	0.844	(0.099)	3.809	(0.355)	4.601	(0.365)
Panel D: Agricultural Output								
Log of Crop Output per Labor Unit	3.568	(0.073)	4.060	(0.072)	4.288	(0.071)	4.395	(0.074)
Log of Crop Output per Hectare	7.755	(0.039)	8.155	(0.049)	8.377	(0.053)	8.401	(0.059)

Notes: All variables are observed for the 254 municipalities in the sample. Standard deviations are reported in parentheses.

Table 1.2: Descriptive Statistics - Population Censuses

	1970		1980		1991	
Panel A: Migration						
Not Born in the State	0.459	(0.001)	0.445	(0.001)	0.392	(0.001)
Not Born in the Municipality	0.596	(0.001)	0.633	(0.001)	0.590	(0.002)
Panel B: Educational Attainment						
Four Years or More of Schooling (0/1) - Full Sample	0.087	(0.001)	0.250	(0.001)	0.409	(0.002)
Four Years or More of Schooling (0/1) - Natives	0.089	(0.001)	0.253	(0.001)	0.410	(0.002)
Four Years or More of Schooling (0/1) - Migrants	0.085	(0.001)	0.246	(0.002)	0.409	(0.002)
Panel C: Occupational Choices						
Skilled Occupation (0/1)	0.006	(0.000)	0.037	(0.000)	0.040	(0.001)
Unskilled Occupation (0/1)	0.006	(0.000)	0.037	(0.000)	0.040	(0.001)
Proprietor or Manager (0/1)	0.030	(0.000)	0.057	(0.001)	0.065	(0.001)

Notes: All variables are observed for the 254 municipalities in the sample. Standard deviations are reported in parentheses.

Table 1.3: The Effect of Technological Change on Soybean Adoption

	Cultivation			Production			Share of Farms		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soybean Potential x 1975	5.609***	5.075***	2.731**	8.630***	7.868***	2.945**	1.287**	1.015**	0.458
	(1.945)	(1.816)	(1.104)	(3.016)	(2.841)	(1.331)	(0.504)	(0.500)	(0.340)
Soybean Potential x 1980	18.645***	17.671***	11.618***	34.842***	32.857***	17.793***	3.706***	3.824***	3.202***
	(5.539)	(5.333)	(3.947)	(10.350)	(9.947)	(6.457)	(1.083)	(1.096)	(1.094)
Soybean Potential x 1985	29.987***	29.561***	24.314***	59.249***	57.658***	42.118***	5.290***	5.571***	4.925***
	(6.704)	(6.660)	(5.527)	(12.998)	(12.843)	(9.825)	(1.268)	(1.288)	(1.304)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016
Number of Municipalities	254	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.1) in the text. The dependent variables are reported on the top of the respective columns. *Cultivation* is the number of hectares cultivated with soybeans by each thousand hectares of farmland. *Production* is the soybean production by each thousand hectares of farmland. *Share of Farms* is the share of farms which cultivates soybeans. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of the distance to Brasília and the log of the distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned bank branches, the number of private bank branches and the dependent variable. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1975, 1980 and 1985. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.4 The Effect of Technological Change on Land Use

	Share of Cropland			Share of Pasture			Share of Forest		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soybean Potential x 1975	1.292	1.691**	1.791*	-0.884	-1.891	0.859	-0.468	-0.420	-2.365
	(0.835)	(0.851)	(0.941)	(1.329)	(1.519)	(1.720)	(1.472)	(1.685)	(1.700)
Soybean Potential x 1980	2.317***	2.700***	3.988***	-1.711	-3.925**	-0.096	1.271	2.908	0.360
	(0.861)	(0.852)	(0.961)	(1.732)	(1.753)	(1.901)	(1.547)	(2.312)	(1.843)
Soybean Potential x 1985	3.289***	4.015***	5.227***	-3.967*	-7.683***	-2.126	0.847	3.003	-0.342
	(0.857)	(0.850)	(1.072)	(2.212)	(2.199)	(2.007)	(1.513)	(1.969)	(1.329)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016
Number of Municipalities	254	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.1) in the text. The dependent variables are reported on the top of the respective columns. *Share of Cropland* is the share of farmland cultivated with temporary crops. *Share of Pasture* is the share of farmland covered with pasture. *Share of Forests* is the share of farmland covered with forests. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the distance to Brasília and the distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned bank branches, the number of private bank branches and the dependent variable. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1975, 1980 and 1985. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.5: The Effect of Technological Change on Input Use

	Labor Use			Tractor Use			Liming Use		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soybean Potential x 1975	-0.120	2.305	-2.431	0.241***	0.248***	0.160**	0.891***	0.747**	0.657***
	(1.824)	(3.217)	(1.841)	(0.089)	(0.095)	(0.078)	(0.320)	(0.291)	(0.214)
Soybean Potential x 1980	0.648	3.566	-0.600	0.395***	0.436***	0.366***	5.430***	5.304***	3.821***
	(1.924)	(3.503)	(2.009)	(0.091)	(0.092)	(0.100)	(1.011)	(0.995)	(0.870)
Soybean Potential x 1985	0.801	4.493	1.201	0.618***	0.697***	0.562***	4.983***	4.899***	3.261***
	(1.913)	(3.191)	(1.927)	(0.122)	(0.127)	(0.130)	(0.969)	(0.959)	(0.831)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016
Number of Municipalities	254	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.1) in the text. The dependent variables are reported on the top of the respective columns. *Labor Use* is total employment per thousand hectares of farmland. *Tractor Use* is the number of tractors per thousand hectares of farmland. *Liming Use* is the share of farms which uses liming. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned bank branches, the number of private bank branches and the dependent variable. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1975, 1980 and 1985. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.6: The Effect of Technological Change on Agricultural Output

	Log of Production Value per Labor Unit			Log of Production Value per Hectare		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Crops						
Soybean Potential x 1975	0.091	0.199*	0.120	0.135	0.222**	0.259**
	(0.091)	(0.104)	(0.108)	(0.087)	(0.098)	(0.111)
Soybean Potential x 1980	0.208*	0.333***	0.371***	0.167	0.248**	0.387***
	(0.119)	(0.124)	(0.124)	(0.120)	(0.125)	(0.126)
Soybean Potential x 1985	0.371***	0.564***	0.573***	0.354***	0.473***	0.548***
	(0.134)	(0.131)	(0.138)	(0.130)	(0.128)	(0.140)
Panel B: Animal Products						
Soybean Potential x 1975	0.009	0.037	0.082	0.053	0.060	0.214**
	(0.068)	(0.071)	(0.082)	(0.077)	(0.080)	(0.086)
Soybean Potential x 1980	0.083	0.064	0.134	0.042	-0.022	0.136
	(0.080)	(0.085)	(0.085)	(0.089)	(0.099)	(0.093)
Soybean Potential x 1985	0.023	-0.005	0.125	0.006	-0.095	0.084
	(0.106)	(0.122)	(0.112)	(0.111)	(0.127)	(0.118)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes
Observations	1,016	1,016	1,016	1,016	1,016	1,016
Number of Municipalities	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.1) in the text. Panels A and B refers to crops and animal products. *Log of Production Value per Labor Unit and Hectare* refer to the log of production value divided by employment and farmland. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of the distance to Brasília and the log of the distance to the coast. *Baseline Controls x Year* are the interaction between year dummies and the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned bank branches, the number of private bank branches and the dependent variable. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1975, 1980 and 1985. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.7: The Effect of Technological Change on Migration

Dependent Variable: Migrant (0/1)	Not Born in the State			Not Born in the Municipality		
	(1)	(2)	(3)	(4)	(5)	(6)
Soybean Potential x 1980	0.013	0.025*	0.033**	0.032*	0.049**	0.043**
	(0.014)	(0.015)	(0.015)	(0.019)	(0.020)	(0.018)
Soybean Potential x 1991	0.022	0.044**	0.061***	0.064**	0.090***	0.092***
	(0.022)	(0.022)	(0.020)	(0.027)	(0.027)	(0.026)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes
Observations	453,187	453,187	453,187	254,555	254,555	254,555
Number of Municipalities	254	254	254	254	254	254

Notes: The table reports estimates from equation (2) in the text. The sample includes individuals with 15-64 years, living in rural areas and either working or looking for a job. Migrants are defined as individuals not born in the state in columns 1 to 3 and as individuals not born in the state in columns 4 to 6. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned and private bank branches and average value of the dependent variable in the municipality. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1980 and 1991. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.8: The Effect of Technological Change on Educational Attainment

Dependent Variable: Four Years or More of Schooling (0/1)	Full Sample			Natives			Migrants		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soybean Potential x 1980	0.026***	0.029***	0.034***	0.034***	0.032***	0.026**	0.007	0.017*	0.035***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
Soybean Potential x 1991	0.039***	0.046***	0.058***	0.041***	0.040***	0.048***	0.022	0.039***	0.065***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes	No	No	Yes
Observations	453,187	453,187	453,187	254,555	254,555	254,555	198,632	198,632	198,632
Number of Municipalities	254	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.2) in the text. The sample is reported on the top of the respective columns. The full sample includes individuals with 15-64 years, living in rural areas and either working or looking for a job. *Natives* are individuals born in the state while *migrants* are individuals born in another state. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned and private bank branches and average value of the dependent variable in the municipality. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1980 and 1991. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.9: The Effect of Technological Change on Educational Attainment – Individuals Born from 1930 to 1955

Dependent Variable: Four Years or More of Schooling (0/1)	Full Sample			Natives			Migrants		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soybean Potential x 1980	0.014*	0.019**	0.026***	0.022**	0.019*	0.015	-0.000	0.014	0.033***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Soybean Potential x 1991	0.021**	0.027***	0.043***	0.023**	0.022*	0.033**	0.011	0.025*	0.046***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)	(0.014)	(0.014)	(0.014)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes	No	No	Yes
Observations	258,927	258,927	258,927	142,573	142,573	142,573	116,354	116,354	116,354
Number of Municipalities	254	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.2) in the text. The sample is reported on the top of the respective columns. The full sample includes individuals born between 1930 and 1955, living in rural areas and either working or looking for a job. *Natives* are individuals born in the state while *migrants* are individuals born in another state. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned and private bank branches and average value of the dependent variable in the municipality. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1980 and 1991. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.10: The Effect of Technological Change on Occupational Choices

	Skilled Occupation (0/1)			Unskilled Occupation (0/1)			Proprietor or Manager (0/1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soybean Potential x 1980	0.015***	0.014***	0.009**	-0.032**	-0.046***	-0.021	-0.000	0.000	0.002
	(0.005)	(0.005)	(0.004)	(0.014)	(0.015)	(0.013)	(0.005)	(0.006)	(0.006)
Soybean Potential x 1991	0.020***	0.020***	0.020***	-0.039***	-0.049***	-0.039**	0.008	0.005	0.011
	(0.005)	(0.005)	(0.006)	(0.015)	(0.015)	(0.016)	(0.006)	(0.007)	(0.007)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes	No	No	Yes
Observations	447,154	447,154	447,154	447,154	447,154	447,154	453,187	453,187	453,187
Number of Municipalities	254	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.2) in the text. The dependent variable is reported on the top of the respective columns. The sample includes individuals with 15-64 years old, living in rural areas and either working or looking for a job. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned and private bank branches and average value of the dependent variable in the municipality. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1980 and 1991. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.11: Migration, Selection and Agricultural Output

	Log of the Value Crop Production per Labor Unit				Log of the Value Crop Production per Hectare			
	1970-1980		1970-1985		1970-1980		1970-1985	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Soybean Potential x Post	0.361**	0.252*	0.482***	0.325**	0.333**	0.231	0.495***	0.352**
	(0.159)	(0.148)	(0.180)	(0.163)	(0.161)	(0.153)	(0.176)	(0.158)
Share in Skilled Occupations		9.736***		10.182***		8.129***		9.199***
		(2.229)		(2.063)		(2.541)		(2.418)
Share with Four Years of Schooling		0.571		0.473		1.074		0.539
		(1.011)		(0.754)		(0.882)		(0.765)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	508	508	508	508	508	508	508	508
Number of Municipalities	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.1) in the text. The dependent variable is reported on the top of the respective columns. *Soybean Potential is* the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned and private bank branches and the dependent variable. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins either for the years 1970 and 1980 or 1970 and 1985. Controls for 1980 are constructed using data from the 1980 Population Census. Controls for 1985 are constructed using data from the 1991 Population Census. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.12: Robustness I – Checking the Parallel Trends Assumption

	Cropland	Share of Pasture	Share of Forests	Labor Use	Tractor Use	Liming Use	Rice Cultivation	Bean Cultivation	Maize Cultivation	Total Wages
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Soybean Potential x 1970	1.387	-2.808	2.484	0.051	0.497	0.092	6.480	-5.142	1.433	0.096
	(1.233)	(3.161)	(1.997)	(0.102)	(0.432)	(0.118)	(9.905)	(3.373)	(2.735)	(0.253)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	386	386	386	386	386	386	386	386	386	386
Number of Municipalities	193	193	193	193	193	193	193	193	193	193

Notes: The table reports estimates from equation (1.1) using data before the technological change. The dependent variables are reported on the top of the respective columns. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of the distance to Brasília and the log of the distance to the coast. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1960 and 1970. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.13: Robustness II – Additional Controls for Agricultural Outcomes

	Price Controls			Land Tenure			Access to Credit		
	Cropland	Tractor Use	Crop Output	Cropland	Tractor Use	Crop Output	Cropland	Tractor Use	Crop Output
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Soybean Potential x 1975	1.930**	0.178**	0.275**	1.503	0.151*	0.195*	1.797*	0.159**	0.237**
	(0.938)	(0.078)	(0.110)	(0.922)	(0.079)	(0.111)	(0.943)	(0.078)	(0.110)
Soybean Potential x 1980	4.186***	0.390***	0.419***	3.535***	0.350***	0.295**	4.014***	0.363***	0.367***
	(0.966)	(0.101)	(0.123)	(0.933)	(0.103)	(0.130)	(0.967)	(0.101)	(0.131)
Soybean Potential x 1985	5.404***	0.584***	0.534***	4.596***	0.541***	0.386***	5.281***	0.561***	0.489***
	(1.067)	(0.129)	(0.138)	(1.024)	(0.134)	(0.146)	(1.083)	(0.132)	(0.148)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016	1,016
Number of Municipalities	254	254	254	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.1) in the text. The dependent variables are reported on the top of the respective columns. *Cropland* is the share of farmland cultivated with crops. *Tractor Use* is the number of tractors per thousand hectares of farmland. *Crop Output* is the log of the value of crop output per labor unit. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls* x Year are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned bank branches, the number of private bank branches and the dependent variable. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1980 and 1991. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

Table 1.14: Robustness II – Additional Controls for Population Outcomes

	Price Control		Land Tenure		Access to Credit	
	Primary Schooling (0/1)	Skilled Occupation (0/1)	Primary Schooling (0/1)	Skilled Occupation (0/1)	Primary Schooling (0/1)	Skilled Occupation (0/1)
	(1)	(2)	(3)	(4)	(5)	(6)
Soybean Potential x 1980	0.034***	0.009*	0.033***	0.008*	0.032***	0.010**
	(0.009)	(0.004)	(0.009)	(0.004)	(0.009)	(0.004)
Soybean Potential x 1991	0.059***	0.020***	0.052***	0.017***	0.054***	0.023***
	(0.012)	(0.006)	(0.012)	(0.006)	(0.012)	(0.006)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls x Year	No	Yes	Yes	No	Yes	Yes
Baseline Controls x Year	No	No	Yes	No	No	Yes
Observations	453,187	447,154	453,187	447,154	453,187	447,154
Number of Municipalities	254	254	254	254	254	254

Notes: The table reports estimates from equation (1.2) in the text. The dependent variable is reported on the top of the respective columns. The sample includes individuals with 15-64 years old, living in rural areas and either working or looking for a job. *Soybean Potential* is the difference of the potential soybean yields under high inputs and under low inputs. *Geographic Controls x Year* are the interaction between year dummies and the log of distance to Brasília and the log of distance to the coast. *Baseline Controls x Year* are the interaction between year dummies are the baseline value of the share of available land, the log of the number of farms, the log of total farmland, the number of state-owned and private bank branches and average value of the dependent variable in the municipality. The sample is composed by all municipalities in the states of Mato Grosso do Sul, Mato Grosso, Goiás and Tocantins for the years 1970, 1980 and 1991. Standard errors clustered at the municipality level are reported in parentheses. * denotes statistical significance at 10% ** denotes statistical significance at 5% *** denotes statistical significance at 1%.

2 Geographic Heterogeneity and Technology Adoption: Evidence from the Direct Planting System

2.1. Introduction

Low adoption of modern agricultural technologies is considered an important constraint to agricultural development across the developing world.[24] This phenomenon is associated with several possible explanations, ranging from market failures to behavioral biases.[25] This paper documents another determinant of under-adoption of modern agricultural technologies: geographic heterogeneity.

Diamond (1997) suggests that the distribution of geographic characteristics can affect agriculture through its influence on technology adoption. The author writes that "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: (...) 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 temporary variations. To a lesser degree, they also tend to share similar diseases, regimes of temperature and rainfall, and habitats or biomes."[26] However, the existing literature focuses on the impact of the level of geographic characteristics on agricultural development, being silent on the effects of the variation in geographic characteristics on agricultural development.[27]

This paper provides evidence that low adoption of modern technologies in agriculture can be related to geographic heterogeneity using data from the utilization of the Direct Planting System (DPS) in the Brazilian agriculture. Using

[24] Estimates indicate that returns to the adoption of modern agricultural technologies are quite high (Duflo et al., 2008; Suri, 2011).

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

[26] See Diamond (1997), p. 178 and p. 183.

[27] See, for instance, Hornbeck (2012) and Hornbeck and Keskin (2014).

soil heterogeneity as a measure of geographic heterogeneity, we present evidence that it has a negative effect on the adoption rate of the DPS.

We propose a simple theoretical model connecting geographic heterogeneity and technology adoption through adaptation costs. In the model, adaptation costs increase and adoption becomes more difficult when farmers observe successful adoption experiences under different geographic conditions.[28] That leads to lower equilibrium adoption rates in economies in which geographic heterogeneity is high. In addition to that, the model predicts that the impact of soil heterogeneity should be zero when adoption rates are either too low or too high. In the former case, adaptation 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 find a neighbor operating under similar geographic conditions regardless geographic heterogeneity. For intermediate adoption levels, the model predicts the impact of heterogeneity to be highest.[29]

In the model, the presence of adaptation costs affects the format of the relationship between adoption levels and geographic heterogeneity. This pattern can be used to evaluate the presence of adaptation costs using indirect evidence. That is important when direct information is hard or impossible to collect.[30] In addition, the model predicts that the relationship between geographic heterogeneity and technology adoption should hold in all periods, allowing the use of cross-sectional data in the empirical investigation.

The model is tested using detailed data on soil characteristics and information on technology adoption of the Direct Planting System (DPS). The DPS was developed in southern Brazil in the 1970s based on previous experiences

[28] An alternative explanation is based on the informational content of experiences performed under different conditions (see, for example, Munshi (2004)). Although this interpretation leads to the same results, we opt for the adaptation costs view as it is more suitable to the actual diffusion process of the DPS in Brazil.

[29] It should be noted that this non-monotonic pattern is related to the traditional S-curve which depicts adoption levels over time: 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 over quantiles of the unconditional distribution of adoption. See the chapter 7 in Jackson (2008) for a theoretical discussion of the S-curve. Foster and Rosenzweig (1995) estimate that adoption of modern technologies in agriculture follows the S-curve.

[30] In a similar vein, Young (2009) explores differences in the adoption rates over time (known as the S-curve) to identify social learning as the actual diffusion channel of a new technology.

with no-till farming.[31] It was developed in areas prone to land degradation. It later evolved into a full farming method with higher revenues and lower costs than the traditional (tillage-based) methods. Inoue (2003) reports that DPS adoption is associated with costs 9% lower and with revenues 17% higher in the case of soybean cultivation.[32] The limited use of tillage also prevents soil degradation and the loss of nutrients due to plowing, increasing long-run productivity.[33]

The DPS has two essential features for the analysis. First, adoption configures an actual technological innovation and does not require large changes in input use. It mainly requires learning about the new way of combining inputs for production and minor modifications in machinery. Second, other constraints to technology adoption are absent. Credit constraints are not relevant as there are no upfront costs, while risk does not seem to be an issue since the DPS decreases risk exposure. There is also no need for additional infrastructure and scale issues do not appear to be relevant as adoption rates are similar across farm sizes.[34]

Despite these features, only 10.1% of the Brazilian farmers adopted the DPS in 2006. The agronomic literature attributes under-adoption of the DPS to lack of knowledge since the practice must be adapted to different geographic conditions to function well. 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”. Derpsch (1999) argues “site specific knowledge of the no-tillage system has most likely been the main limitation to the spread of the system in (...) Latin America”. Therefore, the DPS have features suggesting that the negative relationship between geographic heterogeneity and technology adoption can be interpreted as evidence of the relevance of adaptation costs.

We use both detailed GIS data on soil characteristics and data from the 2006 Brazilian Agricultural Census to examine the relationship between geographic heterogeneity and DPS adoption. We choose soil heterogeneity to be the relevant

[31] 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.

[32] See Sorrenson and Portillo (1997) and Trigo et al. (2009) for evidence on DPS benefits in other South American countries.

[33] The DPS adoption is also associated to an increase in carbon sequestration and a reduction in greenhouse gas emissions in agriculture. These environmental benefits have been documented in several setting. See Tesla et al. (1992), West et al. (2002), and Metay et al (2007) for some evidence on these gains.

[34] Detailed accounts of these features of the DPS can be found in Landers (2005) and Derpsch et al. (2010).

geographic heterogeneity measure because soils affect how the DPS should be used. The composition of each soil affects physical properties like temperature. These properties affect the implementation of the DPS. For example, a higher soil temperature calls for a thicker layer of residue on the surface.

We measure soil heterogeneity using a physicochemical classification of soil types that is invariant to land use. We use this classification to construct the share of the municipal area covered with each soil. These shares are used to build a Herfindahl index (HHI) and the inverse of this index is used as the heterogeneity measure. It is important to notice that this measure does not have a direct impact on farming as it does not affect agricultural output or the use of other inputs.[35]

Using a sample of Brazilian municipalities, we estimate that soil heterogeneity reduces DPS adoption even when controlling for the several geographic characteristics (soil types, rainfall, temperature, land gradient, altitude, latitude and longitude) and socioeconomic characteristics (education, number of farms, farm revenues, government technical assistance and state fixed effects). The estimated impact is meaningful: an increase in one standard deviation in soil heterogeneity decreases DPS adoption in 1 to 1.3 percentage points. The results are robust to the inclusion of measures of land use, cooperatives and access to credit as additional controls. Results are also robust to changes in sample definition.

Placebo tests provide evidence that soil heterogeneity neither influences the adoption of non-agricultural technologies (such as electricity) nor the adoption of technologies related to harvesting (such as the combine harvester). These tests provide suggestive evidence that adaptation cost mechanism proposed in the theoretical model.

Further investigation of the proposed mechanism is done using an unconditional quantile regression estimator suggested by Firpo et al. (2009). The estimator uses a regression approach based on Recentered Influence Functions (RIF) to estimate the impact of soil heterogeneity across different quantiles of the adoption distribution. This method enables us to test if the effect of soil heterogeneity on DPS adoption is non-monotonic as the theoretical model

[35] We choose this measure because it has a simple interpretation. The inverse of the HHI index is a measure of the effective number of soils. However, the literature suggests some alternative measures. See, for instance, Esteban and Ray (2011) for a discussion of alternative measures in an investigation between ethnic fractionalization and conflict.

predicts. Results are consistent with the theoretical model. The effect of soil heterogeneity is higher than the average impact when adoption rates range from 20 to 50 percent (percentiles 50 to 75 in the sample). It peaks at an adoption rate of 40% percent (percentile 70). In this rate, an increase in one standard deviation in soil heterogeneity reduces DPS adoption by 4.5 percentage points.

These results contribute to two fields of the literature. First, it contributes to the strand that investigates the relationship between geographic characteristics and economic outcomes. A substantial literature documents the impact of geography on determinants of economic development such as historical institutions, ethnic fractionalization, and cultural formation (Durante, 2010; Michalopoulos, 2012; Fenske, 2014; Alsan, 2015). We provide evidence that technology adoption is another channel through which geographic characteristics influences economic outcomes. Our results support the view that geographic similarities facilitate the adoption of modern technologies proposed by Diamond (1997).

Second, we contribute to the literature on the determinants of under-adoption of modern technologies in agriculture. The literature stresses the importance of formal training (including educational levels) and social learning in technology adoption (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010). The literature also stresses that market failures in credit and insurance markets reduce technology adoption in agriculture due to significant setup costs and risks often involved in the adoption of modern technologies (Udry, 2010; Karlan et al., 2014). We provide evidence that geographic heterogeneity can also reduce technology adoption.[36]

The remaining of 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 report the main estimates and robustness tests. Section 6 reports the unconditional quantile results. Section 7 concludes.

[36] 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.

2.2. Historical Background

2.2.1. Overview of the Direct Planting System

The DPS is a no-till technique developed in Brazil at the beginning of the 1970s. These techniques can be described as agricultural practices in which tillage is limited or absent and crop residue is left on the surface. Soil is then preserved: loss of nutrients due to plowing and rain erosion decrease. However, the use of no-till techniques in large-scale agriculture is only possible when effective herbicides are available as tillage is an important tool for weed control.

The no-till techniques challenge a long established notion in agriculture: the importance of tillage. The plow can be considered one of the main historical determinants of agricultural development as it facilitated weed control. The development of plows capable of inverting soil layers in the 17th century and other subsequent technological advances made tillage even more important and contributed to a significant increase in food production. As Derpsch (1997) put it, “because the modern plow saved Europe from famine and poverty it became a symbol of “modern” agriculture (...). Colonies in America, Asia and Africa simply followed the European pattern”.

The plow's substantial gains in terms of weed control and soil scarification meant that it was worth using it despite its cost in terms of land degradation and erosion. Indeed, modern no-till techniques were developed just after the 1940s when herbicides became more efficient. The development of more effective forms of weed control in the following decades triggered more research on no-till techniques. These techniques have become a popular feature among proponents of sustainable agricultural practices (Baker et al., 2007).

The DPS is a particular no-till method in which absence of tillage is permanent and the use of green manure crops to cover the soil is widespread (Derpsch et al., 2010). Both features resulted from the effort to adapt no-till techniques to the specific geographic conditions Brazilian farmers faced. This technique has become popular in other countries in South America as well.

The adoption of the DPS characterizes the adoption of a novel production technology as adopters continue to use similar the same inputs to obtain higher output. It can thus be characterized as the adoption of a different production process that uses the same inputs (as opposed to the adoption of formerly underused inputs in the same production process).[37] This is an important feature of the technique for the empirical investigation since it is often difficult to separate adoption from input underuse (Foster and Rosenzweig, 2010).

DPS adoption is known for having both public and private gains. Table 2.1 describes the benefits from the technique. Public gains are presented in Panel A and are unambiguous. These main benefits come both from lower carbon emissions and higher carbon sequestration. Both changes have positive externalities to the environment and mitigate climate change (Tesla et al., 1992; West et al., 2002; Metay et al, 2007). Other gains have been reported in terms of reduced environmental contamination and increased biodiversity (Derpsch et al., 2010; Camargo et al., 2011).

Private gains are presented in Table 2.1, panel B. These benefits come from a combination of higher revenues and lower costs. The DPS reduces soil degradation and erosion and improves soil properties, resulting in higher revenues. It also decreases the use of machines to plow the soil. Although expenditures with fertilizers increase, the costs fall even in the short term (Derpsch et al., 2010; Baker et al., 2007).

A substantial literature quantifies the economic benefits from the DPS. Inoue (2003) presents evidence that DPS adoption decreases soybean productivity in 17% in Brazil. The author also presents evidence that average costs decrease 9% with DPS adoption. Sorrenson and Portillo (1997) reports that DPS increases net income by 33% in the first year of adoption among farmers in Paraguay. The authors also argue that the benefit from the DPS increases over time. Trigo et al (2009) estimates substantial economic benefits from DPS adoption in Argentina coming both from increases in production and decreases in costs. Ringler et al (2013) simulates that widespread adoption of no-till techniques would increase yields of staple crops even considering the effects of climate change on temperature and rainfall. The authors argue that no-till is a promising farming techniques to mitigate climate change’s impact on agriculture.

An important feature of the DPS is that neither credit constraints nor incomplete insurance seem to be barriers to its adoption. First, the technique has

[37] The optimal choice of inputs often 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.

no upfront costs, suggesting that access to credit is not a constraint for adoption. Second, the method reduces production risks as input demand decline and yield volatility decline. This feature suggests that lack of insurance is also not a barrier to DPS adoption. Furthermore, adoption of the DPS does not require additional infrastructure and scale issues also seem to be irrelevant since adoption rates are similar across farm sizes.

Information, on the other hand, appears to be the major barrier to DPS adoption. Derpsch (1999) describes the adjustments needed to use the technique in tropical soils that are often "acid or have toxic aluminum". The author argues that adjustment required to make the DPS suitable are unique to the type of soil under consideration (although there are some general practices that must be used in all contexts). He suggests that lack of "site specific knowledge" has been a significant barrier to the diffusion of DPS in Latin America. Indeed, his first two recommendations for farmers willing to adopt such techniques are:

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

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

2.2.2. The Diffusion of the Direct Planting System in Brazil

Brazil is the fifth largest in the world and agricultural conditions differ substantially across its regions. The DPS was first implemented at the beginning of the 1970s in southern Brazil. This region's main geographic characteristics are the sub-tropical climate and fertile soils. These features attracted European immigrants in the late 1800s which compose a large share of the farmers in the region.

The first tests with the DPS in Brazil happened at the beginning of the 1970s with sorghum and wheat. The technique was developed to fight rain erosion that affected soils in the region of *Ponta Grossa* in the state of *Paraná*. Pioneer farmers studied no-till techniques abroad and assumed the risk of importing equipment and knowledge and testing the method on large scale. These farmers exerted a significant influence on the development of the DPS in Brazil and induced research on the technology in private institutes as well as public universities.

For instance, the IAPAR (Agronomic Institute of Paraná – a private institution) started a soil conservation program that promoted the DPS in 1975. Later Embrapa (the Brazilian Agricultural Research Corporation – a public institution) also began to influence the development of the DPS. Since its creation, the technique evolved from a practice to reduce rain erosion to a complete production method.

Anecdotal evidence suggests that large farmers in the *Ponta Grossa* region started adopting the DPS in 1976. The first adopters were concentrated in southern Brazil, but later the farmers from northern areas started to use the technique. These northern regions feature diverse tropical environments, in particular in the Cerrado biome. The first attempts to implement the DPS in this biome happened in the 1980s. Adoption in the region accelerated since the 1990s.

An important feature of the DPS diffusion was the creation of an association called *Clube da Minhoca*[38] (henceforth CM) in 1979. The CM is located in *Ponta Grossa* and is a diffusion center with the goal of spreading knowledge about the technique. The organization promoted meetings where farmers (adopters and non-adopters) would discuss issues related to farming. It also organized national meetings and sponsored the publication of technical material about the DPS.

The CM inspired the creation of private associations with a similar objective in other localities. These associations are called *Clube Amigos da Terra*[39] (henceforth CAT) and the first was established in 1982 in the state of *Rio Grande do Sul*. These associations were an essential tool for the diffusion of the DPS throughout Brazil. The CATs coordinate learning efforts and information exchange among farmers. The CATs and other organizations that promote the technique were essential to spread information and knowledge about the method. Indeed, these private organizations seem to have been more important to DPS diffusion than the public extension services.

However, the presence of these associations was not sufficient to induce most Brazilian farmers to adopt the DPS. Almost 90% of the farmers did not adopt the technique despite the substantial increase in adoption since the 1990s depicted in Figure 2.1. The adoption rate is similar across farm sizes and is higher in the crop-intensive areas in southern and central Brazil.

[38] Translated as "Earthworm club" as the presence of earthworm was a sign of soil vitality.
[39] Translated as "Friends-of-the-earth club".

The next section proposes a formal model to deal with the need to adjust the DPS for different geographic conditions. Notice that such differences have no direct impact on agriculture as we only analyze soils where agriculture is viable in the first place under both traditional tillage and DPS. We interpret them as a barrier to adaptation to different soil types where DPS has not been used before.[40]

2.3. Model

Consider a simple economy with a continuous mass of farmers with size normalized to one. Each farmer i has a soil $\theta_i \in \mathbb{R}^N$. Soils are distributed according to a single-peaked joint distribution $G(\theta; \sigma^2)$ with associated density g. The variance σ^2 is assumed to be strictly positive and determines how much soils differ: soil heterogeneity is captured by a higher σ^2. We assume that the probability that $\theta_i = \theta_j$ is zero for all $i \neq j$.[41]

There are two technologies available for crop production: a traditional technology and a new technology. We assume (discounted) profits from the new technology, $\overline{\pi}$, are larger than under the current one, $\underline{\pi}$. Define $\Delta\pi = \overline{\pi} - \underline{\pi} > 0$. Despite the difference in profits, farmers might not use the new technology since there is a non-pecuniary cost to adopt it. In each period t, the adoption decision is described by a_{it}: $a_{it} = 1$ if he adopts the new technology and $a_{it} = 0$ otherwise. Each farmer i is then characterized by a sequence $(\theta_i, a_{it})_t$.

The adoption cost reflects the need to make some adjustments to the new technology (a micro-innovation) in order to use it in a different type of soil. We assume that this cost will be lower when the farmer has neighboring farmers who adopted the technology. This assumption captures the intuition that farmers can learn from their peers' experiences. Therefore, 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 $\min_j d(\theta_i - a_{jt}\theta_j)$, in which d is the Euclidean distance.

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[40] 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.

[41] 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.

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

$$N(\theta_i) = \{\theta_j : d(\theta_i, \theta_j) \le R\} \tag{2.1}$$

This is the set from which a farmer can learn from. This set has mass $M(N(\theta_i)) = \int_{N(\theta_i)} g(\theta) d\theta$. We also define the set of adopters in i's neighborhood in period t as:

$$N_A^t(\theta_i) = \{\theta_j : d(\theta_i, \theta_j) \le R \; and \; a_{jt} = 1\} \tag{2.2}$$

This set has mass $M(N_A^t(\theta_i)) = \int_{N_A^t(\theta_i)} g(\theta) d\theta$. The cost of adaptation $c(.)$ is a function of this set. This cost function $c\left(M\left(N_A^t(\theta_i)\right)\right)$ is assumed to have the following properties:

i. $c(0) > \Delta\pi$
ii. $c(.)$ is decreasing in its argument and there is $m < 1$ such that $c(m) < \Delta\pi$.

Assumption (i) 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 adapt from (and no alternative diffusion channel). Hence, we are modeling the diffusion and not the initial innovation process.

Assumption (ii) captures the adaptation channel. The presence of adopters in the R-neighborhood decreases the cost of adaptation as farmers can learn about the technology by observing other adopters operating close to them. Moreover, the new technology is viable for a high enough adoption rate in the farmer's neighborhood.

The farmers can also have access to some alternative diffusion channel that reduces adoption costs. This alternative is interpreted as access to formal diffusion channels as extension services, cooperatives, and dissemination centers. These channels are labeled F_t such that $F_t = 0$ represents the absence of such channel in that period. The total cost of adaptation is defined as:

$$c\left(M\left(N_A^t(\theta_i)\right)\right) - F_t \tag{2.3}$$

It is important to note that 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 distribution of types (θ_i) and initial adopters (a_i^0) is drawn;

$t = 1$: beginning of the period: non-adopters decide whether to adopt or not the technology based on (θ_i, a_i^0);

$t = 1$: end of the period: new distribution of adopters is observed by all agents;

$t = 2$: beginning of the period: non-adopters decide whether to adopt or not the technology based on (θ_i, a_i^1);

And so forth.

An agent will adopt the new technology whenever the gain in profit is higher than the cost of adaptation. Therefore, a farmer i will adopt the technology in period t ($a_{it} = 1$) if:

$$\Delta\pi \geq c\left(M\left(N_A^t(\theta_i)\right)\right) - F_t \tag{2.4}$$

Let $\overline{M} = c^{-1}(\Delta\pi)$. This is the lowest mass of adopters, in a given neighborhood, that allows diffusion to take place. Define $M^U = M\left(N_A^0(\theta_i)\right)$ as the initial mass of adopters around θ_i under the uniform distribution and notice that is must be the same for all i. We further assume 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.[42] The intuition is that the initial level of adoption 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 not essential 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. In the presence of operational differences in the use of the new technology among different soils, it is necessary to incur a cost to adjust it. This cost is by construction lower when previous adopters operate under similar conditions as non-adopters.[43]

[42] This assumption is trivially satisfied if the support of types is unbounded. If $\theta \in \mathbb{R}$ this assumption boils down to $\overline{M} > 2R\alpha$.

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

Decisions in period t induce a (possibly changed) end-of-period distribution of adopters with associated mass $M\left(N_A^t(\theta_i)\right)$. We are implicitly assuming that farmers need at least one period to adapt the new technology (intuitively, they have to observe a whole growing cycle). We have $M\left(N_A^t(\theta_i)\right) \geq M\left(N_A^{t-1}(\theta_i)\right)$ as the set of adopters never decreases.

An allocation is a vector of adoption decisions $\{a_i\}_i^t$. An equilibrium path is defined as follows.

Definition 1: For a given vector θ and initial distribution $\{a_i\}_i^0$, an equilibrium profile $\{a_i^*\}_i^t$ is such that for all i and for all $t \geq 1$, $a_{it}^* = 1$ if and only if equation (2.4) holds.

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

The expected level of A^t should depend on σ^2 for all t. More dispersion in soils reduces the likelihood that a farmer will find enough adopters in the neighborhood to make adoption profitable. However, the impact will depend on the adoption level A^t as the following proposition establishes. We assume that the derivative $\partial A^t/\partial\sigma^2$ exists.[44]

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

Proof. Consider an initial situation in which $a_i = 0$ for all i. Assumption 1 implies that no agent finds profitable to adopt the modern technology. Adaptation cannot take place in the absence of adopters in the neighborhood. Therefore, $A^t(\sigma^2) = 0$ and $\partial A^t/\partial\sigma^2 = 0$. Reasoning is similar for a profile $\{a_i^*\}_i$ such that $M\left(N_A(\theta_i)\right) > m$ for all i. Assumption 2 implies that all agents find profitable to adopt the modern technology. Therefore, $A^t(\sigma^2) = 1$ and $\partial A^t/\partial\sigma^2 = 0$. To prove that $\partial A^t/\partial\sigma^2 < 0$ for some intermediate value, it suffices to prove that a higher variance will lead to lower adoption in the initial period ($t = 1$). It follows that adoption will be lower in all subsequent periods as non-adopters will have a lower mass of adopters to learn from. Since G is single-peaked and $\overline{M} > M^U$, the set of farmers such that adoption is profitable decreases when σ^2 increases.[45]

[44] It is straightforward to rewrite the argument for a non-differentiable function A^t.
[45] It is possible to show that if G is not single-peaked, A^t decreases non-monotonically in σ^2.

Intuition is straightforward. When adoption levels are too low, there is no one from whom to learn and adapt the new technology and diffusion cannot take place at all. It follows that the impact of heterogeneity on adoption is zero. When adoption levels are high enough, the cost of adaptation becomes lower than the benefit. Adoption will be so widespread that farmers will be able to adapt no matter how different their soils are.[46] Nevertheless, at intermediate levels, an increase in heterogeneity must reduce adoption. The level of adopters in any given neighborhood goes below the minimum needed to allow adaptation.

Without further structure on the distribution G, one cannot derive additional properties of $\partial A^t/\partial\sigma^2$. For illustration purposes, assume from that $A^t(\sigma^2)$ is continuously differentiable and has one local minimum labeled A^c. These assumptions facilitate the interpretation of the empirical results. The following result is then immediate.

Corollary 1: The derivative $\partial A^t/\partial\sigma^2$ is increasing for $A^t \in (0, A^c)$ and decreasing for $A^t \in (A^c, 1)$.

We now turn to the relationship between adaptation costs and other diffusion channels.

Corollary 2: An increase in the use of the formal channel F_t can either crowd out or reinforce the adaptation channel.

These institutions can either weaken or strengthen the relationship between soil heterogeneity and adoption of the new technology. The formal channel causes adaptation costs 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, this adoption rate can be associated either to a higher impact or a lower one. In the former case, formal channels substitute adaptation and thus weaken this relationship. In the latter, these alternative learning mechanisms complement adaptation.

Notice that this result does not rely on any assumption of the cross derivative of adaptation costs on M and F which is zero in the present setup. Were it positive (negative), the region where F_t and adaptation were substitutes would be larger (smaller). However, there will be no qualitative change in the results.

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

The empirical counterparts of the economies described in the model are municipalities. The variables (σ^2, α, R, G) describe these economies. The model predicts that municipalities with higher soil heterogeneity σ^2 should have (on average and for any given t) lower adoption rates of the DPS. Moreover, 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). Therefore, the model suggests a specific format for the relationship between soil heterogeneity and technology adoption. This format is related to the adaptation costs mechanism and can be used to infer the presence of this channel.

It is worth stressing that the predictions above hold at an aggregate level and can be tested without using individual-level data. However, it is also worth emphasizing that farmers are heterogeneous within and across Brazilian municipalities in several dimensions not considered in the model. Both profits and adaptation costs might be correlated with farmers' characteristics, being an important challenge for estimation to control for these characteristics.

2.4. Data

2.4.1. Soil Heterogeneity

We build the soil heterogeneity measure using detailed GIS information from a Brazilian soil map developed by Embrapa, the Brazilian Agricultural Research Corporation (Embrapa, 2011). The data is based on an international soil classification system (Santos, 2006). This classification 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, the map does not report information beyond the third level. Information is at scale 1:5.000.000 for each level.

The classification system is based on soils' physicochemical composition. This composition is a major determinant of the physical properties of each type of soil. Physical properties, in their turn, define the suitability for different agricultural methods. For example, in the case of the DPS, higher soil temperature often calls for a thicker layer of residue on the surface in order to decrease exposure to sunlight and avoid excessive heat. Hence, a different type of soil calls for some adjustment (a micro-innovation) in the use of the DPS. This classification system is "smooth" in the sense that, for agricultural purposes, the difference in physical properties between two soils is roughly the same for soil pair.

The baseline empirical specification considers the most general level (order) to construct the soil heterogeneity measure. This level has the advantage of being invariant to 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. Therefore, measures built using this level can be assumed not to depend on the adoption of the DPS or of other agricultural practices. We provide evidence in the robustness section that results are unchanged when one considers the more refined levels (a natural result since the correlation between alternative soil heterogeneity measures is quite high).

There are 35 different orders across Brazil. We merge the soil map with the map of municipalities to build a measure of the share of each municipality covered by each soil order. We use the same procedure to build measures for the other levels. These shares are used to construct a Herfindahl index (HHI) of soil types for each municipality. The index varies from zero to one 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 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. We choose this measure because it is simple to interpret. Nevertheless, it is important to highlight that other literatures suggest the use of alternative measures.[47]

We expect a higher S to reduce adoption of the DPS. We also expect the impact of S on DPS adoption to be non-monotonic and higher at intermediate adoption rates. The intuition is that neighbors' experiences are less informative in more heterogeneous municipalities: adaptation costs are larger and adoption decreases. Notice that this result is independent of S having an impact on

[47] See Esteban and Ray (2011) for an example.

agricultural output. Indeed, it is worth stressing that *S* is an artificial variable with no direct impact on production.

Table 2.2 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 soil orders.

It is important to note that our approach for measuring heterogeneity in growing conditions contrasts with Munshi's (2004) learning study. The author classifies regions as more or less heterogeneous using information on the crops cultivated in each of them. He argues that rice growing areas 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 approach of Michalopoulos (2012) and Fenske (2014) who correlate similar measures to historical and institutional development.

2.4.2. Agricultural Outcomes

Data on agricultural outcomes is drawn from the 2006 Brazilian Agricultural Census. The main agricultural outcome used in our empirical exercises is the Direct Planting System adoption rate. We define it as the share of farms that use the DPS. We restrict the baseline estimates to municipalities with adoption levels above 5% to ensure that we are investigating adoption in municipalities in which the DPS is viable. The results are robust to including municipalities below this threshold. We also drop the upper one percent tail of the soil heterogeneity. We have a final sample of 1,628 municipalities.

Table 2.3 reports the distribution of adoption rates in the restricted sample. The average adoption rate is 30% (standard deviation equal to 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 Central Brazil (*Goiás*, *Mato Grosso do Sul*, and *Mato Grosso*). These are the states that concentrate most soybean production that is the crop under for which adoption rates are higher. Adoption rates are around 10% in the other states.

Other agricultural outcomes are used as controls in the empirical analysis. The agricultural outcomes used are the 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 2.2 reports summary statistics for these variables.

2.4.3. Other Variables

The empirical specifications include several other geographic and socioeconomic variables as controls. Average temporary rainfall and temperature for the period 1970 to 2010 are calculated for each observation using gridded data on rainfall and temperature obtained from the Terrestrial Air Temperature and Precipitation Version 3.01. Rainfall is measured in millimeters of precipitation, while temperature is measured in Celsius degrees. Land gradient is computed using raster data from the 90-meter Shuttle Radar Topography Mission (SRTM) radar. The raster data was used to construct the average land gradient for the Brazilian municipalities using GIS software (ArcMap 10.1). The gradient is measured in degrees.

The distance to the nearest diffusion center (CAT) is calculated using the distance between municipalities' centroids. The distance is calculated in kilometers. Administrative data on the location of bank branches obtained from the Brazilian Central Bank is used to calculate the number of bank branches in each observation. We calculate the number of *Banco do Brasil* and non-*Banco do Brasil* bank branches since this financial institution is the principal supplier of rural credit in Brazil. Latitude, longitude and altitude were obtained through the Ipeadata website. Table 2.2 reports summary statistics for these variables.

2.5. Soil Heterogeneity and Technology Adoption

2.5.1. Baseline Results

We begin examining whether soil heterogeneity reduces technology adoption as predicted by the theoretical model. We test this relationship using the following specification:

$$A_{ms} = \beta S_{ms} + \boldsymbol{X}_{ms}\Gamma + \delta_s + u_{ms} \tag{2.5}$$

where A_{ms} is the share of farmers who adopt the Direct Planting System and S_{ms} is the inverse of the Herfindahl index of soil heterogeneity in municipality m and state s. $\boldsymbol{X}_{ms}$ is a vector of controls that includes geographic characteristics and other relevant determinants of technology adoption in agriculture and δ_s represents state fixed effects.

Causal interpretation of the estimated β from equation (2.5) relies on the assumption that soil heterogeneity is uncorrelated with unobserved factors that might influence technology adoption. Soil heterogeneity may be correlated with the level of geographic characteristics and these characteristics may influence adoption. Therefore, we include several geographic characteristics as controls to mitigate the concern that the level geographical characteristics drive the results.[48]

The interpretation of the coefficient on soil heterogeneity based on the assumption that soil heterogeneity does not affect technology adoption through channels other than adaptation costs. We add several socioeconomic characteristics as controls to mitigate the concern that socioeconomic characteristics correlated both with soil heterogeneity and technology adoption are driving the result. We provide evidence that results are robust to the choice of socioeconomic controls.[49]

Table 2.4 presents the baseline estimates. Column 1 reports the results from the regression of the DPS adoption rate on soil heterogeneity conditional on the level of several geographic characteristics. Controls included are the share of the municipality covered by each soil type, historical temperature and rainfall in each season, latitude, longitude and land gradient. The coefficient on soil heterogeneity is significantly negative which implies that soil heterogeneity reduces the adoption rate as predicted by the theoretical model. The coefficient suggests that an increase in one standard deviation in soil heterogeneity (0.69 in the sample) reduces the DPS adoption rate by 1.1 percentage point.

Column 2 includes state fixed effects as controls. The fixed effects aim to capture for unobserved socioeconomic characteristics that might change at the state level. The coefficient on soil heterogeneity is significantly negative and its absolute value increases.

[48] Another concern would be reverse causation. However, the soil classification used to construct the soil heterogeneity measure is insensitive to land use and, therefore, reverse causation is not a relevant issue to the estimation.

[49] Notice that causal inference is unaffected by the inclusion of socioeconomic characteristics as additional controls since soil heterogeneity is invariant to socioeconomic characteristics. The inclusion of socioeconomic characteristics assesses the “adaptation cost” mechanism proposed in the theoretical model.

In column 3 we further includes farm characteristics as additional controls. The inclusion of these controls tests whether the results are caused by the correlation between soil heterogeneity and socioeconomic determinants of DPS adoption. The controls included are the log of the number of farms, the log of farm revenues, the share of farmers who completed high school, the share of farmers with access to government provided technical assistance, and log of the number of tractors. The coefficient on soil heterogeneity remains similar both in magnitude and significance. Its magnitude implies that an increase in one standard deviation in soil heterogeneity (0.67 in the sample) reduces the DPS adoption rate by 1.4 percentage points.[50]

The results from columns 1 to 3 provide support to the idea that adaptation costs are the mechanism connecting higher soil heterogeneity and lower technology adoption. The results also suggest that some important farm characteristics such as revenues, schooling and access to government provided technical assistance are not correlated with technology adoption (conditional on the geographic controls). That suggests that neither capital nor formal training are constraints to DPS adoption.

The baseline estimates are consistent with the theoretical model and provide evidence that geographic heterogeneity reduces technology adoption. Our results suggest that under-adoption of modern technologies in agriculture can be an issue in heterogeneous areas whenever adaptation costs are present.

An important question is whether the presence of other learning channels mitigates the impact of geographic heterogeneity on technology adoption. It should be noted that the theoretical model suggests 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

[50] A common problem in inference when using data on quite small spatial units is the presence of spatial correlation in the error term. This 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 1 to 3 increase about 20% when the 50 kilometers cutoff. These standard errors increase, respectively, about 33% and 65% when the 100 and the 150 kilometers cutoffs are used. Estimates from the preferred specification in Column 3 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.

straightforward. The presence of a formal channel decreases adaptation costs and increases in the share of adopters. Since the impact of soil heterogeneity on adoption is non-monotonic, the new level of adoption may be associated with either a higher or a lower impact.

We investigate the issue using the information on the presence of cooperatives and proximity to diffusion centers. Cooperatives are an important institution in rural Brazil and help farmers to acquire inputs and sell their products. Cooperatives also help farmers in experimenting with different crop varieties and fertilizers (Jepson, 2006b). We construct a dummy variable to indicate whether cooperatives are important for a given municipality. The variable is 1 when the share of producers associated with cooperatives is above the sample median and 0 otherwise. Diffusion centers known as CAT are also an important institution in the dissemination of the Direct Planting System throughout Brazil.[51] Its primary task is to spread knowledge on the DPS and adapt it whenever needed. There were 56 diffusion centers in Brazil in 2006. We construct a dummy variable to indicate whether diffusion centers are near a given observation. The variable is 1 when the distance to the nearest diffusion center is below the sample median and 0 otherwise.

We examine whether formal learning channels change the impact of soil heterogeneity on technology adoption using the following specification:

$$A_{ms} = \beta_1 S_{ms} + \beta_2 (S_{ms} * F_{ms}) + \beta_3 F_{ms} + \boldsymbol{X}_{ms}\Gamma + \delta_s + u_{ms} \qquad (2.6)$$

where F_{ms} is an indicator that denotes the presence of the formal learning channel.

Table 2.4, column 4 reports the coefficients of the regression of the DPS adoption rate on soil heterogeneity conditional on the presence of formal learning channels. The presence of cooperatives and diffusion centers is associated with higher adoption rates as expected. The presence of formal learning channels might respond to DPS and its inclusion might bias the coefficient on soil heterogeneity downwards.[52] However, the impact of soil heterogeneity on DPS adoption estimated in column 4 is quite similar to the coefficient estimated in column 3.

Column 5 investigates the interaction effect of the presence of cooperatives. The coefficient on soil heterogeneity is zero which implies that soil heterogeneity

[51] See Section 2 for a detailed explanation on the role of the CATs.
[52] For instance, farmers might create formal learning institutions to learn about the DPS.

have no impact on DPS adoption in municipalities where cooperatives are not relevant. However, the interaction effect is significantly negative which means that soil heterogeneity decreases DPS use in municipalities where cooperatives are important. The magnitude of the estimates implies that an increase in one standard deviation increase in soil heterogeneity decreases DPS adoption by 3.4 percentage points in municipalities where cooperatives are important.

Column 6 investigates the interaction effect of the proximity to diffusion centers. The coefficient on soil heterogeneity is negative which implies that soil heterogeneity decreases DPS adoption even in municipalities located far from diffusion centers. However, the interaction effect is significantly negative which suggests that soil heterogeneity decreases DPS adoption more in municipalities where near diffusion centers. The magnitude of the estimates implies that an increase in one standard deviation increase in soil heterogeneity decreases DPS adoption by 4.3 percentage points in municipalities near diffusion centers.[53]

Table 2.4, column 7 includes both interaction effects. Results are similar to the ones from columns 5 and 6 from the same table. The estimates provide evidence that the presence of other learning channels reinforces the impact of soil heterogeneity on DPS adoption.

2.5.2. Alternative Measures and Samples

We consider the robustness of the baseline results to alternative soil heterogeneity definitions and samples. First, we consider alternative soil heterogeneity measures. The measure used in the baseline estimates was constructed using the most general level of the Embrapa (2011) soil map and information at the municipality level. The alternative measures based on different soil classifications and other geographic classifications.

The first alternative measure is constructed with more refined information from the soil map. The main pitfall of this measure is that more detailed components of the soil might be affected by land use. However, the measure can be used to test the robustness of the baseline results to alternative soil classifications.

[53] It is possible to include “distance to the initial adopting region” (i.e., the original innovator) in this exercise – 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.

The correlation between the original and the variable is 0.83. Table 2.5, column 1 reports the results from the regression of the DPS adoption rate on soil heterogeneity conditional on the full set of controls included in column 3 from Table 2.4. The estimated coefficient on soil heterogeneity changes little (-1.95) in comparison to the coefficient estimated using the original measure (-2.08).

The second alternative measure of soil heterogeneity is also constructed using information on soil heterogeneity from neighboring municipalities. The measure is the weighted average of the soil heterogeneity from the municipality and its neighbors. Weights are the area of the spatial units. The main pitfall of this alternative measure is that it creates spatial correlation between the soil heterogeneity measures from different observations. Therefore, the computed standard errors should be interpreted with caution. However, the alternative measure can be used to test the robustness of the baseline results to alternative geographic classifications.

The correlation between the original and the alternative measure defined above is 0.62. Table 2.5, column 2 reports the results from the regression of the DPS adoption rate on soil heterogeneity conditional on the full set of controls included in column 3 from Table 2.4. The estimated coefficient on soil heterogeneity increases in absolute value (-5.17) in comparison to the coefficient estimated using the original measure (-2.08). 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. The result suggests that the original measure understates the relevant soil heterogeneity and ends up attenuating the impact of soil heterogeneity on DPS 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.

Second, we consider alternative samples. The baseline estimates exclude municipalities with low adoption levels. This restriction is consistent with the theoretical model which suggest that adaptation costs are not relevant when adoption is non-existent or small. 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.

Table 2.5, column 3 reports the results from the regression of the DPS adoption rate on soil heterogeneity conditional on the full set of controls included in column 3 from Table 2.4 using all observations in the sample. The number of observations increases to 5,060. The coefficient on soil heterogeneity is significantly negative as in the baseline estimates. However, its absolute value is smaller than the estimates from the baseline exercise. It should be noted that a smaller coefficient is expected since the theoretical model suggests that adaptation costs and soil heterogeneity are not relevant to the observations included in the sample. Table 2.5, column 4 repeats the exercise using the municipalities in which DPS adoption is positive. The coefficient on soil heterogeneity is significantly negative and similar to the one estimated in the full sample.

2.5.3. Additional Controls

We also consider the robustness of the baseline results to the inclusion of other controls. The additional covariates are included to examine whether the relationship between soil heterogeneity and DPS adoption is driven not because adaptation costs, but because the correlation between soil heterogeneity and some socioeconomic characteristics.[54]

First, we consider whether the estimates are robust to the inclusion of controls for land distribution. Land distribution can be correlated with DPS adoption to the baseline estimates since it may be easier for larger farms to incur the adaptation costs needed to adopt the DPS. That is a potential concern to the extent that soil heterogeneity and land distribution are correlated. In this case, the baseline estimates might confound the impact of soil heterogeneity through adaptation costs with the impact of soil heterogeneity through land distribution.

We examine whether this is the case including measures of land distribution as additional controls. The measures included are the share of farmland covered by farms of different sizes. Table 2.6, column 1 reports the results. The coefficient of interest is quite similar to the one estimated in the baseline specification (-1.91 versus -2.08).

Second, we consider whether the estimates are robust to the inclusion of controls for access to financial services. Access to finance can be correlated with

[54] Notice that the baseline specification in column 3 in Table 4 includes some socioeconomic characteristics related to technology adoption.

DPS adoption since it may be easier for farmers to incur with the adaptation costs needed to adopt the technology. The literature suggests that access to finance can be significant to explain technology adoption (Karlan et al., 2014). While the literature on the DPS suggests that access to finance is not relevant to its adoption since it involves no upfront costs or increased risk, it is useful to account for access to finance in the estimates.

Table 2.6, columns 2 and 3 include measures of financial access as additional covariates. Column 2 controls for the number of bank branches. We account separately for the number of *Banco do Brasil* bank branches and the number of other bank branches since *Banco do Brasil* is the primary provider of rural credit in Brazil. Column 3 also controls for the average value of farm debt as another measure of financial access. The number of observations decreases in column 3 since nine municipalities have no data on farm debts.

The coefficient of interest estimated in both columns (-2.12 and -1.99) is similar to the one estimated in the baseline specification (-2.08). The results also suggest that the number of bank branches is not correlated with DPS adoption while the value of farm debts is positively correlated with DPS adoption.

Third, we consider we examine whether the estimates are robust to the inclusion of controls for land use. The agronomic literature argues that DPS adoption increases yields in a range of crops. Its adoption can be more profitable to some crops. The baseline results can confound the impact on DPS of soil heterogeneity and land use to the extent that these variables are correlated. It should be noted that land use is endogenous and as it might be influenced by technology adoption and we might be over-controlling the specification. We believe that it still is useful to estimate the impact of soil heterogeneity on DPS conditional on land use to mitigate concerns on the mechanism that generates the relationship between heterogeneity and adoption. Table 2.6, column 4 reports the results and provides evidence that soil heterogeneity significantly reduces DPS adoption even conditional on land use. The coefficient (-1.56) is about 25 percent smaller than the coefficient from the baseline specification (-2.08).

2.5.4. Falsification Tests

Both the baseline estimates and robustness exercises provide evidence that the impact of soil heterogeneity on technology adoption is robust to the inclusion of several socioeconomic characteristics. However, there is still the concern that the relationship is capturing some unobserved socioeconomic characteristic which is correlated both with adoption and with soil heterogeneity. That would invalidate the adaptation cost mechanism that we emphasize in the paper.

Therefore, we perform two different falsification tests to reinforce the interpretation that adaptation costs are the mechanism that connects soil heterogeneity and technology adoption in the context studied. We estimate the relationship between soil heterogeneity and electricity use and the relationship between soil heterogeneity and the adoption of combine harvesters. The adaptation cost mechanism suggest that we should not observe a significant relationship in both cases since adaptation costs about the DPS should not be relevant to the adoption of non-agricultural technologies (such as electricity) and since it should also not be relevant to the adoption of technologies associated with harvesting (such as the use of combine harvester).

However, these relationships may exist if the mechanism linking soil heterogeneity and DPS adoption is not adaptation costs. For instance, a link between soil heterogeneity and the adoption of non-agricultural technologies might exist if soil heterogeneity affects DPS adoption because it influences local institutions or culture. Also, a connection between soil heterogeneity and the adoption of harvesting technologies might exist if soil heterogeneity affects DPS adoption because changes agricultural risk and risk sharing arrangements.

Table 2.7 reports the results of the falsification tests. Columns 1 to 3 present the results when the dependent variable is the percentage of farms with access to electricity. Columns 4 to 6 present the results when the dependent variable is the proportion of farms that use a combine harvester. The specifications are equivalent to the ones used in the baseline estimates from columns 1 to 3 from Table 2.4.

Estimates from columns 1 and 4 suggest that there is soil heterogeneity impact the adoption of both technologies. The estimated coefficients are significant at the 10% level both for electricity use and harvester use. The relationship disappears when we control for state fixed effects (columns 2 and 5) and farm characteristics (columns 3 and 6).

These results suggest that the correlations observed in columns 1 and 4 where due to correlation between soil heterogeneity and other economic characteristics that affect adoption of these alternative technologies. The coefficients are not statistically different from zero and the point estimates are much smaller. The point estimate of the impact of soil heterogeneity on electricity use falls by 96% with the addition of controls while the point estimate of the effect of soil heterogeneity on harvester use falls by 52% with the addition of controls. It is also important to highlight that adoption of these alternative technologies is positively correlated with farm characteristics such as schooling and revenues. These variables are not correlated with DPS adoption as shown in Table 2.4.

The results indicate that soil heterogeneity does not affect either non-agricultural technologies or harvesting techniques. That rules out interpretations that soil heterogeneity reduces DPS adoption because it affects technology adoption in general and provides support to the interpretation that soil heterogeneity reduces DPS adoption by increasing adaptation costs.

2.6. Is the Impact of Soil Heterogeneity Non-Monotonic?

The baseline estimates document that soil heterogeneity reduces DPS adoption. This result is consistent with the theoretical model which suggests that soil heterogeneity reduce DPS adoption by increasing adaptation costs. The robustness checks and falsification tests also provide support that adaptation costs is the mechanism connecting soil heterogeneity and DPS adoption as outlined in the theoretical model.

We provide further support to the mechanism outlined in the theoretical model by testing the prediction that the impact of soil heterogeneity should be non-monotonic. The model predicts that soil heterogeneity should have a higher impact on DPS adoption at intermediate adoption rates. It also predicts the impact to be zero at either low or high levels of technology adoption.

Testing this prediction requires computing the impact of soil heterogeneity at different quantiles of the distribution of DPS adoption across municipalities (which we denote as F_A). These estimates cannot be computed using traditional quantile regression since proposed by Koenker and Basset (1978) since this method compute the impact of soil heterogeneity at different quantiles of the distribution of DPS adoption conditional on soil heterogeneity and the whole set of covariates included in the estimates (which we denote as $F_{A|X}$). Recovering unconditional quantile estimates from conditional quantile estimates is not simple and requires several assumptions as it involves computing marginal distributions from conditional distributions as shown by Machado and Mata (2005).

Therefore, we choose to examine this prediction using the unconditional quantile estimator proposed by Firpo et al. (2009). The estimator is simple and can be computed using OLS estimation. It is based on the concept of influence function. The influence function $IF(A, v, F_A)$ of a distributional statistic $v(F_A)$ is the influence of an individual observation on that statistic. The IF can be used to compute the Re-centered Influence Function (RIF) which is $RIF(A, v, F_A) = v(F_A) + IF(A, v, F_A)$ for a general distributional statistic and $RIF(A, q_\tau, F_A) = v(F_A) + IF(A, q_\tau, F_A)$ for the τth quantile of the distribution of the dependent variable.

Firpo et al. (2009) prove that the marginal effect of a change in the distribution of covariates on the unconditional quantile of the distribution of the dependent variable is the coefficient from a regression of $RIF(A, q_\tau, F_A)$ on the covariates. Hence, the impact of soil heterogeneity on technology adoption on the τth quantile of the distribution of DPS adoption is the soil heterogeneity coefficient of the regression of $RIF(A, q_\tau, F_A)$ on soil heterogeneity and other covariates.[55]

We estimate the impact of soil heterogeneity on DPS adoption on all quantiles of the adoption distribution using RIF regressions. The controls included are the same included in the baseline specification from column 3 in Table 2.4. Results are similar when we implement the estimator using different specifications. The coefficients and 95% confidence intervals on soil heterogeneity are presented in Figure 2.2. The results provide evidence that the impact of soil heterogeneity on DPS adoption is non-monotonic as predicted by the theoretical model. The impact is zero either at small or high adoption rates and significantly negative at intermediate adoption rates. The coefficients are

[55] 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).

significant and above the baseline estimates when the adoption rate is between 20 and 50 percent. These adoption rates correspond to the percentiles 50 and 75 in the sample.

The impact of soil heterogeneity on DPS adoption reaches its maximum at the adoption rate of 40 percent. An increase in one standard deviation in soil heterogeneity decreases DPS adoption by 5.8 percentage points in this quantile. This impact is four times the average impact estimated in the previous section. These results provide further support to the adaptation costs mechanism proposed in the theoretical model.

We also perform the two falsification tests from the previous subsection across all quantiles to test whether there is evidence that soil heterogeneity affects the use of electricity (a non-agricultural technology) or harvesters (a technology disconnected to planting). The controls included are the same from columns 3 and 6 from Table 2.7. The results are presented in Figures 2.3 and 2.4 and provide further evidence that soil heterogeneity does not have a U-shaped impact on the use of alternative technologies. This evidence provides further support for the idea that soil heterogeneity affects DPS adoption through its effects on adaptation costs.[56]

2.7. Conclusion

Low adoption of modern technologies is the object of extensive research in economics due to its impact on economic development. We provide evidence that low adoption of modern technologies in agriculture is associated with geographic heterogeneity using data from the adoption of the Direct Planting System (DPS) in the Brazilian agriculture.

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 method with no upfront costs and little change in input use. The primary constraint to adoption is the need to learn how to operate the system and adapt it to specific site conditions. Therefore,

[56] The U-shaped impact of soil heterogeneity on DPS adoption is robust to the use of alternative samples, soil heterogeneity measures and controls discussed at length in the robustness section. We also estimate that the U-shaped impact exists only across municipalities with high prevalence of farmers' cooperatives and near to diffusion centers. These results are available upon request.

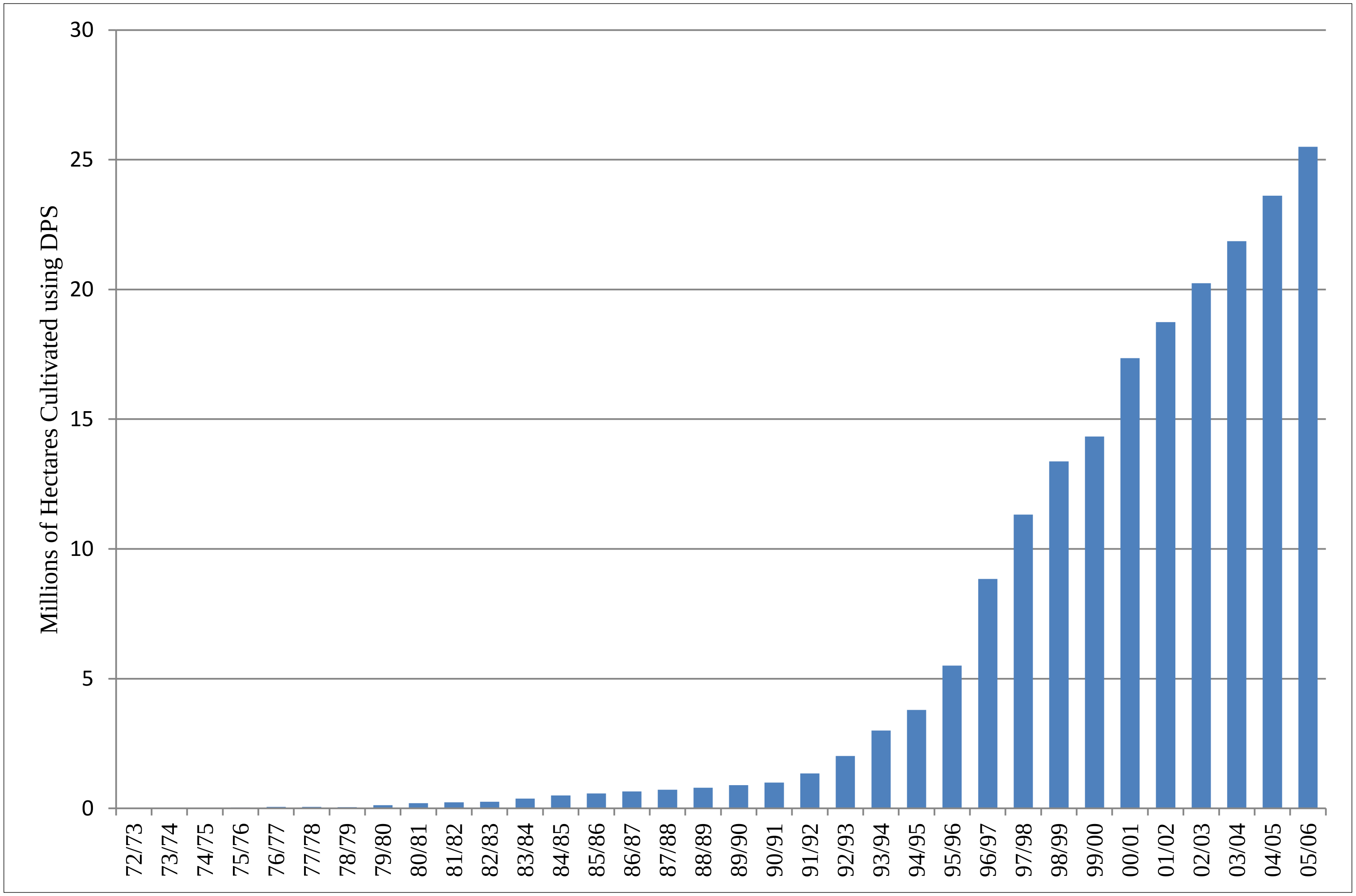
the context in which DPS adoption takes place is unique in the sense that the correlation between geographic heterogeneity and under-adoption can be traced to adaptation costs.

We present a simple theoretical model that formalizes the intuition that adaptation is more difficult 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 adaptation cannot take place) or when adoption is widespread (and adaptation will develop in spite of different geographic characteristics). The impact is predicted to be higher for intermediate adoption rates (when adaptation is possible but depends on geographic similarities).

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. These findings illustrate that the process of learning and adapting can be deterred by heterogeneity across adopters as suggested theoretically by Ellison and Fudenberg (1993) and empirically by Munshi (2004).

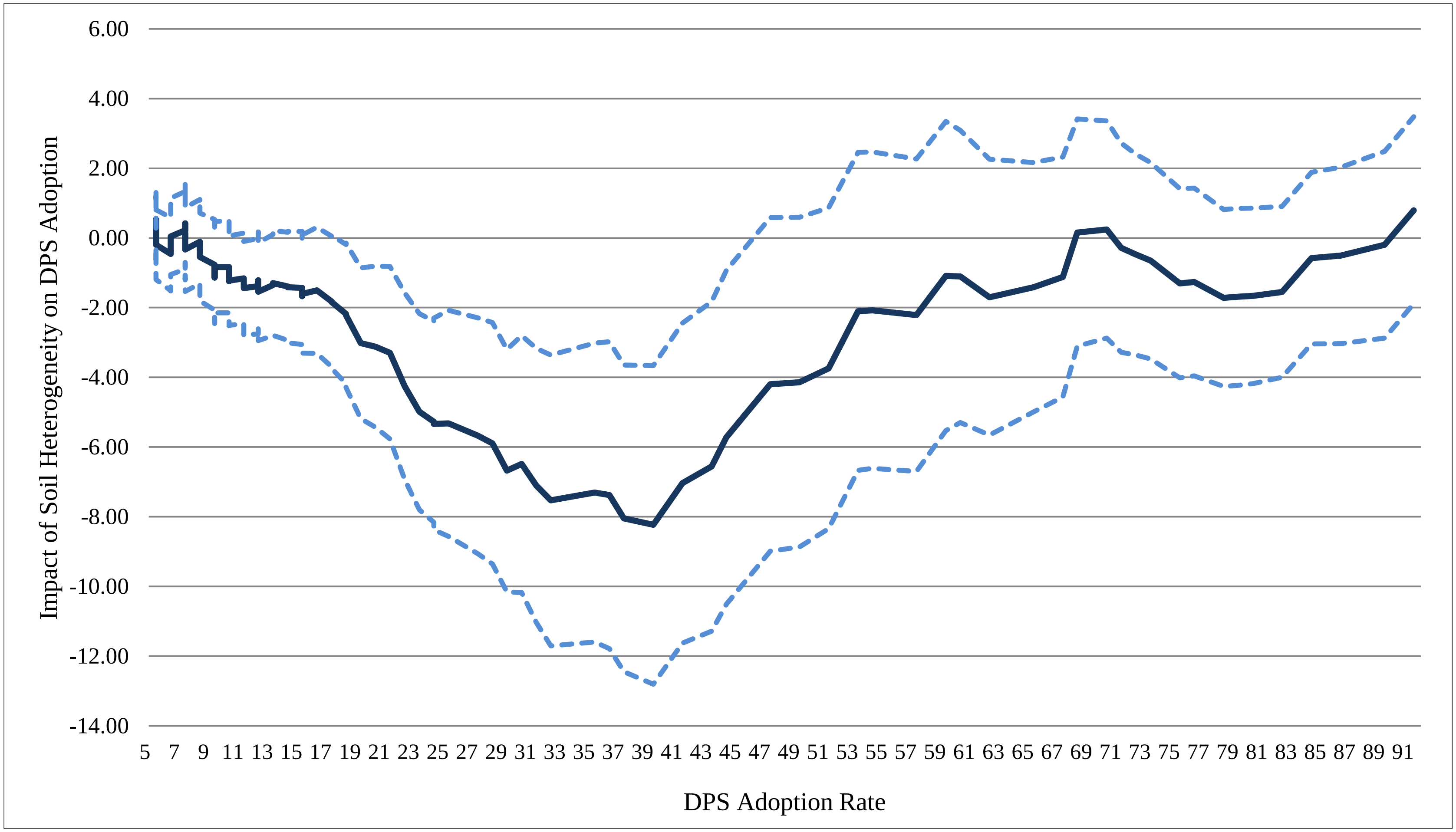
Further research is needed to understand whether soil heterogeneity matters in other contexts and more detailed data might help to provide further support to the adaptation cost mechanism. Nevertheless, the findings have important implications for policies aimed at promoting technology adoption. Providing 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 adaptation can be harder.

Figure 2.1: The Diffusion of the DPS in Brazil



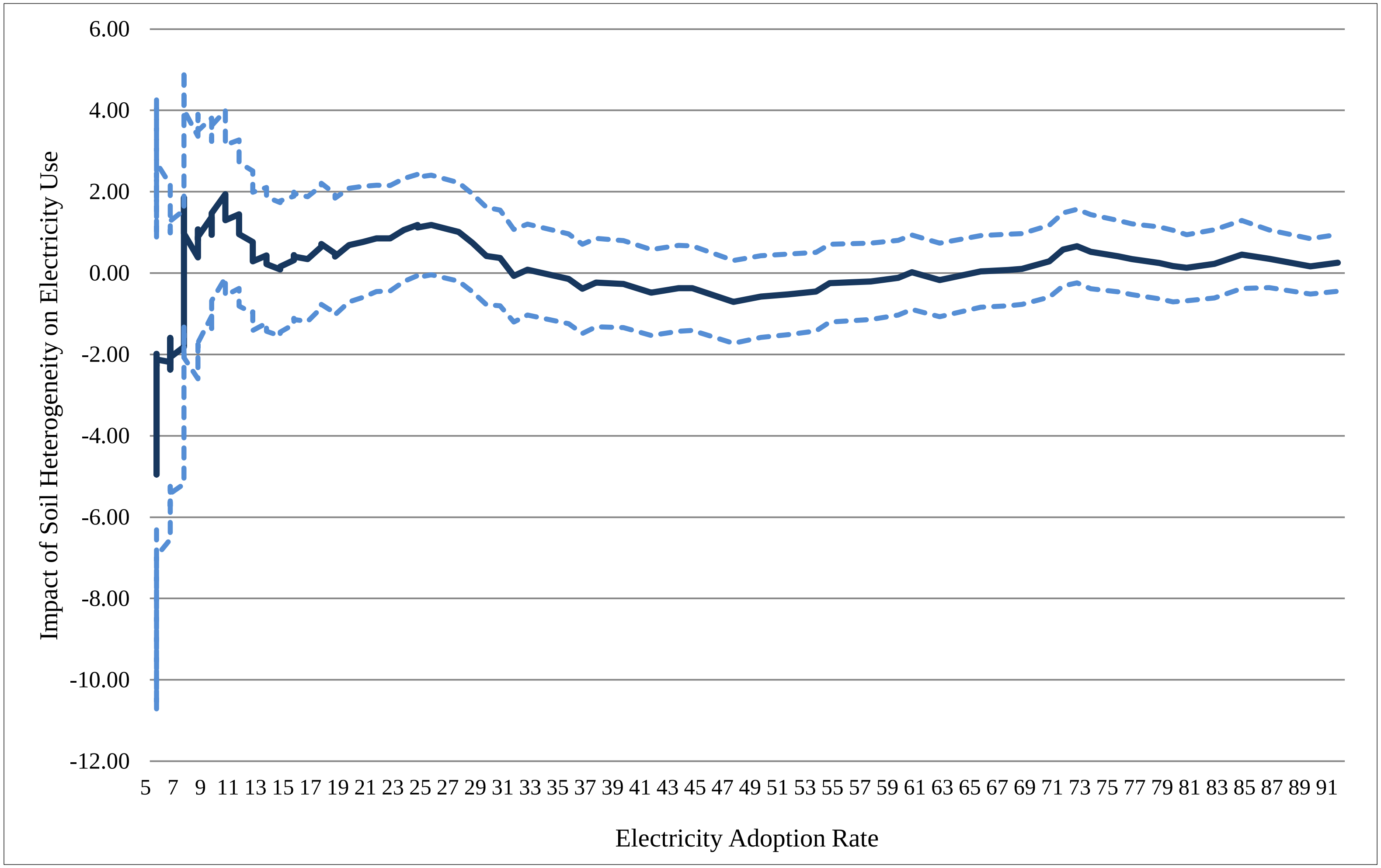
Note: The figure presents estimates of the area cultivated using the Direct Planting System (DPS) in Brazil from 1972 to 2006. Data comes from the Brazilian Federation of Direct Planting System (FEBRAPDP).

Figure 2.2: Soil Heterogeneity and DPS Adoption at Different Quantiles



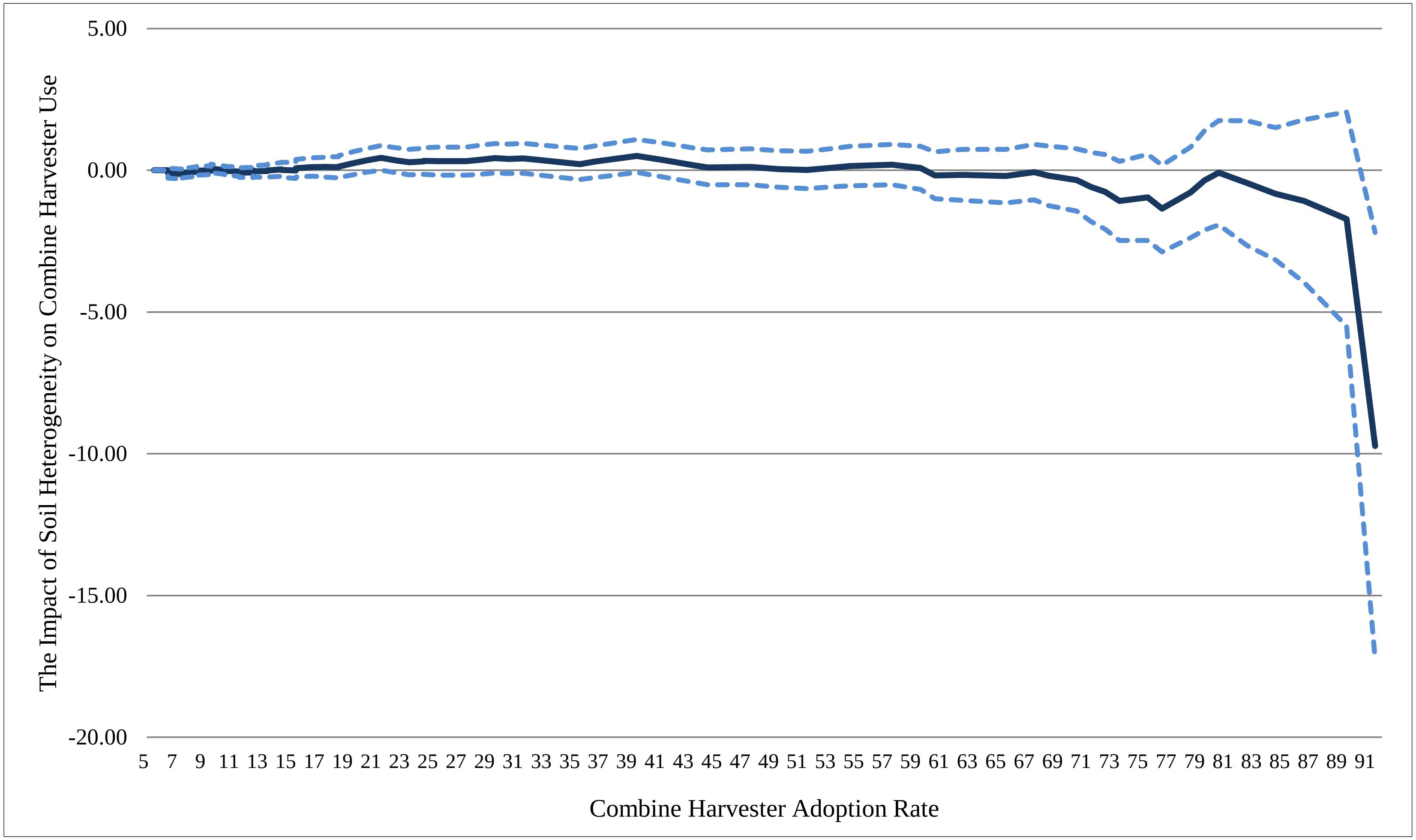
Note: The solid line reports the estimated impact of soil heterogeneity on DPS adoption estimated at different adoption levels using the unconditional quantile estimator proposed by Firpo et al. (2009). The dashed lines report 95% confidence intervals of the estimated coefficients. Controls are the same included in Column 3 from Table 2.4.

Figure 2.3: Soil Heterogeneity and Electricity Use at Different Quantiles



Note: The solid line reports the estimated impact of soil heterogeneity on electricity adoption estimated at different adoption levels using the unconditional quantile estimator proposed by Firpo et al. (2009). The dashed lines report 95% confidence intervals of the estimated coefficients. Controls are the same included in Column 3 from Table 2.7.

Figure 2.4: Soil Heterogeneity and Harvester Use at Different Quantiles



Note: The solid line reports the estimated impact of soil heterogeneity on combine harvester adoption estimated at different adoption levels using the unconditional quantile estimator proposed by Firpo et al. (2009). The dashed lines report 95% confidence intervals of the estimated coefficients. Controls are the same included in Column 6 from Table 2.7.

Table 2.1: Costs and Benefits from the DPS

	Costs	Benefits
PANEL A: Public		
		Lower carbon emission to the atmosphere
Agricultural / Environmental		Increase of carbon and nitrogen stocks
		Increased biodiversity
		Reduction in environmental contamination
PANEL B: Private		
	Increased cost of herbicides	Lower fuel Consumption
Economic		Agricultural Machinery lasts longer
		Lower fertilizer consumption
	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
Agricultural / Environmental		Less water and soil shedding
		Lower thermal ad hydraulic amplitude
		Reduction of erosion losses
		Increase of life in soil (mainly earthworms)
		Soil protection against solar radiation
		Reduction of time between harvest and sowing

Table 2.2: Descriptive Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Panel A: Main Variable					
Soil Heterogeneity	1628	1.68	0.69	1.00	7.89
Panel B: Geographic Controls					
Average monthly rainfall in the summer	1628	174.43	53.69	36.51	441.45
Average monthly rainfall in the autumn	1628	118.52	55.66	14.49	354.02
Average monthly rainfall during the winter	1628	87.21	52.51	3.31	222.74
Average monthly rainfall during the spring	1628	143.80	51.35	7.14	383.66
Average temperature in the summer	1628	23.40	1.86	18.10	28.42
Average temperature in the autumn	1628	19.27	3.88	12.68	27.69
Average temperature in the winter	1628	18.59	4.46	11.14	28.69
Average temperature in the spring	1628	22.39	2.82	16.17	29.19
Log of average gradient	1628	5.73	3.33	0.71	15.97
Panel B: Farm Characteristics					
Log of number of farms	1628	6.57	0.87	2.64	9.20
Log of average revenues	1628	3.08	1.38	-0.99	8.38
Log of revenues per hectare	1628	-0.68	1.37	-5.66	2.54
Eight or more years of schooling	1628	24.76	14.28	2.80	86.49
Eleven or more years of schooling	1628	13.69	9.96	0.93	56.94
Access to government provided technical assistance	1628	15.43	15.29	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	1628	49.20	22.37	0.00	96.08
Distance to Diffusion Center (in 100km)	1628	3.30	2.94	0.00	19.78

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 heterogeneity. Rainfall and temperature variables are temporary averages for the period 1971-2010.

Table 2.3: Adoption Rates per State

State	Direct Planting System Adoption					
	Adoption equal or above 5%			All municipalities		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Rondônia	7.23	2.38	14	3.60	2.88	52
Acre	16.53	5.77	9	8.28	8.21	22
Amazonas	10.39	4.64	3	1.98	4.09	62
Roraima	8.90	4.29	4	3.21	4.27	15
Pará	12.12	7.99	38	4.94	8.26	142
Amapá	21.05		1	3.09	6.21	16
Tocantins	11.96	6.31	25	2.83	5.14	139
Maranhão	13.02	8.19	64	5.56	7.62	217
Piauí	13.77	8.81	45	5.05	7.56	221
Ceará	12.14	7.56	38	4.03	6.15	184
Rio Grande do Norte	12.54	6.38	6	1.00	2.87	165
Paraíba	9.61	4.45	26	2.45	6.15	220
Pernambuco	11.49	6.37	32	3.15	6.06	182
Alagoas	11.96	6.53	15	2.89	5.15	101
Sergipe	9.39	4.95	3	0.91	2.13	72
Bahia	9.53	4.08	68	2.50	4.04	414
Minas Gerais	12.61	9.54	183	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	17.27	15.68	82	3.02	7.89	643
Paraná	41.48	23.31	306	32.27	26.47	398
Santa Catarina	42.81	26.16	213	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	30.88	26.79	1628	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 2.4: OLS Regressions

Dependent Variable	Direct Planting System Adoption Rate						
	Geographic Controls	State FE	Farm Characteristics	Learning Mechanisms	Cooperatives	Diffusion Centers	Both Variables
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Soil Heterogeneity	-1.624**	-2.080***	-2.078***	-2.059***	0.222	-1.941***	0.376
	(0.705)	(0.683)	(0.697)	(0.691)	(0.731)	(0.707)	(0.740)
Presence of cooperatives				8.989***	17.445***		17.477***
				(0.972)	(2.287)		(2.281)
Close to Diffusion Centers				1.198		11.618*	12.927**
				(2.295)		(5.995)	(5.303)
Soil Heterogeneity x Presence of cooperatives					-4.906***		-4.909***
					(1.134)		(1.133)
Soil Heterogeneity x Close to Diffusion Centers						-6.290**	-6.966**
						(3.073)	(2.709)
Geographic Characteristics	Y	Y	Y	Y	Y	Y	Y
Soil Types	Y	Y	Y	Y	Y	Y	Y
Rainfall and Temperature	Y	Y	Y	Y	Y	Y	Y
State FE	N	Y	Y	Y	Y	Y	Y
Farm Characteristics	N	N	Y	Y	Y	Y	Y
Observations	1,628	1,628	1,628	1,628	1,628	1,628	1,628
R-squared	0.605	0.661	0.670	0.688	0.692	0.671	0.692

Notes: The table reports estimates from equation (2.5) in the text. Sample includes municipalities with adoption rates above 5% and for which soil heterogeneity does not take extreme values. Geographic Characteristics are controls for latitude, longitude, land gradient and altitude. Soil Types are controls for the share of the municipality area covered by each of the 35 soil orders that exist in Brazil. Rainfall and Temperature are controls for the average rainfall or temperature in each season. Farm Characteristics are the log of the number of farms, the log of average revenues, the log of number of tractors and the shares of farmers with high school and access to government provided technical assistance. Robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 2.5: Alternative Heterogeneity Measures and Alternative Samples

Dependent Variable	Direct Planting System Adoption Rate			
	Alternative Soil Heterogeneity		Alternative Samples	
	More Detailed Soil Classification	Neighboring Municipalities	Full Sample	Positive Adoption
	(1)	(2)	(3)	(4)
Soil Heterogeneity	-1.954***	-5.166***	-1.004***	-1.051***
	(0.496)	(1.077)	(0.256)	(0.293)
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: The table reports estimates from equation (2.5) in the text. Sample includes all municipalities for which adoption rates are above 5% and for which soil heterogeneity does not take extreme values. More Detailed Soil Classification is the soil heterogeneity calculated using data on soil orders, groups and subgroups. Neighboring Municipalities is the mean value of soil heterogeneity in the municipality and in its neighbors weighted by each municipality area. Geographic Characteristics are controls for latitude, longitude, land gradient and altitude and the share of the municipality area covered by each of the 35 soil orders that exist in Brazil. Rainfall and Temperature are controls for the average rainfall or temperature in each season. Socioeconomic Characteristics are the log of the number of farms, the log of average revenues, the log of number of tractors and the shares of farmers with high school and access to government provided technical assistance. Robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 2.6: Land Distribution, Credit and Access to Markets

Dependent Variable	Direct Planting System Adoption Rate			
	Land Distribution	Bank Branches	Total Debt	Crop Mix
	(1)	(2)	(3)	(4)
Soil Heterogeneity	-1.910***	-2.115***	-1.986***	-1.560***
	(0.692)	(0.700)	(0.696)	(0.566)
Banco do Brasil Bank Branches		1.304	1.284	0.230
		(0.826)	(0.805)	(0.676)
Other Bank Branches		-0.189	-0.182	-0.018
		(0.131)	(0.128)	(0.107)
Log of average farm debts			3.509***	2.434***
			(0.515)	(0.485)
Share of farmland cultivated with soybeans				0.528***
				(0.074)
Share of farmland cultivated with maize				0.111***
				(0.040)
Share of farmland cultivated with sugarcane				-0.034
				(0.039)
Share of farmland cultivated with rice				-0.066
				(0.147)
Share of farmland cultivated with beans				-0.242***
				(0.051)
Share of farmland cultivated with cotton				-0.438
				(0.294)
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	0.692	0.671	0.684	0.766

Notes: The table reports estimates from equation (2.5) in the text. Sample includes municipalities with adoption rates above 5% and for which soil heterogeneity does not take extreme values. Geographic Characteristics are controls for latitude, longitude, land gradient and altitude and for the share of the municipality area covered by each of the 35 soil orders that exist in Brazil. Rainfall and Temperature are controls for the average rainfall or temperature in each season. Farm Characteristics are the log of the number of farms, the log of average revenues, the log of number of tractors and the shares of farmers with high school and access to government provided technical assistance. Robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 2.7: Falsification Tests

Dependent Variable	Electricity Use			Harvester Use		
	Geographic Controls	State FE	Farm Characteristics	Geographic Controls	State FE	Farm Characteristics
	(1)	(2)	(3)	(4)	(5)	(6)
Soil Heterogeneity	-1.156*	-0.333	-0.044	-0.385*	-0.236	-0.184
	(0.668)	(0.540)	(0.551)	(0.221)	(0.205)	(0.180)
Geographic Characteristics	Y	Y	Y	Y	Y	Y
Soil Types	Y	Y	Y	Y	Y	Y
Rainfall and Temperature	Y	Y	Y	Y	Y	Y
State FE	N	Y	Y	N	Y	Y
Farm Characteristics	N	N	Y	N	N	Y
Observations	1,628	1,628	1,628	1,628	1,628	1,628
R-squared	0.508	0.639	0.653	0.388	0.468	0.586

Notes: The table reports estimates from equation (2.5) in the text. Sample includes municipalities with adoption rates above 5% and for which soil heterogeneity does not take extreme values. Geographic Characteristics are controls for latitude, longitude, land gradient and altitude. Soil Types are controls for the share of the municipality area covered by each of the 35 soil orders that exist in Brazil. Rainfall and Temperature are controls for the average rainfall or temperature in each season. Farm Characteristics are the log of the number of farms, the log of average revenues, the log of number of tractors and the shares of farmers with high school and access to government provided technical assistance. Robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

3 Special Interests and Government Policies: The Impact of Farmer Politicians on Deforestation in the Brazilian Amazon

3.1. Introduction

Deforestation is responsible for about one fifth of global greenhouse emissions, being at the center of the debate on climate change (Stern, 2007; Kindermann et al., 2008; IPCC, 2014). Curbing deforestation is considered essential to mitigate climate change and governments and international organizations are becoming more interested in the design of conservation policies. However, these policies reduce rents and, as a consequence, face opposition from industries such as agriculture and logging. A critical issue for the design of conservation policies is whether these industries are able to use their political influence to affect the implementation of policies aimed at reducing deforestation.

This paper documents that elected officials connected to agricultural interests are able to influence deforestation in the Brazilian Amazon. Using unique data on the occupation of candidates running for office in Brazil, I construct a measure that indicates whether a politician is a farmer. I interpret this measure as an indicator of connection to agricultural interests. I then examine whether municipalities with mayors connected to agriculture have higher deforestation rates than other municipalities using a Regression Discontinuity (RD) design. The RD design compares deforestation in municipalities in which a politician connected to agriculture won the election by a small margin with municipalities in which a politician connected to agriculture lost by a small margin to investigate the effect of connection to agricultural interests on deforestation.

The Brazilian Amazon presents the ideal context to investigate the influence of special interests on conservation policies. Forest coverage in the Brazilian Amazon was decreasing fast until the beginning of the last decade, being the main driver of Brazilian greenhouse gases emissions. Increasing deforestation induced the Brazilian government to introduce several measures to reduce forest clearing in the region after 2004 (IPAM, 2009; IPEA et al., 2011; Assunção et al., 2012). These measures faced opposition from associations representing farmers as conservation policies can reduce rents from agricultural activities. Such associations have considerable political power in Brazil and have often been able to force the Brazilian government to favor their interests (Helfand, 1999; Richardson, 2012). This political landscape offers a context in which politicians connected to the agricultural interests might be able to influence conservation policies and deforestation rates.

The results indicate that deforestation increases near elections in municipalities governed by politicians connected to agriculture. The results are robust to different specifications and deforestation measures. The magnitude of the estimates implies that deforestation increases from .41 to .71 standard deviations near elections in the municipalities in which the mayor is connected to agriculture. Assuming that the local RD estimates represent the average impact of special interests on the sample, I calculate that special interests increased deforestation in about 1,800 to 2,100 square kilometers in the period 2005 to 2012. This represents 8.8 to 10.4% of the total deforestation observed in the sample municipalities during the period.

Politicians connected to agriculture might oppose conservation policies for two main reasons. First, these politicians might oppose conservation policies due to their ideological preferences as suggested by Osborne and Slivinsky (1996) and Besley and Coate (1997). Second, they might oppose these policies due to the influence of agricultural interests in their behavior as suggested by Cox and Mc-Cubbins (1986) and Dixit and Londregan (1996).

The timing of the impact of connection to agriculture on deforestation suggests that the results are not related to differences in the preferences on deforestation of the politicians. Politicians connected to agriculture should enact deforestation-increasing policies in all periods if preferences driving the results. However, deforestation changes just near elections, which indicate that electoral incentives are essential in shaping the timing of the change in environmental policies.

These findings are consistent with a model in which politicians connected to agriculture signal their commitment to special interests of agricultural businesses, guaranteeing their support in the elections. This mechanism is similar to the one discussed in Rogoff (1990).[57] The results are also consistent with politicians shifting to targeted distribution near elections to signal their commitment as discussed in Drazen and Eslava (2010).

To further understand the evidence presented above, I test whether the influence of politicians connected to agriculture on conservation policies in the Brazilian Amazon is heterogeneous according to some local and political characteristics. I start investigating whether the results are heterogeneous for politicians with and without reelection incentives motivated by a long literature documenting that these incentives affect politicians' behavior (Besley and Case, 1995; List and Sturm, 2006; Ferraz and Finan, 2011). The results suggest that reelection incentives matter. Connection to agriculture influences deforestation in the sample of politicians that can run for reelection, but not in the sample of politicians that cannot run for another term. Indeed, point estimates are close to zero when politicians do not face reelection incentives in all but one specification. These findings reinforce the interpretation that electoral incentives induce politicians connected to agriculture to change their behavior near elections.

I also test whether the impact is heterogeneous for politicians allied and not allied to the federal government. Previous literature suggests that allied politicians might find easier to affect the federal initiatives such as conservation policies.[58] The results point out that the effects are similar regardless alignment to the federal government. I then analyze whether competence influences the results using schooling as a proxy for competence.[59] Point estimates are larger in the sample of better educated politicians compared to the sample of less educated politicians. These estimates are suggestive that better politicians might be more able to influence deforestation near elections. However, it is important to note that the differences in point estimates are not large.

An important issue is which policies local officials use to influence deforestation. That is a difficult question as several policies that can affect

[57] The literature on electoral cycles indicates that signaling can induce politicians to behave different close to elections and far from it. See Persson and Tabellini (2002) for a discussion of such models.

[58] Previous papers have identified that political connection to the federal government matters for government transfers (Brollo and Nannicini, 2012) and access to credit (Leão et al, 2013).

[59] Previous literature discusses the role of the competence of the politicians to public policies. See Besley (2007) for a theoretical discussion of political selection and Ferraz and Finan (2009), Besley et al. (2011) and Martinez-Bravo (2014) for empirical evidence on some of its determinants.

deforestation involve illegal activities and are not observed. However, it is possible to provide some evidence on these policies using data on environmental fines. Since fines reflect the equilibrium between the demand for deforestation and the enforcement of the environmental policies, this data is useful to understand the mechanisms that local politicians use to influence deforestation.[60] An increase in deforestation near elections should be related to a rise in fines if it is connected to an increase in demand for deforestation. However, it should be associated with a reduction in fines if it is related to a decrease in the enforcement of environmental fines.

I provide evidence that the number and the value of fines decrease near elections in municipalities in which the politician holding office is connected to agriculture. Estimates are large and significant in all but one RD specification. This result implies that changes in the incidence of conservation policies are the principal mechanism that explains the rise in deforestation.

The results from this paper contribute to a growing literature on environmental policies in developing countries reviewed in Greenstone and Jack (2013). Some papers in this literature emphasize the role of political factors on environmental policies. Ferraz (2007), Morjaria (2013) and Abman (2014) document the role of electoral incentives on conservation policies while Burgess et al. (2012) documents the role of corruption on deforestation in Indonesia. I add to this literature showing the role that special interests have on environmental policies.

This paper also contributes to the literature on special interests documenting their influence on politicians' behavior in the context of environmental policies in the Brazilian Amazon, using exogenous variation coming from close elections. This evidence complements the findings from Mian et al. (2010) in the context of voting behavior in the American legislative.[61]

Furthermore, these results contribute to the literature on political cycles. Akhmedov and Zhuravskaya (2004) document the existence of opportunistic political cycles in Russia while Bertrand et al. (2006) and Sukhtankar (2012)

[60] Demand for deforestation is a measure of "willingness" to deforest. It is similar to a demand curve in the sense that is negatively related with enforcement (which can be thought as a price that farmers and loggers face when decide deforest a plot). The term demand for deforestation is also used in Souza-Rodrigues (2013).

[61] See Grossman and Helpman (2001) for a theoretical discussion of special interest politics.

document the existence of political cycles in the behavior of firms connected to politicians both in France and India. I add to this literature providing evidence that political connections change the behavior of politicians near elections.

The remaining of the paper is organized as follows. Section 2 provides background information on deforestation and politics in the Brazilian Amazon. Section 3 describes the data used in the estimated. Section 4 outlines the RD design implemented in the empirical section. It also conducts some robustness tests to validate the empirical strategy. Section 5 presents the effects of the mayor's connection to agricultural interests on deforestation. Section 6 discusses mechanisms. Section 7 concludes.

3.2. Institutional Background

3.2.1. Rural Politics in Brazil

Farmers constitute an important interest group in Brazil. There are well-organized associations and unions that represent the interests of farmers both at the local and national levels. Leaders of these organizations are often elected politicians. For instance, the president of the leading farmers' organization – the Brazilian Confederation of Agriculture – is a senator. The associations representing farmers also have ties with several other politicians across the country. A total of 11 senators (13.5% of the total) and 191 (37.2% of the total) federal deputies are official members of the Agricultural Caucus in the Brazilian Congress.[62]

Support from legislators connected to agriculture is often essential for the approval of most bills. The Brazilian federal government often makes concessions to attract representatives connected to agriculture to the government coalition. In exchange of support to the government coalition, the legislators representing agricultural interests obtain "club public goods" and appoint members of their caucus to important offices in the Ministry of Agriculture (Piedra, 2013). The importance of the agricultural interests is so high that a recent issue of the Brazilian magazine *Piauí* quotes the coordinator of a presidential campaign

[62] Information retrieved from www.camara.gov.br in June 30, 2014.

stating that: "… in 30 years doing political campaigns I have never seen someone be elected without the support [from agribusiness]".[63]

Brazilian farmers became more organized during the re-democratization period in the 1980s (Helfand, 1999). Farmers feared progressive political forces that proposed agrarian reform and organized a powerful interest group in Congress to fight attempts to redistribute land (Richardson, 2012). Organizations and politicians connected to agriculture were successful in curbing land reform in the 1990s. These organizations and politicians were also able to secure farmers preferential access to credit and favorable tax treatment once the land reform issue was settled (Piedra, 2013).

Land use issues in the Brazilian Amazon became more important in the agenda of rural politics in during the past decade (Richardson, 2012). Expansion of logging, cattle ranching and agricultural cultivation in the Brazilian Amazon involves substantial land clearing. That created a tension between interests of the agricultural sector in the region and environmental legislation. This tension increased as innovative policies to fight deforestation were implemented in the last decade. Organizations and politicians connected to agriculture have opposed these innovations. Farmers and their representatives have proposed reforms in the legislation to make land use policies in the Brazilian Amazon less stringent.[64]

Such political scenario suggests that politicians connected to agriculture will oppose conservation policies in Brazil in order to maintain support from the powerful organizations representing farmers and agricultural elites (Cisneros et al., 2013). In particular, mayors connected to agricultural interests can attempt to curb conservation policies and induce activities that lead to more deforestation.

The mechanism described above can be of particular importance during electoral periods. Anecdotal evidence suggests that deforestation increases near elections. The newspaper *Folha de São Paulo* wrote in a recent article on the rise of deforestation in the months preceding the previous election that "(…) electoral years usually have increases in deforestation, supposedly due to lower

[63] *Piauí*, July 2014, p. 22.
[64] The Economist (2012) reports the tension between farmers' interests and environmental conservation in the debates around the reform of the Brazilian Forest Code.

fiscalization (…)".[65] Hence, it is important to investigate the effect of agricultural interests on deforestation in different moments of the electoral cycle.

3.2.2. Deforestation in the Brazilian Amazon

Deforestation in the Brazilian Amazon became an important public policy issue over the past decades. More than 750,000 square kilometers of forest area were deforested over the past four decades in the region. The main drivers of deforestation were the construction of roads and the expansion of population in the area after 1970 (Pfaff, 1999; Pfaff et al., 2007). These factors induced logging and cattle ranching activities that involve substantial land clearing. Poor institutions reinforced the incentives for unsustainable land use as clearing often helps to secure land rights in the Brazilian Amazon (Alston et al., 2000).

Increased deforestation led to a major reorganization in conservation policies in the Brazilian Amazon. In 2004, the federal government created Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAM). This initiative integrated actions across different agencies and introduced innovative tools for monitoring deforestation and curbing deforestation (IPAM, 2009).

Policies implemented under the PPCDAM can be divided into two phases. At the beginning, the government focused on the establishment of protected areas, in the improvement of deforestation monitoring using satellite data and in the expansion of the number of operations from the environmental protection agency (IBAMA). These initiatives resulted in the establishment of over 180,000 square kilometers of protected areas and the creation of a real-time deforestation monitoring system using satellite data (DETER).

Better data and investments in staffing and training the environmental protection agency led to a sharp increase in the number of fines in the period (Hargrave and Kis-Katos, 2013). However, environmental fines are often not paid. Its coercive effect on deforestation comes from consequences from the operations that lead to fines such as the embargo of the land and the expropriation of the deforested timber (Assunção et al., 2013*a*).

[65] "Desmatamento na Amazônia dispara em agosto e setembro", *Folha de São Paulo*, November 11, 2014.

The government expanded the set of polices implemented under the PPCDAM after 2008. First, it conditioned access to credit for agricultural activities in the Brazilian Amazon to compliance with the environmental legislation (Assunção et al., 2013*b*). Second, it created a blacklist of high deforestation municipalities in which conservation efforts were concentrated. Politicians, credit agencies and agricultural traders operating in these municipalities also face pressure from the federal government to induce changes in practices related to unsustainable land use that result in forest clearing. Blacklisted municipalities face higher presence of the environmental protection agency (IBAMA) and other government agencies involved with land use.

The combination of these initiatives led to a reduction in deforestation in the Brazilian Amazon over the last decade (IPEA et al., 2011; Assunção et al., 2012). This decline highlights the importance of the federal government in fighting deforestation in the region. However, there is still substantial variation in deforestation rates across municipalities in the Brazilian Amazon. Local policies and economic characteristics continue to be important determinants of the deforestation rates.

3.2.3. Role of Mayors on Environmental Policies

Municipalities are the lower administrative division in Brazil. Municipal governments are managed by an elected mayor (*Prefeito*) and an elected city council (*Câmara dos Vereadore*s). Municipal elections are held at the same time in all municipalities and happen in October of the election year. The elected officers start a four years term in January of the following year.

Local councilors are elected using a proportional system. Mayors are elected for a four years term using a plurality rule in all municipalities with less than 200,000 eligible voters and a majority rule in municipalities with more than 200,000 eligible voters.[66] Mayors can run for reelection once while local councilors can run for reelection indefinitely.

Mayors are responsible for the executive branch while councilors are responsible for the legislative branch of the municipal government. The executive branch concentrates the most relevant choices concerning public policies. It is the

[66] The empirical analysis focuses on municipalities with less than 200,000 voters.

executive branch who establishes partnerships with the federal and state governments, proposes a budget, and implements public policies (Brollo et al., 2013).

Municipal governments are responsible for a substantial share of the provision of public goods and services in areas such as education, healthcare, and infrastructure. Local governments also manage the distribution of conditional cash transfers as well as most schools and health facilities.[67] A large share of the expenditures on these public goods is financed from transfers from the federal government.[68]

The municipal governments also have responsibilities regarding environmental policies often acting in cooperation with higher levels of government (Leme, 2011). These governments can influence the effectiveness of conservation policies and affect deforestation enacting policies that change the demand for deforestation. For instance, land clearing is often associated with activities such as illegal land sales, land grabbing, and logging. These activities require consent from local authorities to take place and therefore municipal governments are crucial in determining the rate that these events take place (Fearnside, 2001; Cisneros et al., 2013).

Local authorities can also affect deforestation changing the incidence of federal policies through lobbying, bribes, and threats. Lobbying with federal authorities can influence the presence of the environmental protection agency or the supply of rural credit in the municipality. Bribes to officers from the environmental protection and credit agencies can have a similar effect. In addition, local authorities can threaten and even use violence against bureaucrats who operate in their municipalities. These actions might changes the incidence of federal policies and affect deforestation.[69]

However, it is important to note that enacting policies to induce higher deforestation can have significant costs to local authorities. These actions often

[67] The Brazilian Constitution from 1988 led to a large restructuring in the provision of public goods in Brazil with municipalities becoming more important in the provision of education, healthcare, sanitation, habitation etc. See Arretche (1999) for an analysis of the decentralization process following the 1988 constitution.

[68] See Afonso and Araújo (2000) for a discussion of the role of transfers and the imbalances it creates.

[69] See Assunção et al. (2013*a*) for evidence on the relationship between presence of the environmental protection agency and deforestation and Assunção et al. (2013*b*) for evidence on the relationship between credit and deforestation.

involve illegal activities and authorities can be punished if these activities are disclosed.[70] These actions can also trigger punishments from the federal government, which can reduce federal transfers municipal governments receive or loans that local businesses obtain from public banks.[71] These punishments can influence public goods provision and economic performance given the importance both of federal transfers for government financing and of access to credit from public banks for firm financing in the Brazilian municipalities.

3.3.Data and Sample Selection

3.3.1. Electoral Data

The empirical design relies on a measure of connection to agricultural interests. This measure indicates whether a candidate for mayor is connected to agriculture and is the treatment variable in the empirical analysis. I construct this measure using data on characteristics of the candidates who ran for mayor in Brazil. I use data from the municipal elections of 2004 and 2008. The data is available from the *Tribunal Superior Eleitoral* (TSE) and provides information on characteristics such as gender, age, education and occupation for all candidates.

I construct the political connection measure using data on occupations. I define a candidate as "connected to agriculture" if the candidate reports having an agricultural occupation as the principal occupation. These candidates are called "farmers" in the remaining of the paper. I code agronomists, land surveyors, farmers, cattle ranchers and farm workers as "farmers". There were 4,749 candidates running for mayor in the municipalities of the Brazilian Amazon in the municipal elections of 2004 and 2008. A total of 743 candidates (15.67 percent) were considered connected to agriculture according to this definition.

The political connection measure defined above underestimates the number of politicians connected to agriculture. There might be many candidates connected to agriculture who report working in "other occupations". Also, some candidates whose original occupation was agricultural might answer working as politicians despite still having interests in agriculture. Other candidates, whose occupation is

[70] Punishment can be either judicial or electoral. Ferraz and Finan (2008) present evidence that disclosure of corrupt activities reduces electoral performance.

[71] The blacklisting initiative described earlier is an example of punishment from the federal government on municipalities with high deforestation rates.

not agricultural, can receive political support from lobbies and interest groups connected to agriculture.

This measurement error in political connection will bias downwards the estimated impact of connection to agriculture on deforestation to the extent that the measurement error is not correlated with deforestation rates. The estimates presented in the following sections are a lower bound of the actual effect of connection to agriculture on deforestation under this scenario. However, alternative assumptions about the relationship between measurement error and deforestation can alter the direction of the bias. If the measurement error is larger in municipalities with higher deforestation, than the estimates presented in the following sections can be biased upwards and represent an upper bound of the relationship between connection to agricultural interests and deforestation.[72]

Other variables drawn from the TSE are also used in the empirical analysis. I use this dataset to construct the following variables: margin of victory, total turnout, number of candidates, vote concentration, age, reelection incentives, alignment with the federal government, and schooling. The margin of victory is used to implement the Regression Discontinuity (RD) design. Total turnout, vote concentration, number of candidates and age are used in specification tests that investigate whether there are discontinuities in pre-determined outcomes. Reelection incentives, alignment with the federal government and schooling are used to test whether the effects of the mayor's connection to agricultural interests are heterogeneous.

3.3.2. Data on Deforestation

The main outcome used in the empirical design is deforestation. The data of deforestation is built using satellite images processed by the Project for Monitoring Deforestation in the Brazilian Amazon (PRODES/INPE). Technicians working for PRODES/INPE treat the raw satellite images to identify deforested

[72] An alternative measure of connection to agriculture could be constructed using data from assets that the candidates report to own. This measure is used in Richardson (2012) who investigates the impact of land conflict on entry of politicians connected to agriculture. The author codes a candidate as connected to agriculture if the candidate reports to own land. However, data to construct it is unavailable for the election of 2004 and would limit sample size.

areas. The areas are then aggregated to produce deforestation estimates for all municipalities in the Brazilian Amazon.[73]

The PRODES project was established in 1999 and produces deforestation for the Brazilian Amazon estimates since then. However, the available data from the period 1999 to 2001 and from period 2002 to 2013 is not comparable due to methodological changes. I use data from 2005 to 2012 to cover the period that mayors elected in 2004 and 2008 were in office. Deforestation is defined as the annual deforestation increment, which is the area of forest cleared over the past twelve months. Deforestation in year t is the area in square kilometers cleared from August 1 of year $t-1$ to July 31 of year t. The timing is an important feature of the data on deforestation as it creates a mismatch data on political connections and deforestation. I return to this issue in the results section.

I smooth differences in deforestation across municipalities using a normalized deforestation measure proposed in Assunção et al. (2012). Let I_{mt} be the number of square kilometers deforested in municipality m and period t. Also let $\bar{I}_m$ be the average deforestation in m and $sd(I_m)$ be the standard deviation of deforestation in m over the sample period. I define the normalized deforestation rate D_{mt} as:

$$D_{mt} = \frac{I_{mt} - \bar{I}_m}{sd(I_{mt})}$$

The normalized deforestation rate D_{mt} indicates whether deforestation in municipality m in year t was high or low compared to the average deforestation in m observed in the sample years. This is the preferred measure of deforestation used throughout the paper. The advantage of the normalized deforestation rate is that it ensures that differences in deforestation observed across municipalities are related to differences in total area or differences in historical land use.

I also use a couple of other measures used in the previous literature in the estimates to check whether the results are driven by the definition of deforestation. First, I follow Morjaria (2013) and define the deforestation rate as the area of forest cleared over the past twelve months.[74] Second, I follow Pfaff (1999) and Pfaff et al. (2007) and define the deforestation rate as the ratio between the area of

[73] Detailed information on the PRODES/INPE and on the construction of the data can be found in PRODES (2013).

[74] Burgess et al. (2012) also uses a similar measure. The main difference is that the deforestation data he uses is discrete.

forest cleared over the past twelve months and the original forest area. Note that the first alternative measure does not smooth out variation in deforestation across municipalities related to differences in total area or historical land use. The second alternative measure smooths out variation in deforestation related to differences in total area, but not to differences in historical land use.

Other data from PRODES/INPE are also used in specification tests. I use the dataset to construct four variables: total area, forest area, unobserved areas, and cloud coverage. These variables are used to test whether there are discontinuities in pre-determined outcomes.

3.3.3.Environmental Fines

I use annual data on environmental fines from the Brazilian Environmental Protection Agency (IBAMA) to test whether connection to agriculture affects both the number and the value of environmental fines in a given year. This data is the same used in Assunção et al. (2013*a*). This data is not available for the year 2012. That limits the analysis to the electoral cycle from 2005 to 2008. I return to this issue in the discussion of the results.

3.3.4.Sample Selection

Data on deforestation is available for all 774 municipalities monitored by PRODES/INPE. Municipalities with no deforestation in all sample years and municipalities in the top 1% of the deforestation distribution in each sample year are excluded from the sample. I drop the first group of municipalities to ensure that the analysis is focused in municipalities in which deforestation is a salient issue. I exclude the second group of municipalities to ensure that outliers are not driving the results. The main estimates are robust to including both groups of municipalities.

The estimates are based on a RD design that compares municipalities in which a candidate connected to agriculture won the election against a candidate not connected to agriculture and municipalities in which a candidate connected to agriculture lost the election to a candidate not connected to agriculture. Therefore, I focus on municipalities in which either the winner or the runner-up is connected to agriculture. I also restrict attention to municipalities with less than 200,000 eligible voters and where at least two candidates ran in the election.

There are 151 municipalities that meet these criteria in the election of 2004 and 155 municipalities that meet these criteria in the election of 2008. Candidates connected to agriculture were elected in 79 municipalities in 2004 and 70 municipalities in 2008. Figure 3.1 presents the municipalities included in the sample. In yellow on the map are the municipalities in the sample in the 2004 elections, in green are the municipalities in the sample in the 2008 elections, and in blue are municipalities in the sample in both elections. The sample in concentrated along the so-called “deforestation arc” in the southern Amazon basin. Table 3.1 presents summary statistics for the sample municipalities.

An important question is whether estimates of the effect of connection to agriculture on deforestation in this selected sample are representative of the Brazilian Amazon as a whole. Figure 3.2 plots the trends in deforestation both from the entire sample of municipalities surveyed by PRODES/INPE and from the sample of municipalities that the election winner or the runner-up was connected to agriculture. The figure shows that deforestation trends are similar across these groups. Aggregate deforestation falls sharply in 2006 and 2009 and is constant across years in the other sample years. Despite these similarities, it is important to highlight that the empirical analysis focus on a selected sample of municipalities from the Brazilian Amazon.

3.4. Identification Strategy

3.4.1.RD Design

Let $D_{ms}(1)$ be the potential deforestation in municipality m during the year s of the mayoral term when the municipality is governed by a politician connected to agriculture and $D_{ms}(0)$ be the potential deforestation in the same municipality and year of the mayoral term when there is no politician connected to agriculture in office. The potential outcomes $D_{ms}(1)$ and $D_{ms}(0)$ are never observed at the same time. What the econometrician observes is the actual deforestation rate $D_{ms} = F_m D_{ms}(1) + (1 - F_m)D_{ms}(0)$ in which F_m indicates whether the mayor of municipality m is connected to agriculture or not.

I am interested in estimating the causal effect of connection to agriculture on deforestation. Consider a simple estimator of the causal effect of connection to agriculture on deforestation in term year s given by:

$$E[D_{ms}|F_m = 1] - E[D_{ms}|F_m = 0]$$

This estimator is a simple comparison of the average deforestation in municipalities governed by politicians connected to agriculture with the average deforestation in municipalities not governed by politicians connected to agriculture. It is well known that this estimator will be biased unless political connected is assigned randomly and there is no selection bias.[75]

However, elections are not random and municipalities in which mayors are connected to agriculture are probably quite different from the other municipalities. It is possible that municipalities in which the political strength of politicians connected to agriculture is higher are municipalities with differences in agricultural potential, land use, access to markets etc. All these factors influence deforestation according to the literature (Pfaff, 1999; Pfaff et al., 2007; Souza-Rodrigues, 2013).

I use a RD design based on close elections to eliminate the selection bias and estimate the causal effect of connection to agriculture on deforestation. The RD design explores the fact that the winner of a close election is random. Hence, there will be no selection bias in close elections and it is possible to estimate the causal effect of connection to agriculture on deforestation in these elections.

Let MV be the margin of victory of the elected candidate. The causal effect of connection to agriculture on deforestation in close elections is:

$$E[D_{ms}(1) - D_{ms}(0)|MV = 0] = \lim_{\varepsilon \downarrow 0} E[D_{ms}|MV = \varepsilon] - \lim_{\varepsilon \uparrow 0} E[D_{ms}|MV = \varepsilon] \quad (3.1)$$

The estimator above is consistent whenever the distribution of the potential outcomes conditional on MV is continuous at the threshold $MV = 0$ (Imbens and Lemieux, 2008). The quantities in the right-hand side of equation (3.1) ($\lim_{\varepsilon \downarrow 0} E[D_{ms}|MV = \varepsilon]$ and $\lim_{\varepsilon \uparrow 0} E[D_{ms}|MV = \varepsilon]$) are observed in the data and therefore the estimator above can be computed using observational data.

There are several alternative methods to estimate equation (3.1). One alternative is to use local linear regression and estimate the following equation for municipalities with close elections in which $MV \in [-b, b]$:

[75] See Angrist and Pischke (2008) for a discussion of the selection bias in a similar framework.

$$D_{ms} = \alpha + \beta_s F_m + \gamma_s MV_m + \rho_s (F_m \text{x} MV_m) + u_{ms} \tag{3.2}$$

The coefficient of interest in the equation above is β_s and it represents the causal effect of connection to agriculture on deforestation during the year s of the mayoral term at $MV = 0$. $\beta_s > 0$ indicates that politicians connected to agriculture increase the deforestation rate in year s of the term.

The local linear estimator presented above has a simple intuition. It fits a line below and above the threshold and identifies the impact as the difference in intercept between these lines at $MV = 0$. Selection of b can be either *ad hoc* or use the optimal bandwidth selection method from Imbens and Kalyanaraman (2012). One should note that a smaller bandwidth reduces the bias at cost of efficiency.

An alternative method is to estimate a polynomial spline of order p using all observations:

$$D_{ms} = \alpha + \beta_s F_m + \sum_{\nu=1}^{p} \gamma_{\nu s} MV_m^{\nu} + \sum_{\nu=1}^{p} \rho_{\nu s} (F_m \text{x} MV_m)^{\nu} + u_{ms} \tag{3.3}$$

The coefficient of interest in the equation above is β_s which again represents the causal effect of connection to agriculture on deforestation at $MV = 0$. The polynomial spline estimator fits a polynomial below and above the threshold and identifies the impact as the difference in intercept between these polynomials at $MV = 0$.

I pool together two electoral terms to increase power of the estimates. Therefore, the main estimates include year dummies as controls in order to increase the precision of the estimates. Year 1 of the mayoral term represents deforestation outcomes in 2005 and 2009. Year 2 represents deforestation outcomes in 2006 and 2010. Year 3 represents deforestation outcomes in 2007 and 2011. Year 4 represents deforestation outcomes in 2008 and 2012.

I estimate β_s for different moments of the mayoral term in order to understand whether mayors connected to agriculture influence deforestation changes across the electoral cycle. That helps to understand whether connection to agriculture affects deforestation due to preferences of the politician or the interest group. Equal β_s across periods indicates that the increase in deforestation is not related to politics and that preferences of the politician are driving the result. However, a higher β_s close to elections indicates that politicians connected to agriculture cater to the preferences of the interest group either when the costs of doing so are not observed or when salience of policies favoring deforestation is higher.

The main pitfall from the RD design is that it estimates a local treatment effect. This effect can be quite different from the average effect in the sample. In the studied context, the RD estimates represent the treatment effect of connection of the politician in office to agricultural interests in the group of municipalities where elections were competitive. This effect can be different from the effect of connection to agriculture in municipalities in which competition is not so high. Therefore, I also report results of OLS and Fixed Effects specifications to compare the results from RD estimates with from other estimation methods.[76]

3.4.2. Specification Tests

The identification assumption of the RD design is that candidates connected to agriculture are not able to sort above or below the threshold. This assumption guarantees that close elections are random and validates the design. Existing research have shown that close elections are not random in some contexts. Therefore, it is important to consider whether there is evidence of sorting before presenting the main estimates.

It is important to highlight that the identification assumption is not testable. However, it is possible to obtain indirect evidence supporting it using specification tests designed in the literature. These tests explore some testable implications of the identification assumption. The first implication concerns the smoothness of the distribution of the treatment variable at the threshold. Sorting around the threshold would make candidates to concentrate at one side of it. This implies that sorting would make the distribution of connection to agriculture to be discontinuous at the threshold. Sorting can be tested using the manipulation test proposed by McCrary (2008).

The results from this test are presented in Figure 3.3. There is no evidence that the distribution of connection to agriculture jumps at the threshold (the point estimate is -0.09 and the standard error is 0.20). The evidence from the McCrary test is consistent with the identification assumption.

[76] It is important to note that coefficients estimated using other estimation methods might not be consistent.

Further evidence favoring the identification assumption can be obtained testing whether predetermined observable characteristics jump at the threshold. Pre-determined variables should not jump at the threshold since close elections are random and connection to agricultural interests must not be correlated with municipal characteristics at $MV = 0$. I test this implication for two different sets of covariates. The first is a group of political outcomes. These outcomes are turnout, number of candidates, vote concentration and age. The second is a group of land use variables. These outcomes are total area, total forest area, area not observed and cloud coverage.

The results from these specification tests are presented in Table 3.2. Columns 1 to 4 present the results for electoral outcomes. Columns 5 to 8 present the results for land use variables. Each panel reports estimates obtained using a different estimation technique. The estimates indicate that pre-determined outcomes do not change at the threshold. No estimated coefficient is significant at the 5% level or the 10% level.

Figure 3.4 presents a graphical representation of the results for the electoral variables using a cubic polynomial splice estimated for the selected bandwidth at $MV \in [-40, 40]$. Figure 3.5 presents the same graphical representation for the land use outcomes. Both figures reinforce the interpretation that predetermined outcomes do not change at the threshold. Pre-determined outcomes seem to be similar in both sides of the threshold. These results lend support to the assumption that the distribution of the potential outcomes conditional on MV is continuous at the threshold.

3.5. Results

3.5.1. Farmers and Deforestation: OLS and FE

I start documenting the correlation between connection to agriculture and deforestation in the sample municipalities. I regress the normalized deforestation rate on interactions between dummies indicating whether the mayor is connected to agriculture (*Farmer*) and the year of the mayoral term (*Year*) and a set of controls. I use four different specifications. The first specification includes only year dummies as controls. The second specification additionally includes the mayor party and interactions between the original forest cover and time dummies as controls. The third specification further includes state fixed effects as controls. The fourth specification replaces state fixed effects by municipal fixed effects and uses only variation coming from municipalities whose mayor connections changed in the period. The results are presented in Figure 3.6. Each panel reports the estimates from one specification. The dots correspond to the coefficients of interest and the dashed lines to 90% confidence intervals.

Panel A reports estimates using no controls. The results indicate that municipalities where a farmer is in office have a higher deforestation rate in the second and the fourth years of the mayoral term. Both are electoral years, with elections for the State and Federal Congresses and Governments happening in the second year and elections for Municipal Governments in the fourth year. The correlation is significant at the 10% level for the second year, but not for the fourth year.

Panels B includes additional covariates in the estimation. The results are similar to the presented in the previous panel. Both the magnitude and the standard errors of the coefficients remains similar. Panel C includes state fixed effects in the estimation. Again, the results are unaltered with the change in the specification.

Panel D replaces the state fixed effects for municipal fixed effects. Point estimates become larger and significant at the 10% level for both the second and the fourth year of the mayoral term. Point estimates remain close to zero and insignificant at the usual statistical levels in the first and third term year. The magnitude of the coefficients implies that municipalities with farmers in office have about .3 standard deviations higher deforestation in electoral periods.[77] These results suggest that politicians connected to agriculture change their behavior near elections to benefit the interests of the farming sector.

However, the presence of politicians connected to agriculture is not random and these results might be biased. For instance, suppose that the likelihood of having a politician connected to agriculture is correlated with the predominance of cattle grazing. In addition, suppose that the federal government expands agricultural credit during electoral periods and that more credit increases deforestation in areas in municipalities in which cattle grazing is predominant as

[77] Note that the normalized deforestation has mean zero and standard deviation one so the interpretation is direct from the estimated coefficients.

documented in Assunção et al. (2013*b*). Under these assumptions, the estimates from Figure 3.6 overestimate the impact of connection to agriculture on deforestation if the correlation between the presence of farmers in office and cattle grazing is positive and underestimate this effect if the correlation is negative.

The RD design deals with the omitted variable bias that might affect the estimates using the specifications presented in Figure 3.6. Nevertheless, it is worth stressing that the RD method estimates the average impact of connection to agriculture on deforestation for a group of municipalities for which elections are competitive. This impact can be different from the average impact in the full sample of municipalities.[78]

3.5.2.Farmers and Deforestation: RD Estimates

Table 3.3 presents the main estimates obtained using the Regression Discontinuity (RD) design described in the previous section. Columns 1 to 4 report estimates in which the dependent variable is normalized deforestation. Columns 5 to 8 report estimates in which the dependent variable is deforestation in square kilometers. Columns 9 to 12 report estimates in which the deforestation measure is the deforestation as a share of the total forest area.

Panel A estimates equation (3.2) using the optimal bandwidth estimator proposed by Imbens and Kalyanaraman (2012). This method uses an optimality rule to select the observations included in the estimation. Panel B estimates equation (3.2) for electoral races in which the margin of victory is smaller than 10% ($MV = [-10, 10]$). Panel C estimates equation (3.3) for a cubic polynomial ($p = 3$) using electoral races in which the margin of victory is smaller than 40% ($MV = [-40, 40]$).

The results from columns 4, 8 and 12 indicate that deforestation is higher in municipalities governed by farmers in the fourth year of the mayoral term. The results are robust to different measures of deforestation and estimation methods and are significant either at the 5% or the 10% level. The coefficients not significant at the 5% level have *p*-values close to 5%.[79]

[78] It is impossible to determine whether differences between effects of connection to agriculture on deforestation estimated using OLS and FE and estimated using RD reflect bias in OLS and FE or different impacts in competitive elections and in all municipalities.

[79] Four of the twelve estimates of the effect of connection to agriculture on deforestation close to elections are not significant at the 5% level. However, these coefficients have p-values close to

The results from the other columns suggest that there are no differences in deforestation across municipalities governed by farmers in the other periods. Point estimates are often close to zero and are not significant at the usual statistical levels for almost all deforestation measures and estimation methods. The exception is the coefficient from column 5 in Panel A that is significant at the 10% level.

It is important to highlight that the impact of connection to agriculture on deforestation is not driven by changes in deforestation after elections (that are held in October). That happens because the deforestation rate in a given year represents the total deforestation between August 1 of the previous year and July 31 of the given year. This feature of the data ensures that the causal impact of connection to agriculture on deforestation estimated in columns 4, 8 and 12 is due to policies implemented before the elections took place.

The magnitude of the estimated impact of connection to agriculture on deforestation in election years is substantial. Estimates in column 4 suggest that having a politician connected to agriculture in office increases deforestation in .64 to .71 standard deviations of the normalized deforestation measure. Estimates in column 8 indicate that having a politician connected to agriculture in office increases deforestation in .41 to .49 standard deviations of deforestation in square kilometers. In addition, estimates in column 12 provide evidence that having a politician connected to agriculture in office increases deforestation in .47 to .58 standard deviations of deforestation as a share of the forest area.

The findings reported above are different from the results from Figure 3.6 in some important aspects. RD estimates do not provide evidence that deforestation increases in municipalities with farmers in office near presidential, gubernatorial and congressional elections as suggested in Figure 3.6. RD estimates also suggest that the impact of farmers on deforestation near municipal elections is higher than suggested in Figure 3.6.

Figures 3.7 and 3.8 present a graphical representation of the results. Figure 3.7 plots the estimates from Panel B, while Figure 3.8 plots the estimates from Panel C. Each graph plots the estimates for a different year of the term. Both

0.05. The coefficient estimated in Panel B, column 8 has *p*-value 0.068; the coefficient estimated in Panel A, column 12 has *p*-value 0.057; the coefficient estimated in Panel B, column 12 has *p*-value 0.054; and the coefficient estimated in Panel C, column 12 has *p*-value 0.059.

figures use the normalized deforestation as the deforestation outcome. The figures provide evidence that the effect of farmers on deforestation close to elections is related to increases in deforestation in municipalities governed by farmers (as opposed to declines in deforestation in these municipalities).

The concentration of the impact of connection to agricultural interests on deforestation near elections implies that preferences of the politician are not explaining the relationship between these variables. If preferences of the politician were the mechanism, deforestation in municipalities in which a farmer is in office should be higher in all periods. The results are consistent with a model in which politicians take costly actions near elections to signal their commitment with particular interest groups and attract their electoral support.[80]

A simple mechanism can explain signaling during electoral periods and not off electoral periods. Suppose that some actions (such as lobbying to reduce the incidence of conservation policies or bribing officials to tolerate deforestation) have benefits observable in the short run, but costs that are observable only in the long run. This is plausible in the context studied as it takes time to the authorities to punish municipalities with high deforestation rates (either through legal action or through reduction of transfers and investments in these municipalities). Suppose also that there are uncertainties on the commitment of incumbent politicians with an interest group. This implies that it is rational for its members to maintain the support to the incumbent politician based on the benefits received during his term of office. In this context, it is optimal for office-seeking politicians to enact policies that benefit the interest groups connected to them near elections and not far from them. The existence of behavioral biases that increase the importance of policies enacted in more salient periods (such as electoral periods) just increases these incentives.

The cost of catering to special interests appears to be substantial. Assume that the local RD estimates represent the average impact of special interests on the sample. In this scenario, it is possible to use the coefficients in column 8 from Table 3.3 to calculate the impact of catering to special interests. I estimate that catering to special interests increased deforestation in about 1,800 to 2,100 square

[80] Rogoff (1990) is an example of a model in which politicians change policies near elections to signal their competence. However, in his model politicians' signal to the electorate while here the results suggest that the politicians signal to interest groups.

kilometers in the period 2005 to 2012. This represents 8.8 to 10.4% of the total deforestation observed in the sample municipalities during the period.

3.5.3.Heterogeneous Effects

The interpretation of the RD results put forward above implies that electoral incentives induce politicians to enact policies that increase the deforestation rate near elections. An additional implication of this interpretation is that politicians with reelection incentives have higher incentives to enact policies that increase deforestation.[81] I test this implication showing that the impact of connection to agriculture on deforestation near elections is different for politicians with and without reelection incentives.

Table 3.4, columns 1 and 2 report the results from these estimations. Panels A to C represent the coefficients estimated using different estimation methods (local linear with optimal bandwidth, local linear with determined bandwidth and cubic spline). Column 1 presents the results from the sample of politicians with reelection incentives while column 2 presents the results from the sample of politicians without reelection incentives. The dependent variable across all specifications is the normalized deforestation rate.

The estimates from column 1 point out that deforestation increases near elections in municipalities with farmers in office when the politicians have reelection incentives. The point estimates are about ten percent higher than the estimates obtained with the full sample and are similar across different estimation methods. In contrast, the estimates from column 2 provide evidence that politicians connected to agriculture do not affect deforestation near elections when the politicians do not have reelection incentives. Point estimates are not significant and are smaller than the point estimates from column 1 across Panels A-C. The point estimates are also close to zero when local linear regressions are used (Panels A and B). The results are consistent with the interpretation of the main estimates. Politicians connected to agriculture seem to change their behavior

[81] Politicians might still get rents from office when help to elect a politician from the same political coalition. However, these rents will be lower than the rents the politician gets when she is in office. Indeed, there is a long literature that documents the importance of reelection incentives to the behavior of incumbent politicians. See, for example, Besley and Case (1995) for evidence on the impact of term limits on the economic performance of the American states, List and Sturm (2006) for evidence on the impact of term limits on environmental policies in the U.S. and Ferraz and Finan (2011) for evidence on the impact of term limits on corruption in Brazil.

to benefit farming interests to increase electoral support and increase their reelection chances.

The impact of connection to agriculture on deforestation near elections can also be heterogeneous according to the membership of the politician in the federal government coalition. Members of the coalition might find easier to influence federal policies that affect deforestation (such as operations from the environmental protection agency or supply of agricultural credit from official banks). I test this implication estimating whether the impact of connection to agriculture on deforestation near elections is different for politicians allied or not with the federal government. Table 3.4, columns 3 and 4 report the results from these estimates. Column 3 reports the impact of connection to agriculture for allied politicians while column 4 reports the impact for non-allied politicians. The estimation methods used across Panels A-C are local linear regression with optimal bandwidth, local linear regression with determined bandwidth, and cubic spline.

The results in columns 3 and 4 from Table 3.4 are inconclusive. Point estimates in the sample of aligned and unaligned politicians are similar across all estimation methods. Standard errors are quite large which limits the statistical inference. There is no consistent evidence that politicians connected to agriculture find it easier to affect deforestation when they belong to the government coalition.

It might also be the case that the effect of connection to agriculture on deforestation is heterogeneous according to differences in educational attainment. A growing literature indicates that educational attainment and other competence measures can matter for political performance (Ferraz and Finan, 2009; Besley et al., 2011; Martinez-Bravo, 2014). In the context studied, competence can help politicians to insulate their actions from special interests or it can help them to favor the special interests. I investigate these mechanisms testing whether the impact of connection to agriculture on deforestation near elections is different in samples of more and less educated politicians. Columns 5 to 6 from Table 3.4 report the results from these estimates. Again, I use three different estimation methods (local linear with optimal bandwidth, local linear with determined bandwidth and cubic spline) across Panels A-C. The results suggest that better educated politicians are more able to favor the special interests and enact policies that increase deforestation. Point estimates for politicians that completed high school (column 5) are higher than for politicians that did not complete high school (column 6). In addition, the point estimates for more educated politicians are significant at the 10% level across the three estimation methods while the estimates for less educated politicians are not significant.

3.6.Mechanism: Enforcement or Demand for Deforestation?

The results from the previous section indicate that mayors connected to agriculture affect deforestation rates near elections. An important question is which policies these politicians use to influence deforestation. For instance, politicians might attempt to lobby, bribe or even threaten bureaucrats from environmental agencies, official banks, and local land registries. While all these actions might affect deforestation, most are unobserved. Therefore, it is hard to pin down the exact policies that politicians connected to agriculture use to influence deforestation in electoral periods.

Despite these difficulties, data on environmental fines is useful to understand the mechanisms that local politicians use to influence deforestation. Environmental fines have a significant coercive effect on deforestation in the Brazilian Amazon. The existing literature indicate that more fines reduce deforestation (Hargrave and Kis-Katos, 2013; Assunção et al., 2013*a*). These fines reflect the equilibrium between the demand for deforestation and the enforcement of environmental policies. Conditional on enforcement, both deforestation and fines increase when the demand for deforestation rises. Conditional on the demand for deforestation, deforestation increases and fines decrease when the enforcement of environmental policies declines. Hence, the changes in fines inform whether the increase in deforestation near elections observed in municipalities with a mayor connected to agriculture is due to a rise in demand or a decline in enforcement.

I test the effect of having a farmer in office on the number and the value of the fines using the same identification strategy used in the previous estimates. However, the estimation methods are different from the ones used before. On the one hand, data on the number of fines is discrete, suggesting that a Poisson model should be used to estimate the effect of having a farmer in office on this variable. On the other hand, data on the value of fines per forest area is left censored, suggesting that a Tobit model should be used to estimate the effect of having a farmer in office on this variable. As discussed earlier, these data is not available for the whole sample period limiting the estimates to data for the period 2005-2008.

The effects of connection to agriculture on environmental fines are reported in Table 3.5. Column 1 reports the bivariate relationship between fines and connection to agriculture. Column 2 controls for the margin of victory using a linear term. Column 3 controls for the margin of victory using a quadratic term. Column 4 controls for the margin of victory using a cubic term. Columns 5, 6 and 7 include splines to allow the polynomials to be different above and below the threshold.

Panel A reports the estimates for the number of fines. Column 1 suggests that there are no differences in the number of fines across municipalities governed by farmers or not. The RD estimates from the other columns indicate that the number of fines falls near elections in municipalities with mayors connected to agriculture. The exception is when the functional form for the running variable is a cubic spline. The point estimates are close to zero and not significant in this case. This result can reflect the use of a demanding functional form in a small sample. The magnitude of the estimates in the other columns indicates a sizable effect of political connection on the number of fines that ranges from .47 to .66 standard deviations of the number of fines.[82]

Panel B reports the estimates for the value of fines per forest area (in 1000s of *reais*). Column 1 points out that there are no differences in the value of fines across municipalities with or without connected mayors. However, the RD estimates from the other columns indicate that the number of fines falls near elections in municipalities with mayors connected to agriculture. The estimates have similar magnitudes across all columns and are significant at either the 5% or the 10% level. The exception is again when the functional form for the running variable is a cubic spline. The *p*-value is around 0.20 in this estimation. The magnitude of the estimates implies a sizable effect of connection to agriculture in the value of fines.

[82] In Poisson models, the marginal effects are different across the distribution of the independent variables. The reported magnitudes are computed for the average value of the independent variables.

The evidence is suggestive that changes in enforcement (as opposed to changes in the demand for deforestation) are the principal mechanism linking politicians connected to agriculture and higher deforestation near elections. These results indicate that politicians affect deforestation bribing, lobbying or threatening officials from environmental agencies to induce them to reduce surveillance in their municipalities.

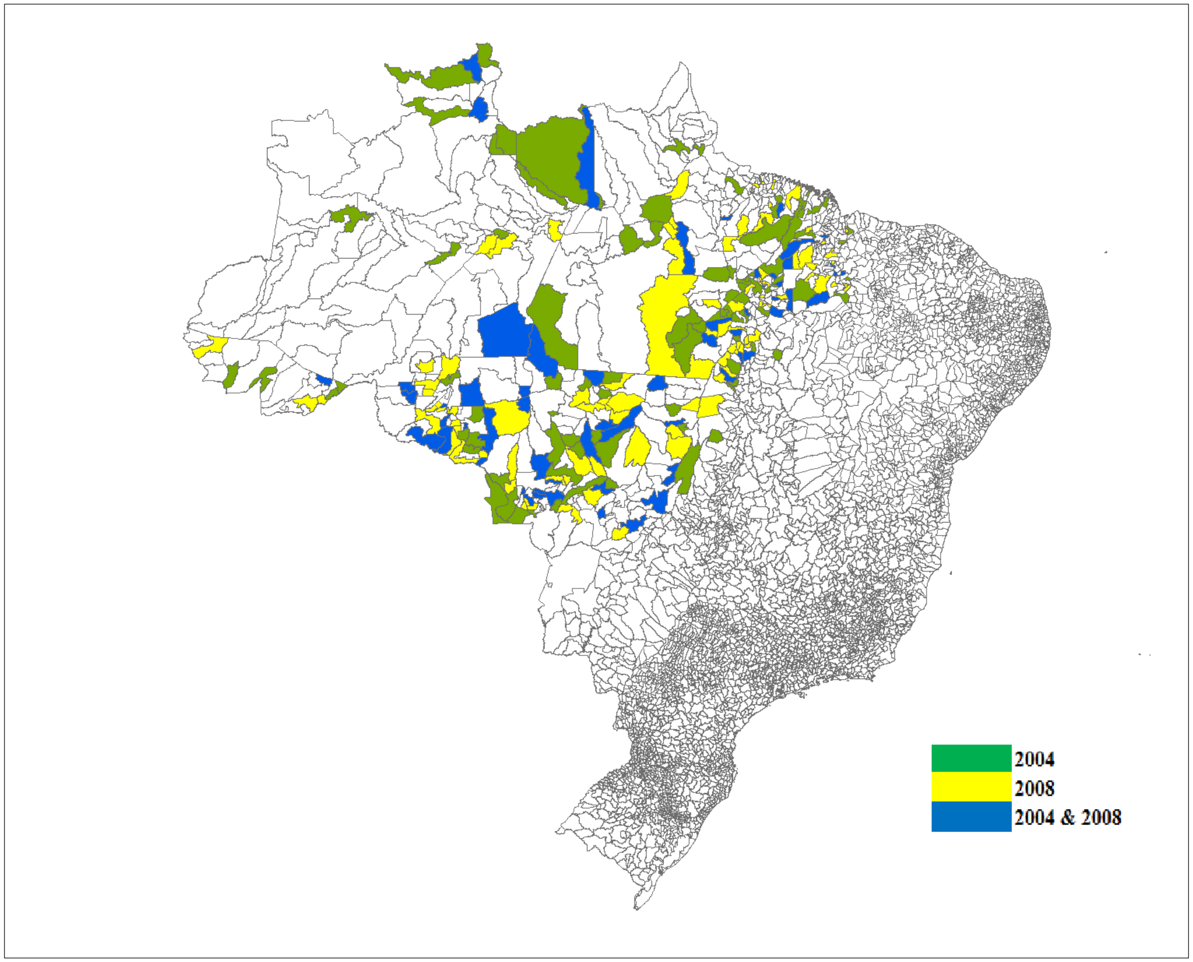
3.7. Conclusion

This paper examines the influence of special interests on deforestation in the Brazilian Amazon. I provide evidence that politicians connected to the agricultural sector change policies near elections to favor agricultural businesses. This change leads to a sizable increase in deforestation near elections. Estimates suggest that catering to the agricultural interests increased total deforestation in the sample municipalities in 1,800 to 2,100 square kilometers in the period 2005 to 2012. This area represents 8.8 to 10.4% of the total deforestation observed in the period.

The evidence also indicates that the change in deforestation is related to changes in the enforcement of the environmental legislation and not to changes in the demand for deforestation. That is consistent with politicians connected to agriculture influencing officials from the environmental protection agencies (through lobbying or bribes) in order to reduce enforcement in their municipalities near elections.

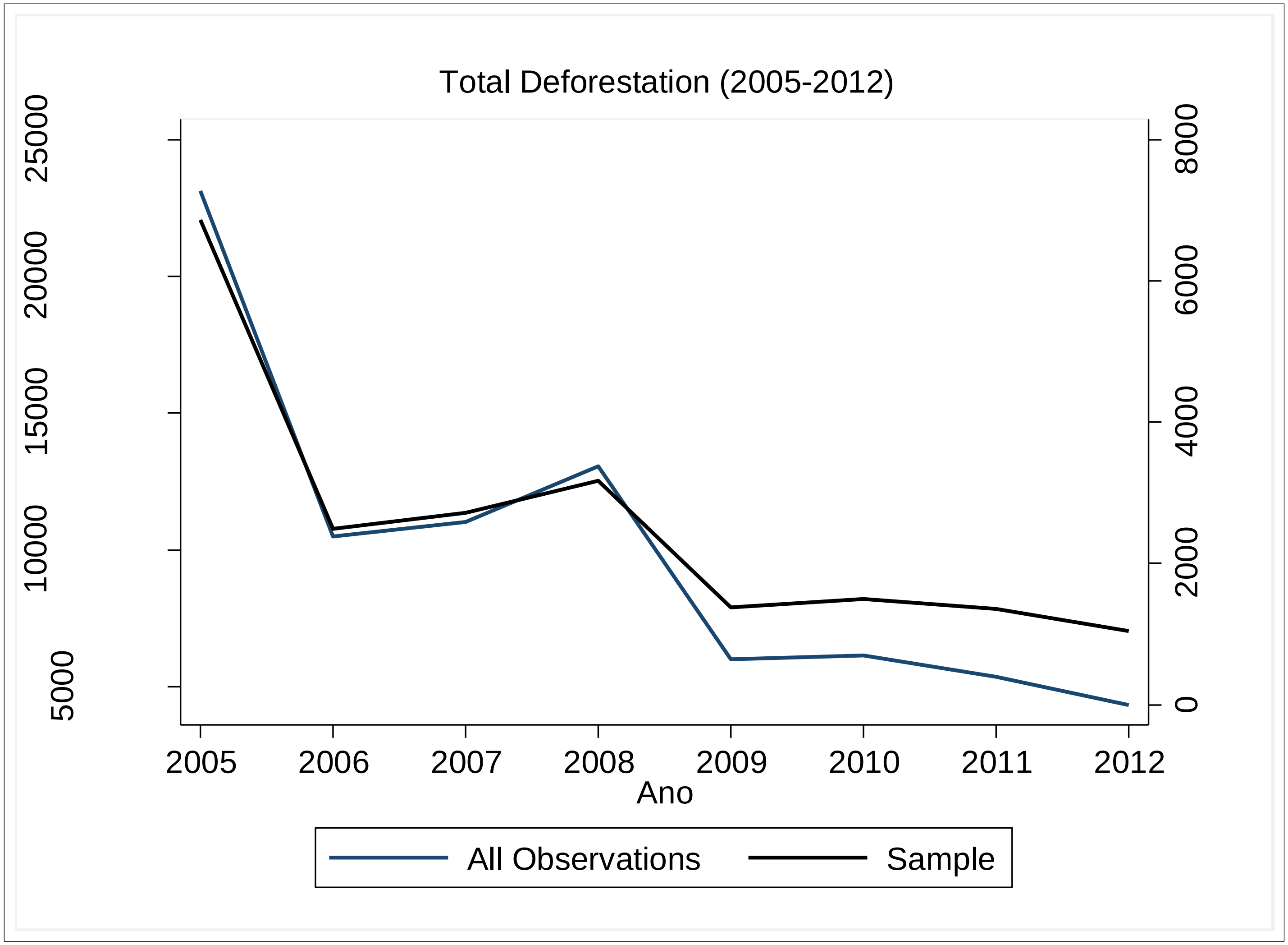
These results illustrate that politicians have strong incentives to distort environmental policies and favor special interests near elections when political competition is high. An essential question is whether these incentives are also present in other policy areas and when political competition is not so intense. Nevertheless, the design of environmental policies should take into consideration the incentives elected official have to distort conservation policies which is documented in this paper. In particular, more transparency, independent audits and different incentives for bureaucrats from environmental agencies might help to reduce the influence of special interests on environmental policies.

Figure 3.1: Sample Municipalities



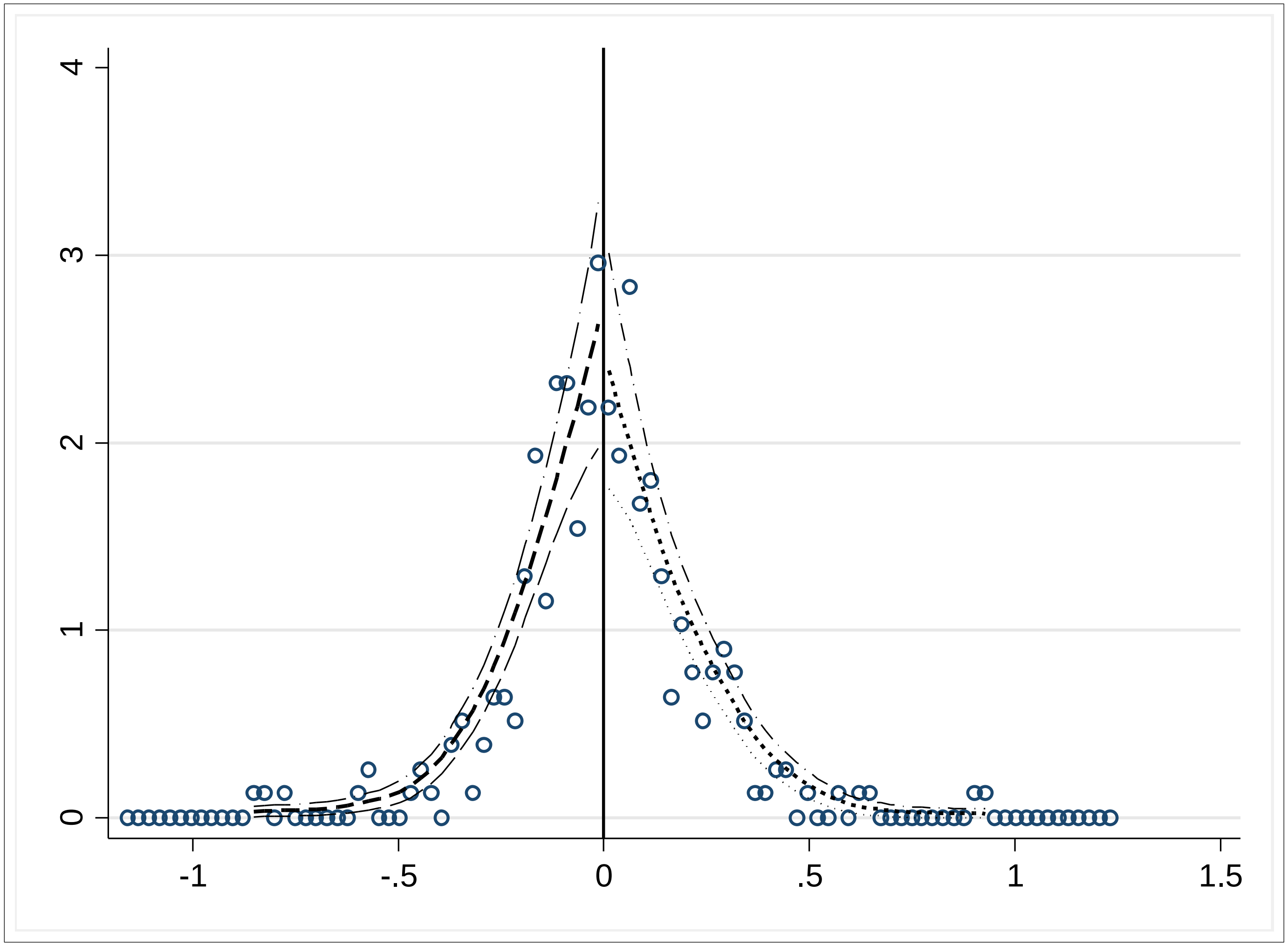
Note: The figure presents the municipalities in the Brazilian Amazon in which either a candidate connected to agriculture won the election against a candidate not connected to agriculture or a candidate connected to agriculture lost the election to a candidate not connected to agriculture. Data comes from the municipal elections of 2004 and 2008. Municipalities in green are included in the sample in 2004. Municipalities in yellow are included in the sample in 2004. Municipalities in blue are included in the sample in both years.

Figure 3.2: Trends in Deforestation



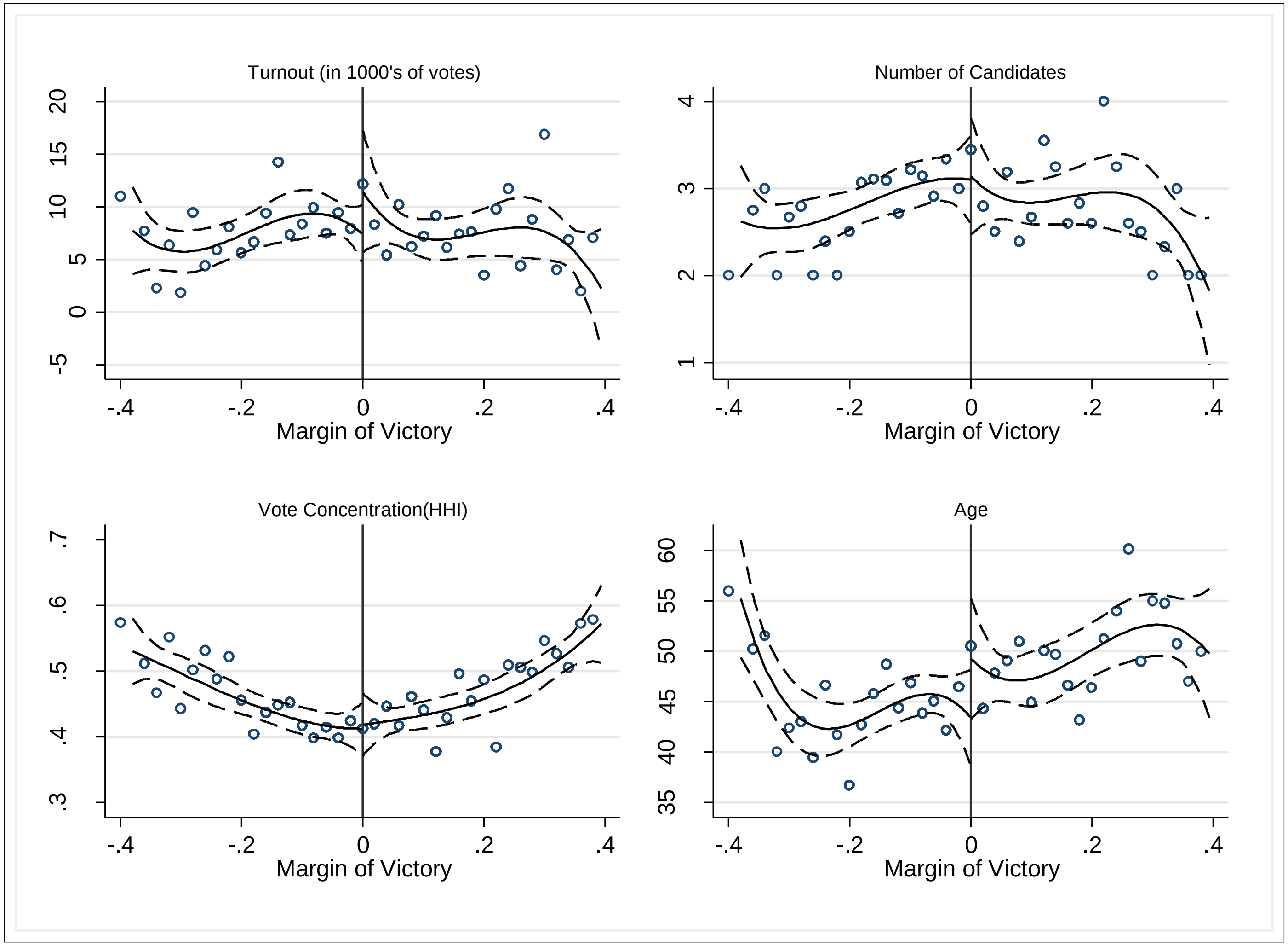
Note: The figure reports the evolution of total deforestation in square kilometers both in the whole Brazilian Amazon (left axis) and in the sample municipalities (left axis). The sample selection is described in the text.

Figure 3.3: McCrary Test



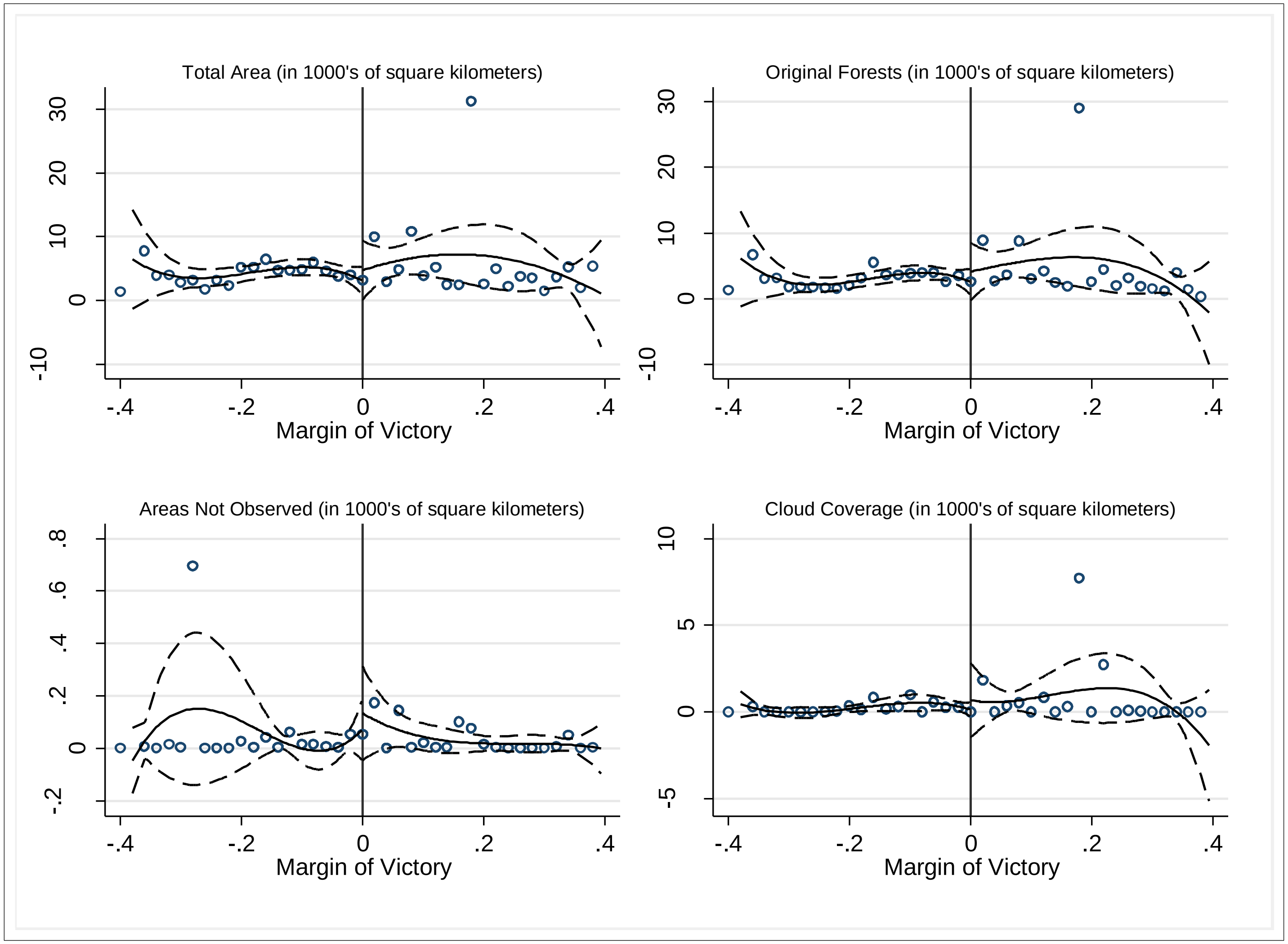
Note: The figure reports the estimated density of the running variable (MV) around the threshold value this of variable ($MV = 0$). Estimates are computed following the procedure described in McCrary (2008). The thick dashed line reports the estimated density values while the thin dashed lines report the confidence intervals. The hollow blue circles represent the actual values averaged 50 bins to each side of the threshold.

Figure 3.4: Balancing Tests – Electoral Covariates



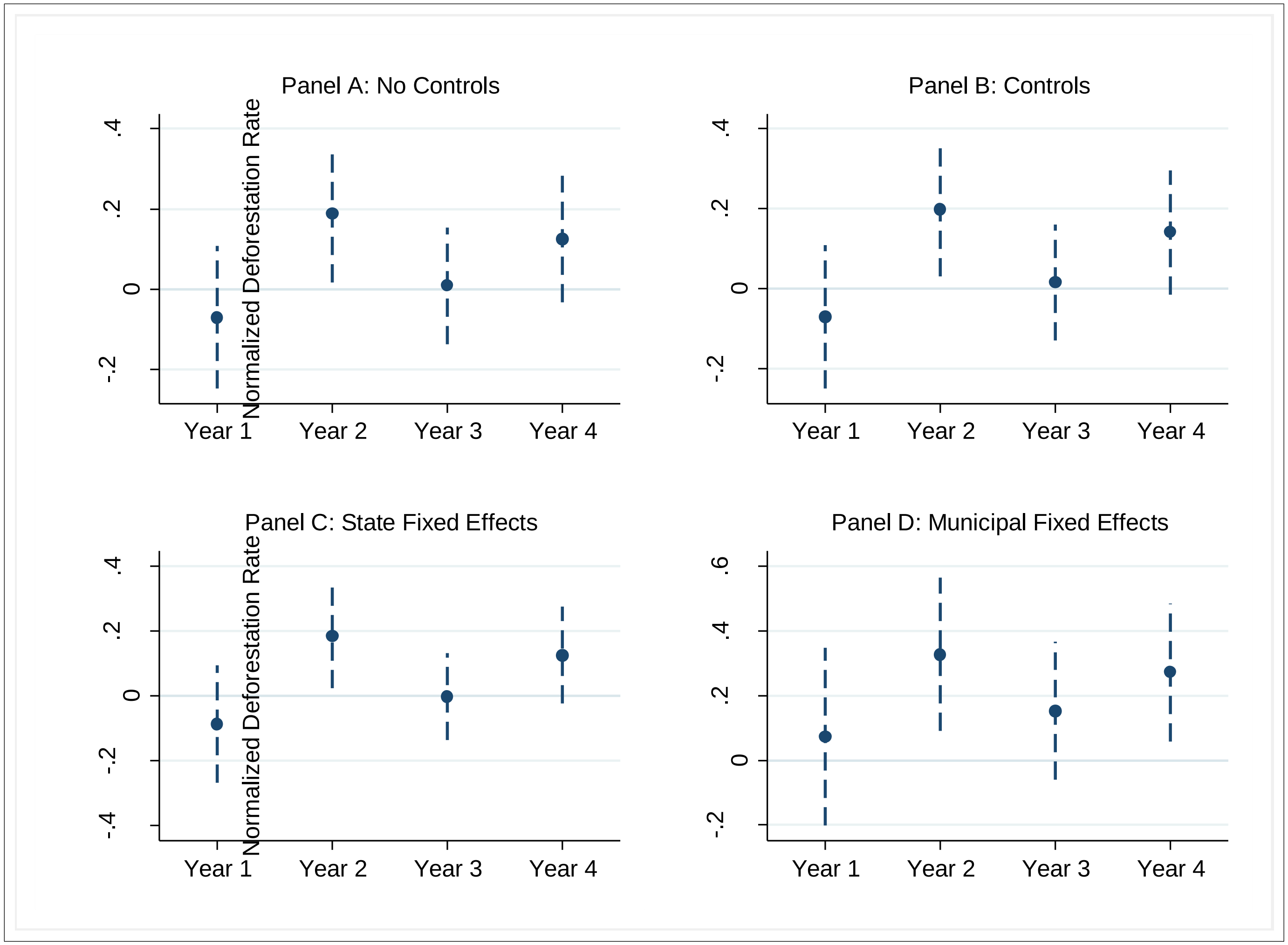
Note: The solid line fits a different cubic polynomial of the running variable (MV) at each side of the threshold value of this variable ($MV = 0$). Dashed lines represent 95% confidence intervals. Scatter points are averaged over 0.02 (2%) intervals. Covariates are presented over each panel and are described in the text.

Figure 3.5: Balancing Tests – Land Use Covariates



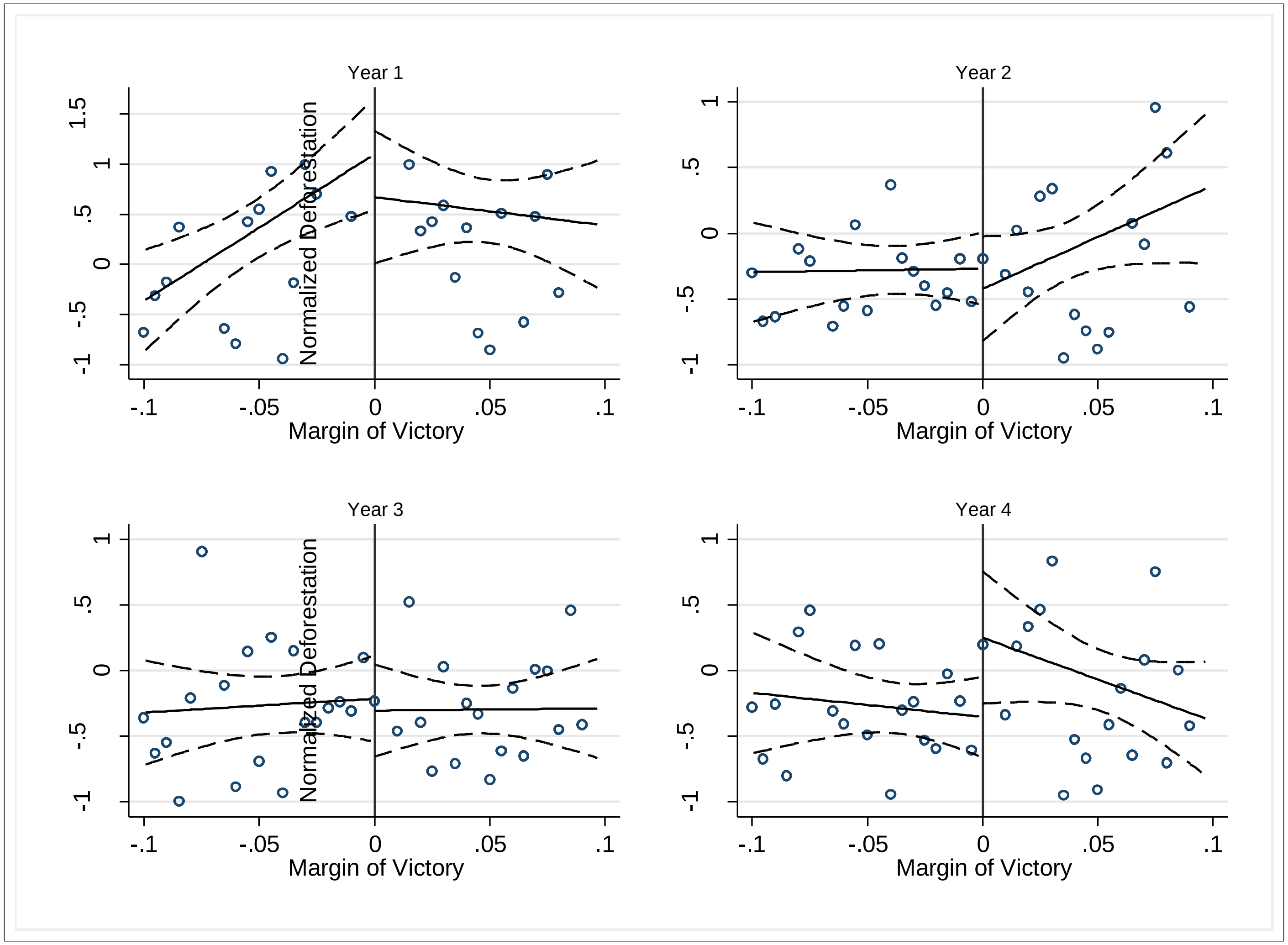
Note: The solid line fits a different cubic polynomial of the running variable (MV) at each side of the threshold value of this variable ($MV = 0$). Dashed lines represent 95% confidence intervals. Scatter points are averaged over 0.02 (2%) intervals. Covariates are presented over each panel and are described in the text.

Figure 3.6: Correlations (OLS and FE)



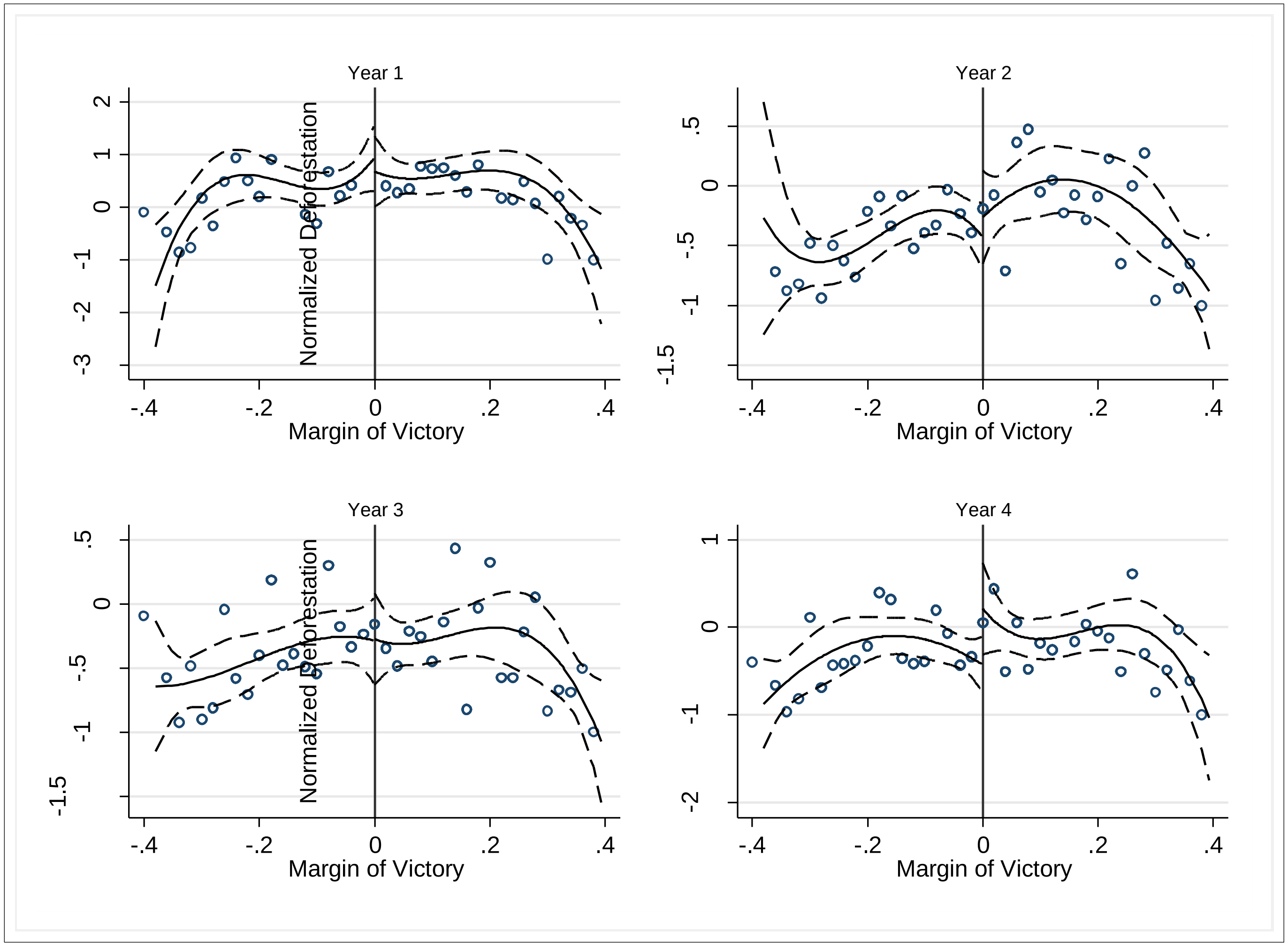
Note: The dots report the coefficients of interactions between interactions between dummies indicating whether the mayor is connected to agriculture (F_m) and the term year (T_s) of the regression $D_{mst} = \alpha_t + \sum_{s=1}^{4} F_m * T_s + \boldsymbol{X}_{mst}\beta + u_{mst}$ in which D_{mst} is the normalized deforestation rate. The dashed lines represent 90% confidence intervals. Each panel reports the estimates from a specification including a different set of controls ($\boldsymbol{X}_{mst}$). Controls are presented in the text.

Figure 3.7: The Impact of Farmers on Deforestation, RD Estimates



Note: The solid line fits a linear term of the running variable (MV) at each side of the threshold value of this variable ($MV = 0$). Dashed lines represent 95% confidence intervals. Scatter points are averaged over 0.005 (0.5%) intervals. Each panel represents a different term year. The dependent variable is the normalized deforestation rate.

Figure 3.8: The Impact of Farmers on Deforestation, RD Estimates



Note: The solid line fits a cubic polynomial of the running variable (MV) at each side of the threshold value of this variable ($MV = 0$). Dashed lines represent 95% confidence intervals. Scatter points are averaged over 0.005 (0.5%) intervals. Each panel represents a different term year. The dependent variable is the normalized deforestation rate.

Table 3.1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.
Panel A: Deforestation			
Normalized Deforestation	1223	-0.06	1.02
Total Deforestation (in Km2)	1223	13.93	29.16
Deforestation as % of Forest Area (in %)	1223	0.42	0.71
Municipality Area	1223	5114.93	9046.70
% of forest area	1223	76.39	31.68
Panel B: Politics			
Mayor Connected to Agriculture (0/1)	1223	0.49	0.50
Margin of Victory	1223	0.00	0.22
Allied Mayor (0/1)	1223	0.42	0.49
Reelection Incentives (0/1)	1219	0.78	0.41
Mayor Completed High School (0/1)	1223	0.59	0.49
Mayor's Age	1223	46.60	9.34
Turnout	1223	8211	7906
Number of Candidates	1223	2.87	1.04
Number of Effective Candidates	1223	2.32	0.61
Panel C: Mechanisms			
Number of Fines	606	9.51	24.67
Value of Fines per Forest Area	606	1.69	17.35

Notes: All variables are observed for the period 2005 to 2012 with the exception of the environmental fines data that is restricted to the period 2005 to 2008.

Table 3.2: The Impact of Mayors Connected to Agriculture on Predetermined Outcomes, RD Estimates

	Electoral Outcomes				Land Use Outcomes			
	Turnout	Candidates	HHI	Age	Total Area	Forest Area	Not Observed	Cloud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Optimal Bandwidth	3.017	-0.075	0.011	3.118	1.206	0.796	0.070	-0.222
	(3.184)	(0.356)	(0.027)	(2.849)	(1.706)	(1.960)	(0.073)	(0.871)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306	306	305	306	306	306	305	306
Panel B: Local Linear [-10; 10]	2.494	0.120	-0.006	2.366	1.557	1.569	0.058	0.215
	(3.112)	(0.411)	(0.031)	(3.677)	(2.714)	(2.517)	(0.081)	(1.238)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	133	134	132	134	133	134	132	134
Panel C: Cubic Spline [-40; 40]	4.100	0.039	0.006	5.912	1.710	1.623	0.047	-0.142
	(3.315)	(0.428)	(0.032)	(3.930)	(2.616)	(2.430)	(0.084)	(1.289)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	286	286	285	286	286	286	285	286

Notes: The table reports RD estimates in which the dependent variable is the predetermined covariate indicated in the column name and the treatment is whether the mayor is a *Farmer*. The sample includes municipalities located in the Brazilian Amazon with positive deforestation in the period 2005 to 2012 and in which either the elected mayor or the runner-up in the last election is a *Farmer*. I exclude the top 1% of observations in terms of total deforestation in square kilometers. Local Linear refers to RD estimates obtained using local linear regressions using the indicated bandwidths. Cubic Spline refers to RD estimates obtained using a third-order polynomial approximation. *** Indicates significance at the 1% level, ** Indicates significance at the 5% level, * Indicates significance at the 10% level

Table 3.3: The Impact of Mayors Connected to Agriculture on Deforestation Rates, RD Estimates

	Normalized Deforestation				Deforestation in Square Kilometers				Deforestation (as % of forest area)			
	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Optimal Bandwidth	-0.240	-0.011	-0.059	0.707**	-15.148*	-0.584	-6.048	12.216**	-0.188	0.001	-0.098	0.409*
	(0.262)	(0.212)	(0.213)	(0.283)	(7.859)	(4.447)	(6.273)	(6.094)	(0.195)	(0.117)	(0.140)	(0.215)
Bandwidth	0.119	0.137	0.142	0.102	0.328	0.301	0.194	0.111	0.524	0.219	0.158	0.090
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306	306	305	306	306	306	305	306	306	306	305	306
Panel B: Local Linear [-10; 10]	-0.342	-0.140	-0.084	0.636**	-14.246	-0.922	-4.684	12.091*	-0.449	0.015	-0.075	0.330*
	(0.296)	(0.249)	(0.238)	(0.269)	(11.636)	(6.423)	(7.166)	(6.564)	(0.377)	(0.150)	(0.153)	(0.170)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	133	134	132	134	133	134	132	134	133	134	132	134
Panel C: Cubic Spline [-40; 40]	-0.209	0.176	0.019	0.658**	-13.062	1.405	-5.034	14.382**	-0.364	0.045	-0.076	0.351*
	(0.305)	(0.248)	(0.244)	(0.278)	(13.322)	(6.878)	(7.635)	(6.781)	(0.371)	(0.154)	(0.166)	(0.186)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	286	286	285	286	286	286	285	286	286	286	285	286

Notes: The table reports RD estimates in which the dependent variable is the municipal deforestation in each term year and the treatment is whether the mayor is a Farmer. Deforestation is measured either as the normalized deforestation in the municipality over the period 2005 to 2012 (columns 1-4), the total deforestation in square kilometers (columns 5-8) or the total deforestation as the share of the original forest area (columns 9-12). The sample includes municipalities located in the Brazilian Amazon with positive deforestation in the period 2005 to 2012 and in which either the elected mayor or the runner-up in the last election is a Farmer. We exclude the top 1% of observations in terms of total deforestation in square kilometers. Local Linear refers to RD estimates obtained using local linear regressions using the indicated bandwidths. Cubic Spline refers to RD estimates obtained using a third-order polynomial approximation. *** Indicates significance at the 1% level, ** Indicates significance at the 5% level, * Indicates significance at the 10% level

Table 3.4: The Impact of Mayors Connected to Agriculture on Deforestation Rates: Heterogeneous Effects

	Reelection Incentives		Allied		Schooling	
	Yes	No	Yes	No	High School or More	Less than High School
	(1)	(2)	(3)	(4)	(5)	(6)
Local Linear (Optimal Bandwidth)	0.770***	0.033	0.740*	0.550*	0.828*	0.296
	(0.298)	(0.472)	(0.379)	(0.326)	(0.426)	(0.355)
Bandwidth	0.114	0.157	0.093	0.182	0.136	0.197
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	238	67	147	159	180	126
Local Linear (Interval [-10; 10])	0.767**	-0.060	0.453	0.592	0.879*	0.608
	(0.293)	(0.610)	(0.394)	(0.399)	(0.465)	(0.435)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109	25	70	64	78	56
Cubic Spline (Interval [-40; 40])	0.690**	0.493	0.241	0.847**	0.903*	0.602
	(0.307)	(0.637)	(0.411)	(0.427)	(0.502)	(0.465)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	224	61	140	146	165	121

Notes: The table reports RD estimates in which the dependent variable is the municipal deforestation in each term year and the treatment is whether the mayor is a *Farmer*. Sample includes only observations in the fourth term year. Deforestation is measured as the normalized deforestation in the municipality over the period 2005 to 2012. The sample includes municipalities located in the Brazilian Amazon with positive deforestation in the period 2005 to 2012 and in which either the elected mayor or the runner-up in the last election is a *Farmer*. We exclude the top 1% of observations in terms of total deforestation in square kilometers. Local Linear refers to RD estimates obtained using local linear regressions using the indicated bandwidths. Cubic Spline refers to RD estimates obtained using a third-order polynomial approximation. *** Indicates significance at the 1% level, ** Indicates significance at the 5% level, * Indicates significance at the 10% level

Table 3.5: Mechanisms Linking Politicians Connected to Agriculture and Deforestation

	No Controls	Linear	Quadratic	Cubic	Linear Spline	Quadratic Spline	Cubic Spline
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Number of Fines							
Mayor Connected to Agriculture	-0.080	-1.223***	-1.395**	-1.722**	-1.256***	-1.685**	-0.123
	(0.440)	(0.453)	(0.557)	(0.714)	(0.461)	(0.843)	(0.670)
Observations	151	151	151	151	151	151	151
Panel B: Value of Fines							
Mayor Connected to Agriculture	-0.541	-1.286**	-1.356*	-1.701**	-1.312*	-1.773*	-1.600
	(0.455)	(0.644)	(0.691)	(0.846)	(0.689)	(0.973)	(1.234)
Observations	151	151	151	151	151	151	151

Notes: The table reports RD estimates in which the dependent variable is the either the number of fines (Panel A) or the value of fines per square kilometer of forest area (Panel B). Data is from 2008 only. The sample includes municipalities located in the Brazilian Amazon with positive deforestation in the period 2005 to 2012 and in which either the elected mayor or the runner-up in the 2004 election is a *Farmer*. We exclude the top 1% of observations in terms of total deforestation in square kilometers. Panel A estimates Poisson models for count data. Panel B estimates Tobit models for censored data models. *** Indicates significance at the 1% level, ** Indicates significance at the 5% level, * Indicates significance at the 10% level

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