The Distributional Impact of Climate Change in Brazilian Agriculture: A Ricardian Quantile Analysis with Census Data

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Abstract

The economic impact of global warming varies across firms because of differences in climate, technology, and adaptive capacity. Aggregate estimates of the average effect of warming are thus insufficient to model climate change vulnerability in developing countries. In this study, I measure the distributional effect of climate change in Brazilian agriculture by estimating the quantile and interquantile regressions of land value on climate, using agricultural census data for 490,000 commercial farms. The effect of a 1°C rise in average temperature on land values ranges from -5% for the most productive farmers located in the colder South region to -34% for the least productive farmers located in the warmer North region. The impact is most severe in the extreme 0.01 quantile of the land value distribution. The productivity inequality between farms in the extremes of the distribution of land values may double with marginal warming.

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[1] Department of Economics and Center for Agricultural and Rural Development, Iowa State University. This article was originally one chapter of my doctoral dissertation at Yale University. It is also one of the studies completed for the Yale–Embrapa partnership for the analysis of climate change impacts and adaptation in Brazil. I am grateful for the invaluable guidance and support of Robert Mendelsohn, Arnulf Grubler, Xiaohong Chen, and Kenneth Gillingham. I thank Leandro Justino for excellent research assistantship with the confidential census dataset in Brazil. I also thank Ary Fortes, Flavio Alves, Geraldo Souza, Rosanna Guidicci, Glaucia Ferreira, and the seminar participants at Yale and at the Yale–Embrapa workshop on Climate Change Impact in Brazil for their comments and suggestions. I am grateful for the support of the research staff from the Brazilian Institute of Geography and Statistics (IBGE) and the Brazilian Agricultural Research Company (Embrapa), especially Carlos Lessa, Luis Carlos Pinto, Ary Fortes, Flavio Alves, and Rosanna Guidicci for access to micro census data, climate, and soil data. I gratefully acknowledge the financial support from Embrapa, the Yale Tropical Resources Institute, the Council for Latin American and Iberian Studies at Yale, the Yale Institute for Biospheric Studies, and the Yale MacMillan Center. Any errors are my own.

What are the distributional effects of climate change in agriculture? The impact of global warming varies across firms and individuals because of differences in their climate, level of economic development, and adaptive capacity (Field, 2014; Mendelsohn and Dinar, 2006; Tol et al., 2004; Rosenzweig and Parry, 1994). The analysis of climate change policy must therefore account for this heterogeneity in vulnerability as well as understand its driving forces and how it could change in the future. However, modeling the distributional effects of climate change at the firm or individual level is challenging because of a lack of data and methodological constraints. In this article, I investigate the diverse climate change impacts along the distribution of farmer productivity by estimating quantile Ricardian functions for 490,000 commercial farmers in Brazil, using the confidential 2006 agricultural census dataset. This study is the first analysis of the distributional impacts of climate change in a developing country using farm-level agricultural census data.

In particular, I model the marginal effect of a 1°C increase in warming at different quantiles of the distribution of land values (Koenker and Basset, 1978; Koenker, 2005; Bushinsky, 1994). The Ricardian model of climate change impacts uses the cross-sectional variation in climate to study the relationship between climate and land value and this is typically estimated by carrying out ordinary least squares (OLS) regressions with county-level data (Mendelsohn, Nordhaus, and Shawn, 1994). Specifically, I follow Chernozhukov and Hansen's (2004, 2005) framework for the quantile estimation, which provides a simple interpretation for quantile Ricardian functions. The unobserved term in the quantile model ranks unobserved farmer productivity such that the quantile-level estimates of the climate change effects capture the climate response at different levels of unobserved productivity. The Ricardian quantile model thus "fixes" unobserved farm productivity to allow me to compare farmers with similar productivity across climates.

The Brazilian case is suitable for the application of the quantile Ricardian model because of the country's diverse climate and economy and availability of micro data. Annual average temperature ranges from 16.9°C to 26.1°C (the 5th to the 95th percentile) and land values vary from R$134 to R$20,000 (the 5th to the 95th percentile). While the south of the country has infrastructure and income per capita comparable with those in developed countries, the local economies in the northern parts of Brazil are comparable with those of African nations. The novel dataset used in this study combines the farm-level version of the agricultural census, surveyed by the Brazilian Institute of Geography and Statistics (IBGE, 2006), with soil characteristics at the municipality level (Embrapa, 2012) and climate data at the census block level (Willmott and Matsuura, 2001). One advantage of using micro census data is the ability to segment the agricultural sector into commercial and subsistence farms. I focus on the commercial segment, which numbers about 500,000 farms; altogether, these farms account for 86% of agricultural production in Brazil and satisfy the profit maximization and perfect land market assumptions in the Ricardian model. I also test the model with a larger sample of 1.38 million farmers and I find that the results are robust across different samples.

The three main contributions of this study are (1) estimating the distributional effect of a 1°C increase in average temperature on the distribution of land values in Brazil, (2) estimating the average effect of warming in Brazil by using a richer set of interaction variables and fixed effects with census data compared with previous studies, and (3) testing the robustness of the Ricardian estimates across quantile and OLS models under alternative specifications to investigate the magnitude of potential omitted variable bias and evaluate the range of climate vulnerability.

Warming changes the location and spread of the conditional distribution of land values in Brazil. At the national level, marginal warming reduces median land values by 20% and increases the 0.1–0.9 quantile spread of the distribution by 3%. Marginal warming thus significantly reduces farm productivity and increases inequality in land values. The distributional effect varies with climate and economic development. In the cold South region, median land values decrease by

12% and the 0.1–0.9 spread increases by 1%. In the northern agricultural frontier, the median land value reduces by 27% and the spread increases by 4%. Across Brazil, the change in the left tail of the distribution is large. Indeed, the extreme interquantile difference for the 0.01–0.1 spread almost doubles in the warmest regions of the country. A 1°C increase in average temperature increases the 0.01–0.1 quantile spread in the South by 41% and in the North by 106%. As a result, inequality in land values between the extreme quantiles, 0.01–0.99, doubles in the warmest regions of Brazil. Further, the least productive farms represent the frontier of climate vulnerability; they tend to be located further from markets and on land less suitable for farming. The marginal effect of warming in the 0.01 quantile is -80% in Brazil.

I estimate that the marginal damage of warming in Brazil is about twice previous estimates based on econometric models, reaching -20% on average at the national level (Sanghi and Mendelsohn, 2008; Timmins, 2006; Massetti, Guiducci, Fortes, and Mendelsohn, 2015). Moreover, the spatial distribution of the marginal effects of warming is consistent across all studies; damage is small in the South and increases for northern regions. The estimated average marginal damage is -12% in the South and -33% in the North. In particular, I find significant damage in the most developed Southeast region, between -12% and -27%. These -12% and -27% reductions in land values in the Southeast region represent losses of $10.5 and $23.7 billion, respectively.

There are four main differences between my estimates and those of previous studies. First, I use farm-level census data for the first time. Second, I restrict my analysis to commercial farms, which, as noted above, represent 86% of agricultural production in Brazil. Third, I estimate quantile models that are robust to outliers and heteroskedasticity. Finally, and most importantly, I include interaction variables between temperature and local market characteristics such as distance to port and cities, population density, and income per capita. I find that the effect of these interactions explains most of the difference in the estimates, indicating positive bias in the Ricardian estimates without interactions.

The two most commonly used econometric methods, the Ricardian model and the fixed-effects model introduced by Deschenes and Greenstone (2007), are subject to bias. The Ricardian model is subject to omitted variable bias from the unobservable time-invariant drivers of land values such the use of irrigation technology, variation in local agricultural policies and in the propensity for land development, and the nonlinear effects of climate variables in farm productivity (Deschenes and Greenstone, 2007; Schlenker, Hanemann, and Fisher, 2005; Schlenker and Roberts, 2009; Ortiz-Bobea, 2013). The fixed-effects model addresses the bias from time-invariant unobservables but is subject to bias from time-variant unobservables. For example, in periods of economic instability in developing countries, such as the hyperinflationary decades of the 1980s and 1990s in Brazil, it is difficult to capture the local effects of policy changes. Fixed-effects models using panel data also suffer from attenuation bias due to measurement errors. Fixed effects absorb time-invariant characteristics, but not errors in variables and therefore tend to bias the coefficients towards zero (Fisher, Hanemann, Roberts, and Schlenker, 2012; Griliches and Hausman, 1985). Further, temperature and precipitation are computed based on spatial interpolations of measurements from meteorological stations and therefore subject to measurement error, particularly in developing countries where there is variation in the density and precision of meteorological stations.

This study contributes to the growing literature on improving Ricardian models (Massetti and Mendelsohn, 2011; Fezzi and Bateman, 2015; Severen, Costello, and Dechenes, 2016; Ortiz-Bobea, 2016; Timmins, 2006). Using the Ricardian model to account for optimal adaptation is particularly important in Brazil where the adaptation of soy for production in the savanna and of corn for double cropping has transformed the country's agricultural sector. I therefore investigate the robustness of the Ricardian climate coefficients by comparing the quantile Ricardian models with the standard Ricardian, the Ricardian with interactions between temperature and market characteristics, and the Ricardian with state fixed effects. I find that when I account for the interactions between temperature and market characteristics, the marginal effects estimated with the quantile Ricardian are consistent with the OLS Ricardian, falling within the 95% confidence interval of -10% to -27%. The exception is the extreme quantile 0.01. The marginal effects estimated with the standard Ricardian and Ricardian with state fixed effects are more optimistic, -11% and -3%, respectively. Whereas the smaller damage predicted with the standard Ricardian model reflects the positive bias from omitting market interactions, the addition of the state fixed effects strengthens the identification assumption but removes most of the climate variation, leading to smaller marginal effects. I thus interpret the estimates from the Ricardian model with fixed effects, -3%, as the upper bound for the marginal effect of warming in Brazilian agriculture.

The remainder of this article is organized as follows. In the next section, I extend the Ricardian model to estimate the quantile Ricardian functions. I describe the dataset in Section 2. Sections 3 and 4 present the empirical results for the quantile and interquantile Ricardian models, and Section 5 describes the robustness analysis. Section 6 concludes with a summary of the key findings, limitations, and applications of this study.

1. Quantile Ricardian Model

The Ricardian model for measuring the impacts of climate change links environmental inputs for agricultural production (e.g. temperature and precipitation) to the value of land through the farmer's profit maximization process (Mendelsohn, Nordhaus, and Shaw, 1994). For a profitmaximizing farmer producing in a perfectly competitive land market, the land rent from agricultural production equals the net revenue for each farm and the land value is the present value of the stream of land rents. The essence of the Ricardian model is thus represented by the following relationship between land values and environmental inputs:

$$(1) \quad V_{LEU} = \int_{0}^{\infty} \frac{[\, P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}, U)]}{L_i(\boldsymbol{E}, \boldsymbol{U})} \; e^{-rt} \, dt$$

The land value per hectare, V_{LEU}, is defined as a plot of land with size L_i, environmental characteristics $\boldsymbol{E}$, and an index for productivity factors, $\boldsymbol{U}$, that are known to the farmer but not to the econometrician. i indexes the best use of land. Net revenue is the output price, P_i, multiplied by the output quantity, Q_i, minus the production cost C_i, expressed in terms of the quantity produced, a vector of input prices, $\boldsymbol{R}$, a vector of environmental inputs, $\boldsymbol{E}$, which includes the climate and soil characteristics, and U. L_i is the farm size in hectares and this could also be expressed as a function of $\boldsymbol{E}$ and U. As farmers choose their land use and inputs according to $\boldsymbol{E}$ and $\boldsymbol{U}$, this framework is consistent with the observed heterogeneity in agricultural production across farms. I assume a positive monotonic relation between land rents and the productivity index. Equation (1) represents an envelope function that implicitly models the best use of land under each type of climate, and thus it accounts for adaptation through land-use change. However, farmers' choices are also influenced by productivity factors such as U and therefore the Ricardian envelope function is likely to differ to reflect the different adaptation possibilities of land types.

The quantile Ricardian function, which extends the Ricardian model by indexing land values using the unobserved productivity factor, allows us to express the Ricardian function as

$V_{LEU} = V(\boldsymbol{E}, U)$. I follow the framework proposed by Chernozhukov and Hansen (2004, 2005) for the quantile treatment model because this provides an intuitive interpretation of the Ricardian quantile function expressed as

$$(2) \quad V = q\,(\,\boldsymbol{E}, \boldsymbol{X}, U\,), \qquad where\ U \sim uniform\ (0,1)$$

Unobserved productivity U is uniformly distributed and this captures the heterogeneity in land values for farms with the same environmental characteristics $\boldsymbol{E}$ and farm characteristics $\boldsymbol{X}$**.** The productivity index U summarizes the specific plot and local characteristics that cannot be observed or measured even with detailed datasets; such characteristics include the specific geographic features of farms (e.g. proximity to water sources), local infrastructure (e.g. quality of roads and storage facilities), and local policies (e.g. state-level subsidies), which all influence farmers' productivity and choices. U is also referred to as the rank variable because it determines the relative ranking of farmers in terms of the unobserved determinants of farmer productivity. $\boldsymbol{X}$ represents a vector of the observable farm characteristics such as distance to market and population density typically used in Ricardian models to control for market effects on land prices.

The quantile Ricardian function $q\,(\,\boldsymbol{E}, \boldsymbol{X}, \tau\,)$ is then the conditional τ-quantile of the conditional distribution of land values. This describes the economic value of a farm with environmental and market access characteristics $\boldsymbol{E}$ and $\boldsymbol{X}$ and with unobserved productivity τ. The Ricardian quantile function models the value of agricultural land in different climates after "fixing" the level of unobserved productivity represented by the quantile τ. Figure 1 shows the Ricardian quantile functions for farmers with high unobserved productivity (solid line labeled τ_{high}) and low unobserved productivity (dashed line labeled τ_{low}). Ricardian quantile functions can have different shapes for different levels of productivity reflecting different land-use choices. For example, in Figure 1, the dashed line function illustrates a different set of crop choices for low productivity farmers compared with the four land-use choices for high productivity farmers.

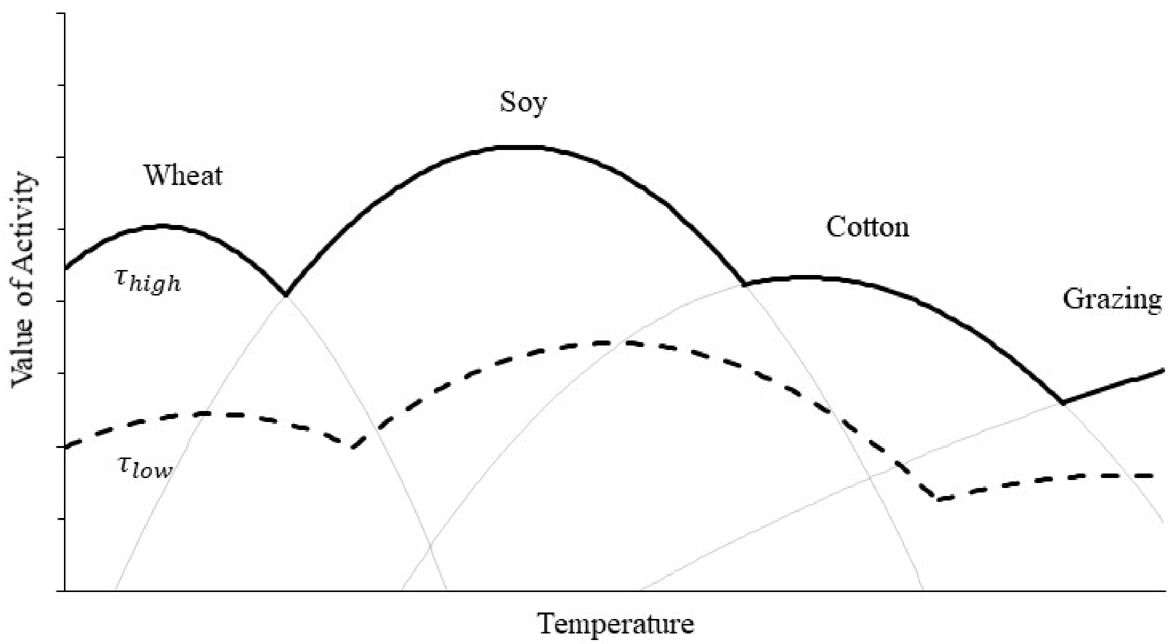

Figure 1 – Ricardian Quantile Functions.

Empirical Models: Quantile and Interquantile Functions

The parameters of interest are the marginal effect of climate change on the log of land values for farmers with unobserved productivity at quantile τ, $m(\tau) = \frac{\partial\, q\,(\boldsymbol{E},\boldsymbol{X},\tau\,)}{\partial\, E}$, and on the distribution of land values, $m(\tau_1 - \tau_2) = \frac{\partial\, iq\,(\boldsymbol{E},\boldsymbol{X},\tau_1 - \tau_2\,)}{\partial\, E}$, where iq is the interquantile function. For changes in average temperature, the marginal effect measures the percentage change in land values and increase in the scale of the distribution of land values resulting from a one degree Celsius increase in the mean temperature. The empirical model is a quantile regression approximation of

Equation (2) estimated at the farm level with a quadratic functional form for environmental inputs:

$$(3) \quad V(\tau) = q_V(\boldsymbol{E},\boldsymbol{X},\tau) = \beta_0(\tau) + \beta_1(\tau)E + \beta_2(\tau)E^2 + \beta_3(\tau)X + \beta_4(\tau)EX + \epsilon(\tau)$$

where the parameters estimated, $\beta_0(\tau)$, $\beta_1(\tau)$, $\beta_2(\tau)$, $\beta_3(\tau)$, and $\beta_4(\tau)$, can differ by quantile τ, and $\epsilon(\tau)$ is the residual at quantile τ. I omit the farm index to simplify the notation. I estimate the quantile regressions for Equation (3) by using quadratic functions for temperature and precipitation measured in the summer and winter in Brazil. My preferred specification includes the interactions between climate and a set of soil characteristics and proxy variables for market access. I also test the model with state fixed effects and for different farm samples.

The interquantile regression is

$$(4) \quad q_V(\boldsymbol{E},\boldsymbol{X},\tau_2) - q_V(\boldsymbol{E},\boldsymbol{X},\tau_1) = \alpha_0(\tau) + \alpha_1(\tau)E + \alpha_2(\tau)E^2 + \alpha_3(\tau)X + \alpha_4(\tau)EX + \epsilon(\tau)$$

The estimated parameters capture the distributional effect of climate on the distribution of land values. I estimate the interquantile regression for the differences q(0.9) – q(0.1), q(0.9) – q(0.5), q(0.5) – q(0.1), q(0.99) – q(0.01), q(0.99) – q(0.9), and q(0.1) – q(0.01).

The identification of climate effects on agriculture using the quantile Ricardian model relies on an independence assumption similar to the one used in the ordinary least squares (OLS) Ricardian model. Specifically, the model assumes that, for each quantile, conditional on a set of control variables $\boldsymbol{X}$, climate $\boldsymbol{E}$ is independent of the error term $\boldsymbol{U}$.

(5) Independence assumption: $q_V(\epsilon|\boldsymbol{E},\boldsymbol{X}) = 0$ for each quantile τ.

As Ricardian models, including the quantile Ricardian model, use cross-sectional variation in climate to identify the effects of climate change, they are thus subject to omitted variable bias[2]. While eliminating the potential bias is not possible, the application of quantile models with rich census data provides a unique opportunity to test the robustness of the Ricardian estimates. I use the quantile model to investigate potential omitted variable bias by comparing the climate change effects across the conditional distribution of land values. Any variation in climate effects at the lower and upper tails of the distribution can imply the influence of omitted variables on farmland values. Further, by fixing the level of unobserved productivity using the quantile Ricardian model, we restrict the effect of omitted variable bias across levels of farm productivity. In other words, we avoid contrasting a highly productive farm in climate A, possibly influenced by an omitted driver of productivity, with a relatively unproductive farm in climate B.

Potential threats to identification include the systematic use of irrigation technology and subsidy of agricultural production in warmer and drier regions. Further, private investment in the most productive land is likely to generate a correlation between climate and development. In these cases, the effect of climate on land values would also incorporate the unobserved contribution of irrigation technology, subsidies, and development. The irrigation effect is not a concern in Brazil since, according to the census data, less than 5% of commercial agriculture in Brazil uses irrigation, most of which is located in the wet southern regions. To account for region- and state-specific policies, I also test the models by using state fixed effects, which absorb the variation in

[2] The formula for omitted variable bias for the linear quantile regressions is similar to the formula for ordinary least squares (Angrist, Chernozhukov, and Fernandez-Val, 2006). In the case of quantile regressions, omitted variable bias is specific for each quantile and can vary across quantiles.

local policies and infrastructure quality at the state level. I use the census dataset to focus my analysis on commercial farms in Brazil. Commercial farmers also tend to specialize in one land use and are more likely to be profit-maximizers. An active land rental market in Brazil also suggests that the perfect land market assumption holds for the commercial market segment. I add the interactions between climate and measures of market access and economic development such as distance to market and income per capita at the micro region level to capture the interaction between climate and development. Finally, the quantile regression is suitable for analyzing the large census dataset because it is robust to outliers and relaxes the homoskedasticity and normality assumptions of OLS models.

2. Data and Descriptive Statistics

The combination of agricultural census data with climate data at the census block level and soil quality characteristics at the municipality level is the most detailed farm/climate dataset available for Brazil. The main dataset is the farm-level agricultural census survey for 2006 in Brazil (IBGE, 2006). The Brazilian Institute for Geography and Statistics (IBGE) surveys over five million farmers in Brazil every 10 years. The census survey data provide the farm's land value, revenue, and expenditure, land-use choices, production technology, and farmer characteristics. I used the confidential farm-level dataset available for academic research at the IBGE Center for Documentation and Dissemination of Information (CDDI) in Rio de Janeiro, Brazil. The only data restriction in this analysis was the selection of commercial farms using a gross revenue threshold of 10 minimum wages[3], following the analysis of Alves, Souza, and Rocha (2012). These authors used the 2006 census to investigate farm profitability and market concentration in the Brazilian agricultural sector and found that the 500,000 farms with gross revenue above 10 minimum wages represented about 86% of agricultural production in Brazil. Furthermore, the Ricardian model assumptions of profit maximization and perfect land markets are a good representation of commercial farming in Brazil. I found that the results are robust when I expand the sample to the 1.38 million farmers with gross revenue over 2 minimum wages.

I integrated the IBGE census data with the University of Delaware climate database (Willmott and Matsuura, 2001) to determine the climate normals, the 30-year average monthly temperature and precipitation, at each rural census block in Brazil. The advantage of the Willmott and Matsuura dataset is that it interpolates the average temperature and precipitation for 1960–1990 with a 0.5 degree latitude/longitude grid resolution, allowing the modeling of climate variation at a lower unit of observation. I used a geographical information system to compute the average climate for the 70,000 rural census blocks in Brazil. Each census block has on average 40 farms. I also tested the Ricardian models by using alternative climate datasets from the Brazilian Agriculture Research Corporation (Embrapa), which interpolates measurements from temperature and precipitation at the municipality level. Brazil has over 5,000 municipalities. In these datasets, monthly temperature and precipitation are averaged for 1960–1990 and 1996–2006 (Embrapa, 2012). Both the University of Delaware and the Embrapa datasets rely on historical data from about 400 meteorological stations in Brazil. I found consistent results for the

[3] The minimum wage in Brazil is defined in terms of monthly income. In 2006, the minimum wage was R$300 per month. Hence, an annual gross revenue of 10 minimum wages per farm corresponds to R$36,000.

Ricardian model using these different climate datasets. Hence, unless noted in the text, all the results reported in the article are based on Willmott and Matsuura's (2001) dataset.

Finally, to capture the variation in land productivity, I integrated a dataset of soil characteristics into the agricultural census data. The soil dataset produced by Embrapa contains 28 soil characteristics at the municipality level (Embrapa, 2012). For example, soil texture is measured as the proportion of land formed of clay, sand, or silt. Clay soil tends to be the best suited for agriculture, as it can hold more water and nutrients. The soil quality measures include a pH index to capture soil acidity as well as the concentration of organic matter and nitrogen. The IBGE agricultural census also contains farm-level information on water access, which identifies the presence of natural water sources such as springs, streams, rivers, and lakes.

Table I presents the summary statistics for the IBGE agricultural census data. The 489,836 commercial farms cover 156 million hectares, equivalent to 73% of the Midwest region in the United States, valued at R$652.6 billion in 2006 prices. The striking feature of this dataset is the large variation in land, farm, and economic characteristics. Table I shows the 10th, 50th, and 90th percentiles for each variable. There is a 10 degree Celsius variation in winter temperature. Land value and farm size at the 90th percentile are 34 times and 100 times larger than those at the 10th percentile, respectively. Appendix A1 describes the variables used in the analysis. Appendix A2 maps the five geographical regions of Brazil and illustrates the cross-sectional variation in land values. Appendix A3 shows the climate variation in Brazil with maps for the main climate variables used in the Ricardian analysis.

Descriptive Climate Change Analysis with Census Data

I first exploit the rich census data to investigate the relationship between land values and climate in Brazil. Ricardian models are normally estimated by using concave quadratic functions, implying the existence of an optimal climate level for agriculture in general or for different crops. However, the exact functional form of the relationship between land values and climate is unknown and likely to vary geographically. Figure 2 plots non-parametric Ricardian functions by using binscatter regression plots that model the non-parametric relationship between two variables by graphing the expected value of each variable after dividing its range into a set number of bins. Figure 1 plots the expected value of log land value against the expected value of average annual temperature with and without partialling out the effects of the control variables such as soil characteristics and proxies for market access. We use 100 bins for the plots in Figure 2 and each point represents one of the 4,834 commercial farms in Brazil. We find that the Ricardian functions follow a quadratic relationship closely. The fitted quadratic functions are also plotted in the graphs as solid lines. Figure 2A plots the Ricardian binscatter without partialling out the effects of the control variables.

The quadratic Ricardian function implies that the climate change impacts vary across farmers located in regions that have different temperatures. The higher the original temperature, the higher is the impact. Brazilian farmers located in regions with an average temperature of about 16 degrees Celsius would thus benefit from warming. One degree of warming would increase the economic value of land by about 15% for these farmers. Farmers located in regions with an average temperature between 18 and 21 degrees Celsius would not be impacted by higher temperatures, whereas farmers located in regions with an average temperature above 22 degrees would experience increasing economic impacts or warming. One degree of warming would decrease the economic value of farms in areas with an average temperature of 22 (35) degrees Celsius by 39% (45%). Most farms in Brazil are located in the decreasing part of the Ricardian quadratic function, indicating the vulnerability of the Brazilian agricultural sector to warming.

The Ricardian function in Figure 2A does not account for location-specific factors that also affect the economic valuation of Brazilian farmers and is therefore subject to omitted variable bias. Adding variables for climate (e.g. precipitation and latitude), for soil characteristics (e.g. soil texture, pH, and nitrogen content), and for market access (e.g. distance to ports and cities, average income, and population density) reduces the bias. Figure 2B shows the Ricardian model for Brazil including the control variables. The partialling out effect reduces the variation in log land values and average temperature used to model the Ricardian relationship, flattening the quadratic function. This flatter Ricardian function indicates the reduced sensitivity of Brazilian agriculture to warming and implies that the Ricardian function in Figure 2A has negative bias.

Although most commercial farms in Brazil still lie in the declining part of the quadratic Ricardian function in Figure 2B, the impact of warming is significantly smaller that in Figure 2A. The economic value of agricultural land decreases by about 25% (33%) with one degree of warming in regions with an average temperature of 22 (35) degrees Celsius.

Appendix A4 shows the binscatter plots for the Ricardian functions including, first, the region fixed effects and then the state fixed effects. Brazil has five geographical regions and 26 states. The fixed effects absorb much of the variation in log land values and average temperature as they account for the average unobserved effects at the region and state levels. The Ricardian functions in Appendix A4 are flatter but similar, suggesting that the state fixed effects do not significantly reduce potential omitted variable bias relative to the region fixed effects.

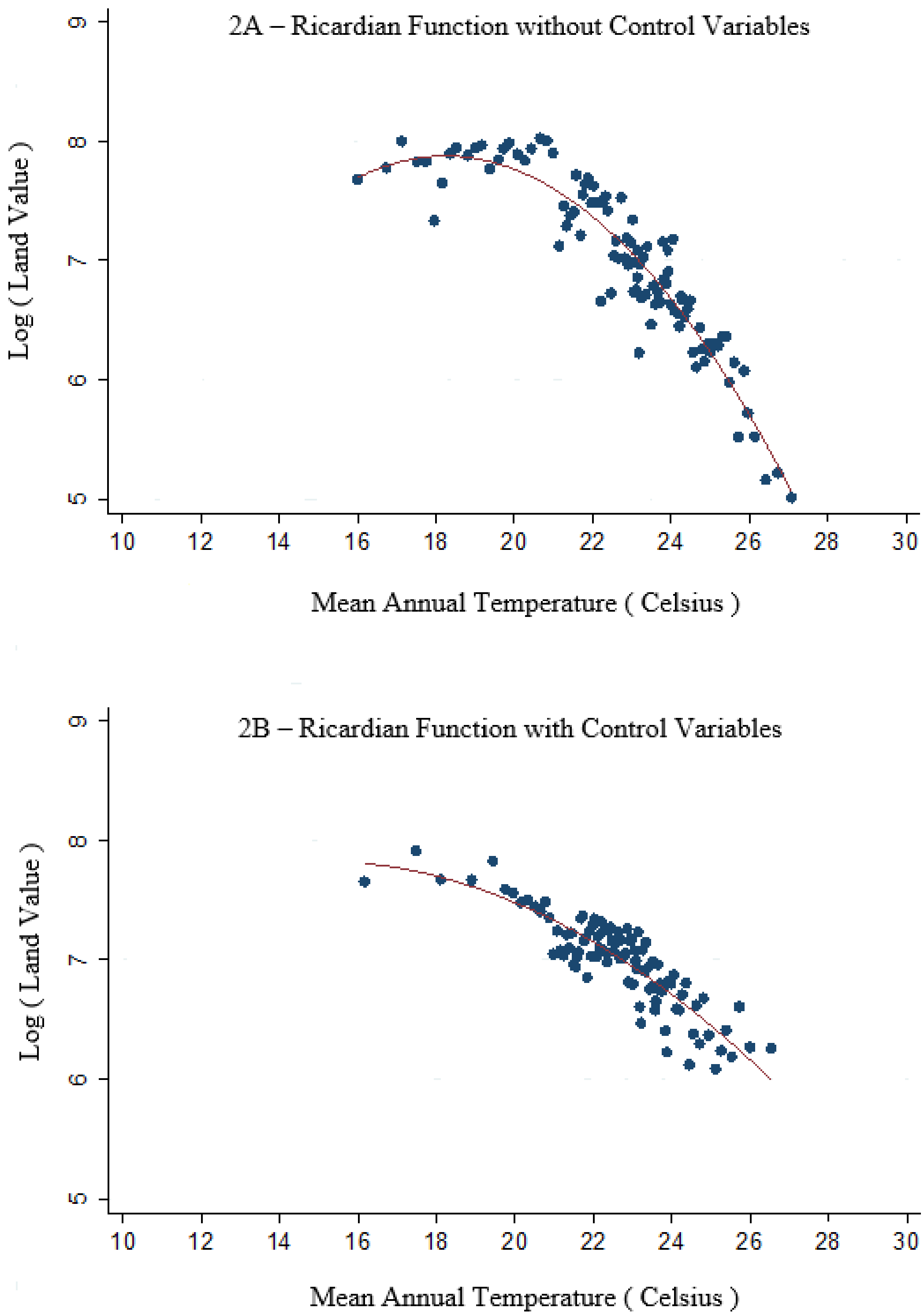

Figure 2 – Non-parametric Ricardian Functions for Brazil.

Notes: Graphs are plots of the binscatter regressions of log land values on average temperature.

Descriptive Statistics by Quantile of Farmer Productivity

Table II presents the summary statistics of the three quantiles of the residual term of the Ricardian model with the set of control variables, the rank variable U in the theoretical model, illustrating the variation in the dependent variables, independent variables, and other variables from the agricultural census not included in the Ricardian model. The average land value for farmers in the top quantile, $\tau = 0.9$, is twice that for farmers in the median quantile, which is over 12 times larger than that for farmers in the bottom quantile, $\tau = 0.1$. Average temperature and distance to port and cities are similar across quantiles. However, the variation in average winter temperatures is much larger than the variation in average summer temperatures. These summary statistics categorize farmers into different quantiles and help interpret the heterogeneous effects of climate change across quantiles.

The differences between the bottom and top quantiles reflect both the endowment of low productivity land and the existence of specialized infrastructure and production systems. The average yield of cereal crops is the same in the three quantiles, about 3.7 tons per hectare, reflecting the consistency of commercial farming in Brazil and the significant explanatory power of the detailed datasets of climate and soil characteristics. On the contrary, the allocation of land across the three main land uses (i.e. grazing, crops, and forest) differs across quantiles. About 50% of land is allocated to grazing in all quantiles. The share of land allocated to crops increases from 19% at the bottom quantile to 33% at the top quantile while the share of forestland decreases by 10 percentage points. The farms at the bottom quantile have a large endowment of marginal land that is not suitable for crop production. The share of forestland variable absorbs unobserved factors that reduce the productivity of the land (e.g. hilly or swampland). Alternatively, the variation in the forestland share could be a result of the heterogeneous enforcement of conservation policies. However, forestry policy in Brazil was only weakly enforced in 2006. The share of cropland integrated into agroindustrial production and trading, including processing companies such as sugar and ethanol producers, also varies across quantiles. The share of crop land integrated into industry increases from 16% in the first quantile to 22% in the top quantile. This pattern is expected to the extent that private capital follows productive land; however, the relatively small difference between the top and bottom quantiles suggests that industrial clustering does not significantly differentiate farm productivity across quantiles.

Finally, Table II also shows the spatial variation across quantiles. The share of farms from the developed southeast region is significantly higher in the top quantile, suggesting a significant effect of the quality of infrastructure on agricultural productivity. If we combine the two most developed regions, southeast and south, the share of farmers is consistent across quantiles. These two regions are close to major ports and have the best infrastructure in the country. The northeast region is the least developed in Brazil, and a significant part of its agricultural production depends on government subsidies such as the subsidies granted to sugarcane production on the northeast coast. Nevertheless, the consistent share of northeast farms across quantiles suggests that subsidies alone cannot compensate for low land productivity. By contrast, the large share of northeast farms in the top quantile indicates the presence of specialty farms (e.g. producing tropical export crops).

3. Empirical Results: Ricardian Quantile Model

The impact of warming on the Brazilian agricultural sector is negative and heterogeneous. The marginal effect of warming varies spatially with temperature and market characteristics (e.g. average income per capita and distance to market) as well as across the distribution of farm productivity. Figure 3 presents the marginal effects of warming on land values for the 0.1 and 0.9 quantiles of farm productivity and average annual temperature in Brazil (in deciles). This figure shows that the marginal effect of warming quadruples from the first to the 10th decile of temperature. In the first temperature decile, average temperature is 16.8°C and a 1°C increase in warming leads to a -6% and -5% reduction in land value for farmers at the 0.1 and 0.9 quantiles of productivity, respectively. The marginal effect decreases to a -27% and -22% reduction in land values from farms in the 10th decile of temperature, where the mean temperature is 26.6°C.

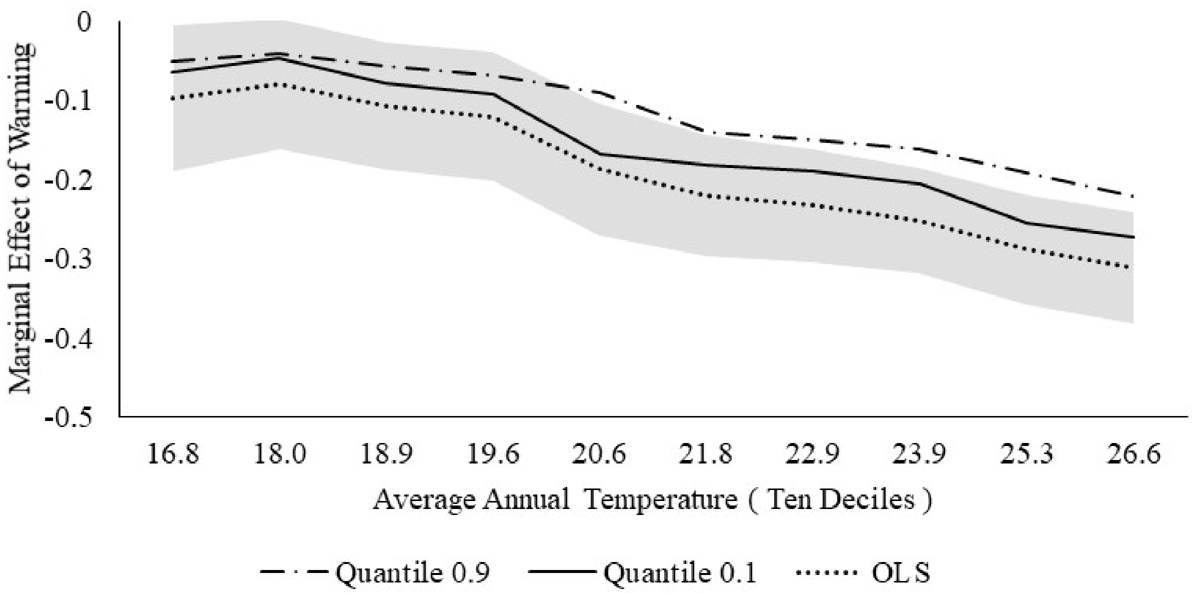

Figure 3. Marginal Effect of Warming in Brazil by Temperature Decile

As the temperature rises, the difference between the marginal effect of climate change between the top and bottom quantiles increases. Farms in the lowest quantiles of productivity are more vulnerable to warming. The difference in the marginal effects across quantiles is even more evident in the extreme quantiles of 0.01 and 0.99. As shown in Figure 4, the marginal effect in the 0.99 quantile decreases from -13% to -21% from the first to the 10th decile of temperature, whereas it remains approximately in the same range of the marginal effect for the quantiles 0.2 to

0.9. By contrast, farmers in the lowest quantile, 0.01, are extremely sensitive to warming. The marginal effect of warming for those farmers is a 41% reduction in land values in the coldest regions of Brazil and a 100% loss after the seventh decile of temperature, where the average annual temperature is 22.9°C. The least productive farmland located in the warmest regions of Brazil is on the frontier of climate vulnerability.

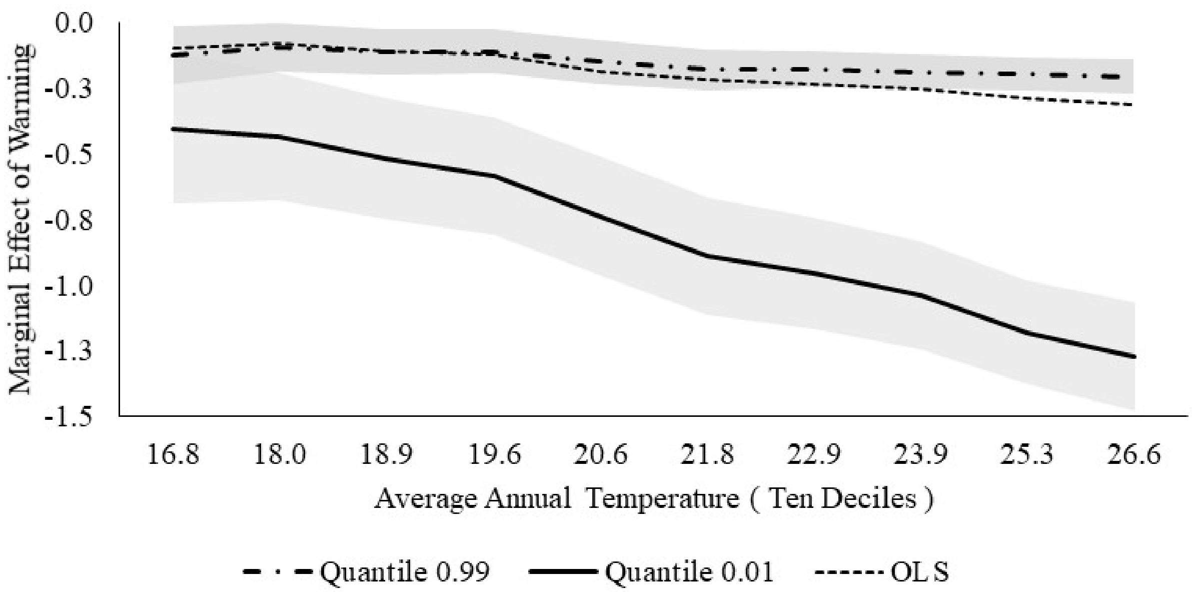

Figure 4. Marginal Effect of Warming in Brazil for the Extreme Quantiles

Based on the descriptive analysis in Table II, low productivity farmers have the highest share of land allocated to forest and the lowest share of agricultural production integrated to industry. These farmers tend to operate on land less suitable for mechanized farming (e.g. rocky land or land at a higher elevation), be further from markets, and tend to be less specialized in terms of land-use choices. They also depend more on environmental inputs to increase their productivity and have fewer adaptation options. Low productivity farmers located in warmer climates are closer to the climate frontier of agricultural production (e.g. drier land and land closer to the equator) and therefore marginal changes in climate can cause significant damage.

Table III shows the estimated coefficients of the temperature variables for the quantile and ordinary least squares regressions. The other variables included in the regressions include a quadratic function for precipitation, interactions for precipitation and temperature, soil characteristics, latitude, mean elevation, dummies for water source in the farm, log of farm size, and proxies for local market characteristics and access at the microregion level (population density, average income per capita, distance to port and distance to capital). Appendix B presents the coefficients of all the variables.

The Ricardian quantile functions differ by farm productivity. The quadratic function for the summer temperature is consistently convex across the examined quantiles but flattens at higher quantiles. The marginal effect of warming in the lower quantiles is more sensitive to the current climate than that in the higher quantiles. The quadratic coefficient of the summer temperature in the 0.1 quantile, 0.0327, is twice that in the 0.9 quantile. Similarly, the quadratic function for the winter temperature is concave and it flattens from the lower to higher quantiles of farm productivity. Although all farms in colder regions benefit from an increase in the winter temperature, those farmers in the lowest quantiles benefit the most. Ignoring the interaction terms, the marginal effect of warming for a farmer in the 0.01 quantile is over +50% in colder regions and below -50% in the warmest regions of the country.

The quantile functions also differ in the interaction terms between the average temperature and precipitation and the variables for market access. For farms in the lowest quantiles of farm productivity, damage from warming increases with distance to market. The coefficients of the interaction terms between the winter temperature and distance to port are statistically significant. This market access effect is much higher for farmers in the lowest quantile. Farms located close to markets are more valuable and have more adaptation options beyond shifting crops and production technologies. The coefficient of the interaction term between the winter temperature and distance to port is positive; however, this result must be interpreted with caution because of the positive correlation between distance to port and distance to large cities in Brazil (0.35 for commercial farms).

Most of the coefficients of the interaction term between income per capita and temperature are not statistically significant, with the exception of the interaction with the winter temperature in the lowest quantile and with the summer temperature in the 0.1 quantile. Even in these cases, however, the coefficients are only significant at the 10% level. When we control for a rich set of climate and soil characteristics as well as for the interactions between climate and market access, the effect of climate on land values does not vary significantly with income level. The omitted interaction between climate and development is concerning in Brazil because there is a clear north/south differentiation in climate and income. Finally, none of the coefficients of any of the interaction terms is statistically significant in the highest quantile of farm productivity. Although these highly productive farms are sensitive to changes in temperature, they tend to be more specialized and integrated into the processing industry such that their location relative to cities and ports does not significantly affect their valuations or climate sensitivity.

Table III also reports the marginal effect of warming for Brazil, the country's five regions, and the region that represents the new agricultural frontier in Brazil, MATOPIBA. I compute these marginal effects by using the mean values of all the variables in each region. The regional pattern of climate sensitivity in Table III is consistent with most studies of climate change impacts in Brazilian agriculture. Climate vulnerability increases as we move north. However, the marginal damage of warming reported herein is twice as large as that in previous economics studies in Brazil. The marginal effect of a 1°C increase in warming is between -12% and -20% in

Brazil, -5% and -12% in the South region, and -20% and -27% in the agricultural frontier depending on the quantile of farm productivity (columns (2), (3), and (4) of Table III). The marginal effects become significantly more negative as I add the interaction effects between climate and market access. Distance to market is negatively correlated with both land values and annual temperature in the set of commercial farms, suggesting a positive omitted variable bias.

4. Empirical Results: Interquantile Model

To measure the distributional effect of warming, I estimate the marginal effect of temperature on the difference between the quantiles of the distribution of log land values, using equation (4). Table IV presents the estimated coefficients of the temperature variables for the interquantile regressions and marginal effects of warming on quantile differences for Brazil and the six abovementioned regions. Appendix C reports the complete results for the interquantile regressions. As in the Ricardian quantile models, I include the quadratic functions of the summer and winter temperature as well as the interaction terms between temperature and precipitation and between temperature and market access. I also use the same set of covariates as in the Ricardian quantile models.

An increase in average temperatures changes the shape of the distribution of land values, increasing the spread between the extreme quantiles and skewing the distribution of land values to the left[4]. I estimate the distributional effect of climate change in four quantile bands: q(0.1)–q(0.01), q(0.5)–q(0.1), q(0.9)–q(0.5), and q(0.99)–q(0.9). At the national level, a 1°C rise in

[4] The estimated effects on a quantile of the distribution of log land values differ from the effects on the actual set of farmers in each quantile. These two effects are equal only if the relative ranks of farmers in the distribution of log land value are preserved with climate change.

average temperature increases the difference between the 0.1 and 0.01 quantiles by 65%, decreases the distance between the 0.5 and 0.1 quantiles by 6%, increases the difference between the 0.9 and 0.5 quantiles by 9%, and does not significantly change the difference between the 0.99 and 0.9 quantiles. Further, a 1°C rise in average temperature increases the difference between the 0.1 and 0.9 quantiles by 3% and the difference between the extreme quantiles, 0.01 and 0.09, by 64% (columns (1) and (2) of Table IV).

The larger distributional effect of warming is at the extreme left tail, as the least productive land could lose most of its value with marginal climate change. This large positive effect results from the convexity of the winter temperature quadratic function and positive interaction effects between the winter temperature and income per capita, distance to the capital, and farm size. By contrast, the effect of warming on the extreme right tail of the distribution is small and this reduces the distance between highly productive and super productive farms, represented by the 0.9 and 0.99 quantiles (column (6) of Table IV). The value of highly productive farmland located close to cities or ports is not sensitive to climate change and the distributional effect in the highest quantiles is larger for farms locater further from markets.

Excluding the tail effects of warming to focus on the 0.1–0.9 quantiles, I find that an increase in temperature skews the distribution of land values to the right. Columns (4) and (5) report the interquantile models for the q(0.1)–q(0.5) and q(0.5)–q(0.9) quantile differences. Whereas the q(0.1)–q(0.5) quantile difference decreases by 6%, the q(0.5)–q(0.9) quantile difference increases by 9% in Brazil and these distributional effects are consistent across the six regions. There are two explanations of these opposite distributional effects. First, the q(0.1)–q(0.5) interquantile difference is more sensitive to changes in the summer and winter temperatures. The quadratic functions for the summer and winter temperatures are flatter for the q(0.5)–q(0.9) interquantile regression than for the q(0.1)–q(0.5) regression. Second, the interaction effect between the summer temperature and market access is negative and large for the q(0.1)–q(0.5) interquantile but positive and only marginally significant for the q(0.5)–q(0.9) interquantile.

As in the Ricardian quantile model, the marginal effect of warming on the interquantiles is a function of temperature and market access. The conditional distribution of log land values differs spatially in Brazil with a variation in climate and market characteristics and the distributional effect of warming varies spatially. Table V summarizes the marginal effects of warming on the conditional distribution of log land values by deciles of average annual temperature in Brazil.

The marginal effect of warming on the spread of the distribution of land values is five times larger in the warmest regions of Brazil than in the coldest. A 1°C rise in average temperature increases the q(0.1)–q(0.9) interquantile distance by 1% in the first decile of temperature and by 5% in the 10th decile. For the extreme interquantile, q(0.01)–q(0.99), the marginal effect increases from 29% in the first decile to 105% in the 10th decile (columns (1) and (2) of Table V). The marginal effect in the extreme interquantile, q(0.01)–q(0.1). increases from 35% to 98%. The interquantile differences in the left tail of the distribution are more sensitive to warming because of the vulnerability of the least productive farmers. Warming tends to elongate the left tail of the distribution, thus increasing the spread between the extreme quantiles. By contrast, the marginal effect in the right tail of the distribution, the q(0.0)–q(0.99) interquantile, is small, starting at -6% in the first decile of temperature and increasing to 2% in the top decile. The right tail of the distribution is less sensitive to increases in average temperature.

In the q(0.1)–q(0.5) and q(0.5)–q(0.9) interquantiles, the marginal effect of warming is surprisingly consistent across the deciles of average temperature in Brazil (columns (4) and (5) of Table V). The marginal effect varies from -3% to -7% in the q(0.1)–q(0.5) interquantile and from 8% to 10% in the q(0.5)–q(0.9) interquantile. In both cases, there is an offsetting effect between the concave quadratic function of the summer temperature and the convex quadratic function of the winter temperature. The interaction terms between the summer temperature and market access are negative and significant in the q(0.1)–q(0.5) interquantile regression and small and only marginally significant in the q(0.5)–q(0.9) interquantile regression. The component of the marginal effect related to the interaction terms varies little across the temperature deciles.

The variation in the marginal effects by temperature implies that the change in the shape of the distribution of land values differs in the cold and warm regions of Brazil. In the South, the effect on the left tail is small relative to the changes in the q(0.1)–q(0.5) and q(0.5)–q(0.9) interquantiles and the distribution may skew to the right. The overall change in the spread of the distribution is thus small. In the North and the agricultural frontier, the Midwest and MATOPIBA regions, the tail effect is large and the positive effect in the q(0.5)–q(0.9) interquantile is larger than the negative effect in the q(0.1)–q(0.5) interquantile (Table V). The overall change in the spread of the distribution is significant, about 5%, and the left and right tails of the distribution elongate. The resulting inequality in land values is much larger in the agricultural frontier that in the South region of Brazil.

5. Robustness Analysis

I use the census data to compare the quantile Ricardian model with three specifications of the OLS Ricardian: the OLS with interactions between climate and local market characteristics, the standard OLS, and the OLS with state fixed effects. Figure 5 graphs the marginal effects of warming for all specifications at the country level. Appendix D shows similar graphs for the six regions of Brazil.

The key finding is the consistency of the marginal effects estimated with the OLS model with interactions as well as by using the quantile regressions. Figure 5 shows the marginal effects at each quantile of farm productivity for Brazil and for the first and 10th deciles of average temperature. Most of the estimated marginal effects by quantiles fall within the confidence interval of the OLS model with interactions, -10% to -27%. The exceptions are the marginal effects in the extreme quantiles of the coldest region of Brazil, about -6%, and in the warmest locations, -31%. Although there is significant heterogeneity in the marginal effect of warming across the different climates and observed market characteristics, the effects are stable across the variation in unobserved productivity. This result is reassuring considering the quantile regression is robust to outliers and relaxes the homoskedasticity assumption of the OLS regressions.

The marginal damage of warming estimated by using the standard OLS and OLS with fixed effects is smaller, -11% and -3%, respectively. For the standard OLS, the inclusion of the interaction terms corrects the positive bias of the omitted interaction between market access and climate. In the sample, market access is negatively correlated with both land values and average temperature. The state fixed effects absorb the unobserved variation across states such as local agricultural policies as well as some of the cross-sectional variation in climate (see the binscatter plots in Appendix A4 for an illustration of the state and region fixed effects). Table VI shows the results for the Ricardian models for alternative samples and specifications. When I add the state fixed effects into the model, the coefficients of the summer temperature variables become not statistically significant and those for the winter temperature half (see columns (10) to (12) in Table VI). The OLS FE estimates rely mostly on the winter temperature variation. The winter temperature captures the climate in the dry season, while the summer temperature captures that in the wet season. Hence, a warming effect should also be expected in the wet season, during which the planting and harvesting of major crops in Brazil such as soybeans occur. I thus interpret the OLS FE results as an upper bound for the damage in Brazil.

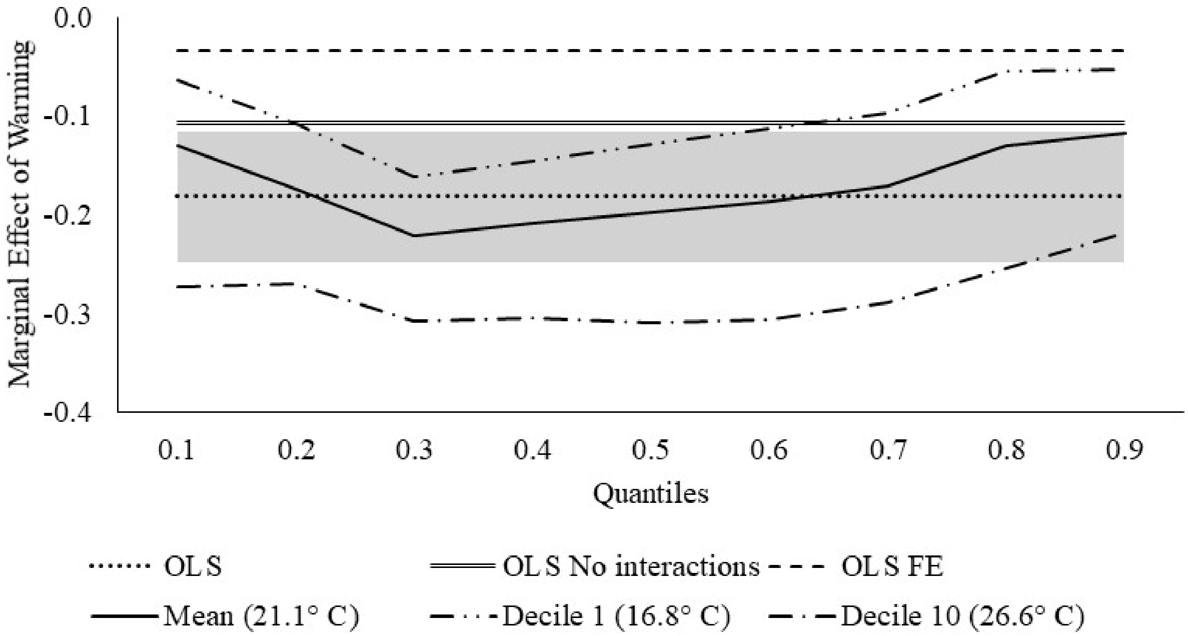

Figure 5. Marginal Effects by Quantiles and Temperature Deciles

A potential concern with the cross-sectional Ricardian models is their robustness across samples. In particular, I find severe damage for the extreme quantiles, which could be a result specific to the set of commercial farms in Brazil adopted in this study. I thus test the models with a larger set of 1.38 million farms that have net revenue in 2006 equal to or greater than twice the minimum wage. The sets of 468 thousand and 1.38 million farms produce 86% and 96% of the agricultural output in Brazil, respectively. I find consistent results for the OLS and quantile models and the same pattern for the extreme quantile models. Columns (2), (5), and (11) of Table VI show the quantile, OLS, and OLS FE models estimated for the larger sets of farmers. The quadratic functions of temperature and most of the interaction terms are not statistically different across samples. The exception is the interaction between the summer temperature and income per capita, which is statistically significant and almost twice as large in the largest sample. I also test the models with a smaller sample of 229 thousand farms larger than 50 hectares. The OLS results are presented in column (6) of Table VI. I find that the marginal effect of warming is smaller in colder locations, -10%, but similar at the highest decile of average temperature, -31%.

The estimated quadratic function for the winter temperature is robust across all specifications and samples. Even in the OLS FE model, the effect of winter temperatures is significant at the 1% level. I investigate the potential effect of spatial correlation on the statistical significance of the estimated coefficients by varying the cluster variables. In my preferred model, I cluster standard errors at the municipality level, which is the equivalent of the county level in the United States. There are on average about 90 commercial farms in each municipality. Column (8) of Table VI shows the results for standard errors clustered at the microregion level. There are 558 microregions in Brazil and on average 838 farms in each microregion. Column (7) presents the results with standard errors clustered at the census block level. There are on average 40 farms per census block. The interaction terms only become statistically insignificant for the clusters at the microregion level. The quadratic functions of temperature are statistically significant for the alternative clustering variables and all the interaction terms are significant when using clusters at the census block level. Appendix E reports the complete results for all regressions in Table VI.

Comparison of the Results with Previous Analyses of Climate Change Impacts in Brazil

The average estimated marginal damage of warming in Brazilian agriculture by using the OLS and median quantile models with census data is twice as large as previous estimates. Previous economic estimates of the impact of climate change in Brazilian agriculture fall within the range of my estimates, namely -3% for OLS FE and -20% for OLS with interactions. Sanghi and

Mendelsohn (2008) estimate Ricardian functions for Brazil by using aggregated census data for 1970, 1975, 1980, and 1985 and find climate change impacts in net revenues of -6.4%, -14.2%, and -28.7% for temperature increases of 1℃, 2℃, and 3.5℃, respectively. Timmins (2006) also uses aggregated data from the 1985 census to estimate a Ricardian function, controlling for land-use choice, simulating an average change in land values in Brazil of approximately -9% for 2℃ of warming. Massetti, Guiducci, Fortes, and Mendelsohn (2015) use census data aggregated at the microregion level for 1975, 1985, 1995, and 2006 to estimate the marginal effects of temperature on land value, finding a range from -7% to -20% in Brazil[5].

In addition to modeling heterogeneity by using quantile regressions, there are several methodological differences between my analysis and those in previous studies. First, I use for the first time micro census data to estimate the specifications with interactions between climate and covariates and state fixed effects. The inclusion of these interaction effects explains most of the difference between my estimates and those presented in previous analyses. Second, I can also separate commercial farms from subsistence farms by using the census dataset. To the extent that previous studies capture damage to the subsistence agricultural sector in Brazil, their results are

[5] The studies by both Massetti and coauthors and Sanghi and Mendelsohn find that the estimates for climate change in Brazil vary across census years. This variation in estimates is likely the result from the economic instability and hyperinflation that characterized the mid-1980s to mid-1990s. During this period, land was used as a hedging mechanism against inflation, which meant that the relationship between land values and land productivity was weaker and varied spatially. The 2006 census in Brazil was the first to be carried out after the implementation of economic stabilization policies.

not comparable to my estimates. However, I estimate higher damage by using two samples that represent up to 96% of agricultural production in Brazil. A dataset with more subsistence farmers should be more vulnerable to climate change. The low estimates for the OLS Ricardian model in Brazil with aggregated data are more likely to reflect the positive bias of omitting the interaction between climate and market characteristics such as access to market and average income level. This bias could be large in Brazil because of the clear north/south differentiation both in climate and in development characteristics.

My estimates for the spatial distribution of climate change impacts are consistent with the results of Sanghi and Mendelson (2008). However, except for when using the OLS FE model, I find negative marginal effects of warming across Brazil, even in the colder southern part of the country where damage ranges from -1% to -16% (95% confidence interval for OLS model with interactions). In addition, previous studies estimate small negative damage in the most developed Southeast region. By contrast, I find significant damage in the Southeast, between -12% and -27% (95% confidence interval for OLS model with interactions). The damage in the Southeast can change the overall climate change impact at the country level, as the agricultural sector in that region has higher economic values in terms of land values and agricultural production. Finally, my estimates of the damage in the extreme quantiles are consistent with a conversion of the more vulnerable marginal land into natural vegetation, similar to the prediction by Timmins (2006) of an expansion of the forested area as warming increases.

6. Conclusion

I investigate the distributional impact of climate change in Brazilian agriculture by using confidential farm-level data from the IBGE agricultural census for the first time. The distributional effect of warming varies with climate and economic development. A 1°C increase in warming reduces land values by 5% for the most productive farmers in the South and by 34% for the least productive farmers in the North. Marginal warming increases the q(0.1)–q(0.9) quantile spread by 1% for farmers in the coldest part of the country (i.e., an average annual temperature of 16.8°C) and by 5% in the warmest regions of Brazil (average annual temperature 26.6°C). The least productive commercial farmers in the northern regions of the country represent the frontier of vulnerability to climate change in Brazil. The average marginal effect of warming in the lowest quantile of farm productivity is -80%. As a result, marginal climate change almost doubles the productivity inequality between farmers in the extremes of the distribution of land values.

I find empirical evidence of the robustness of Ricardian quantile models applied to commercial farming in Brazil once I account for the interaction between temperature and local market characteristics. However, the Ricardian quantile analysis of climate change impacts does not account for the general equilibrium price effects resulting from changes in agricultural productivity, the positive effect of CO_2 fertilization, or the design of new climate adaptation strategies. In Brazil, continuing research on climate adaptation is particularly important because the agricultural frontier is vulnerable to climate change. In the past four decades, the Brazilian agricultural sector has expanded through the adaptation of tropical crops such as soy to enable production in the vast and warmer savanna land. New technologies and management practices may thus reduce the projected climate change impacts in the Brazilian savanna.

The quantile Ricardian analysis of climate change in Brazil could be extended and applied to identify the most vulnerable farmers in other developing countries. Modeling the response functions of climate change by using quantile regressions is a first step toward uncovering the diverse array of damage levels. That said, the frontier of climate vulnerability is likely to change over time and more research is therefore needed to investigate how it will evolve and how to increase the resilience of the most vulnerable farms. Finally, many countries carry out national agricultural censuses regularly following the international standards promoted by the Food and Agriculture Organization World Programme for the Census of Agriculture. The application of quantile Ricardian models of climate change impacts by using standardized census data would allow for the comparison of results across developing countries and the identification of the most vulnerable segments of the agricultural sector in each region.

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Table I. Summary Statistics

Panel A: Summary of Agricultural Census Dataset	
Number of commercial farms	489,836
Total area in million hectares	156.6
Total land value in billion 2006 Reals	652.6

Panel B: Summary Statistics for Main Variables

Variables	Mean	Standard Deviation	p10	p50	p90
Land value (R$ 2006)	7,542	80,728	421	4,167	14,414
Farm size (hectares)	319.7	1,719.0	6.0	178.0	600.0
Temperature summer (°C)	23.6	1.8	21.2	23.5	25.9
Temperature winter (°C)	18.2	4.0	13.2	17.7	24.6
Precipitation summer (mm)	550.8	195.2	305.0	518.6	813.1
Precipitation winter (mm)	217.8	161.3	33.6	191.3	436.4
Latitude (°)	-19.7	7.9	-28.7	-21.2	-6.9
Share of clay in top soil	0.35	0.14	0.17	0.34	0.57
Share of sand in top soil	0.44	0.19	0.18	0.46	0.68
Organic matter index	3.3	1.6	1.8	2.9	5.4
Nitrogen index	0.2	0.1	0.1	0.2	0.3
Elevation - mean (meters)	485.1	263.5	141.5	473.6	868.6
Elevation - std dev	112.4	56.8	46.0	105.1	189.4
Distance to capital city (km)	236.8	121.5	82.9	226.2	397.1
Distance to port (km)	134.1	76.1	38.0	129.0	236.2
Pop density (people per sq km)	48.9	108.3	6.0	32.6	81.5
Income per capita (1,000 2006 R$)	10.5	5.6	3.5	10.1	17.5

Notes: Columns p10, p50, and p90 show the 10^{th}, 50^{th}, and 90^{th} percentiles for each variable.

Table II. Summary Statistics by the Quantiles of Unobserved Productivity.

Variables / means and standard deviations	By quantiles of the Ricardian model residual $\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$
Dependent variable:			
Land value (2006 Reals)	358	4,604	9,507
	(469)	(2,939)	(6,101)
Independent variables:			
Temperature summer (Celsius)	23.8	23.7	24.1
	(2.1)	(2.1)	(2.1)
Temperature winter (Celsius)	18.8	18.1	19.4
	(4.5)	(4.4)	(4.2)
Distance to city or port (Km)	432	427	391
	(315)	(275)	(287)
Variables not in the Ricardian model:			
Yield cereals (ton/hectare)	3.7	3.7	3.8
Share of grazing area	51%	52%	46%
Share of crop area	19%	20%	33%
Share of forest area	31%	28%	21%
Share of crop area with industrial integration	16%	18%	22%
Percentage of farms by region:			
North	10%	6%	8%
Northeast	16%	14%	18%
Southeast	24%	21%	39%
South	36%	46%	26%
Midwest	14%	13%	9%
Total	100%	100%	100%
Number of farms	47,291	47,290	47,290

Notes: Standard deviations in parentheses. Quantiles are determined over the residual component of a linear Ricardian regression with control variables, including the climate variables, soil characteristics, and proxies for market access.

Table III. Ricardian Quantile Regression Estimates

	Quantile Regression Estimates					OLS
	0.01	0.1	0.5	0.9	0.99	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Temp summer	-3.078***	-1.560***	-0.905***	-0.754***	-1.042***	-1.209***
	(0.860)	(0.383)	(0.251)	(0.272)	(0.354)	(0.259)
Temp summer squared	0.0453***	0.0317***	0.0165***	0.0136***	0.0179***	0.0232***
	(0.0170)	(0.00745)	(0.00469)	(0.00496)	(0.00669)	(0.00493)
Temp winter	2.451***	0.867***	0.635***	0.530***	0.561***	0.778***
	(0.227)	(0.145)	(0.0779)	(0.0911)	(0.126)	(0.0833)
Temp winter squared	-0.0559***	-0.0230***	-0.0156***	-0.0126***	-0.0121***	-0.0199***
	(0.00527)	(0.00311)	(0.00162)	(0.00197)	(0.00263)	(0.00183)
Temp summer x Distance to city	0.226	-0.237	-0.216**	-0.176*	0.0350	-0.159
	(0.408)	(0.151)	(0.0843)	(0.0997)	(0.141)	(0.0983)
Temp summer x Distance to port	0.586	0.0429	-0.402***	-0.355**	-0.0453	-0.191
	(0.497)	(0.243)	(0.131)	(0.153)	(0.201)	(0.141)
Temp summer x Income per capita	-6.793	-6.418*	-3.365	-2.171	-4.972	-5.567**
	(10.28)	(3.383)	(2.976)	(4.020)	(5.234)	(2.636)
Temp winter x Distance to city	-0.592***	-0.205***	-0.0897**	-0.0257	-0.0417	-0.113**
	(0.177)	(0.0754)	(0.0399)	(0.0375)	(0.0577)	(0.0443)
Temp winter x Distance to port	0.339*	0.240**	0.158***	0.130**	-0.0909	0.148**
	(0.194)	(0.122)	(0.0601)	(0.0565)	(0.0850)	(0.0603)
Temp winter x Income per capita	-8.217*	0.948	0.0192	3.352*	3.193	1.428
	(4.945)	(1.527)	(1.529)	(1.975)	(2.575)	(1.324)
Observations	468,596	468,596	468,596	468,596	468,596	468,596
R2						0.256
Marginal effects of temperature:						
Brazil	-0.80	-0.15	-0.20	-0.12	-0.16	-0.18
North	-1.40	-0.34	-0.33	-0.24	-0.25	-0.35
Northeast	-1.04	-0.20	-0.25	-0.18	-0.18	-0.25
Southeast	-0.82	-0.17	-0.21	-0.12	-0.17	-0.20
South	-0.47	-0.05	-0.12	-0.05	-0.10	-0.09
Midwest	-1.11	-0.20	-0.26	-0.17	-0.21	-0.26
Matopiba	-1.15	-0.24	-0.27	-0.20	-0.20	-0.28

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Only the coefficients for the temperature variables are presented. All the regressions include the full set of controls and standard errors are clustered at the municipality level. Standard errors for the quantile regressions are bootstrapped with 500 repetitions. Marginal effects are computed at the mean values of all the variables in each region.

Table IV. Interquantile Regression Estimates

	Interquantiles					
	0.1 - 0.9	0.01 - 0.99	0.01 - 0.1	0.1 - 0.5	0.5 - 0.9	0.9 - 0.99
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Temp summer	0.807***	2.036***	1.518***	0.655***	0.152**	-0.289*
	(0.141)	(0.557)	(0.522)	(0.117)	(0.0642)	(0.160)
Temp summer squared	-0.0181***	-0.0274**	-0.0136	-0.0153***	-0.00283**	0.00431
	(0.00276)	(0.0110)	(0.0102)	(0.00230)	(0.00125)	(0.00315)
Temp winter	-0.337***	-1.889***	-1.584***	-0.232***	-0.105***	0.0313
	(0.0423)	(0.156)	(0.139)	(0.0394)	(0.0174)	(0.0533)
Temp winter squared	0.0104***	0.0438***	0.0329***	0.00734***	0.00304***	0.000466
	(0.000891)	(0.00354)	(0.00319)	(0.000852)	(0.000384)	(0.00116)
Temp summer x Distance to city	0.0617	-0.191	-0.463***	0.0211	0.0406**	0.211***
	(0.0499)	(0.183)	(0.165)	(0.0436)	(0.0181)	(0.0625)
Temp summer x Distance to port	-0.398***	-0.632**	-0.543**	-0.445***	0.0466*	0.310***
	(0.0741)	(0.269)	(0.250)	(0.0648)	(0.0259)	(0.0873)
Temp summer x Income per capita	4.247***	1.821	0.375	3.053***	1.194*	-2.801
	(1.041)	(6.931)	(6.121)	(0.848)	(0.645)	(2.039)
Temp winter x Distance to city	0.179***	0.551***	0.387***	0.115***	0.0640***	-0.0159
	(0.0237)	(0.0768)	(0.0668)	(0.0213)	(0.00825)	(0.0286)
Temp winter x Distance to port	-0.110***	-0.430***	-0.0987	-0.0820**	-0.0284***	-0.220***
	(0.0353)	(0.109)	(0.101)	(0.0340)	(0.0110)	(0.0403)
Temp winter x Income per capita	2.403***	11.41***	9.165***	-0.929**	3.332***	-0.158
	(0.534)	(3.441)	(3.064)	(0.417)	(0.321)	(0.967)
Observations	468,596	468,596	468,596	468,596	468,596	468,596
Marginal effects of temperature:						
Brazil	0.03	0.64	0.65	-0.06	0.09	-0.03
North	0.10	1.15	1.06	0.00	0.10	0.00
Northeast	0.02	0.85	0.84	-0.06	0.08	0.01
Southeast	0.05	0.65	0.64	-0.04	0.10	-0.04
South	0.01	0.37	0.41	-0.07	0.08	-0.04
Midwest	0.04	0.90	0.91	-0.06	0.10	-0.03
Matopiba	0.04	0.96	0.91	-0.05	0.08	0.01

Notes: *** p<0.01, ** p<0.05, * p<0.1. Only the coefficients for the temperature variables are presented. All the regressions include the full set of controls and standard errors are clustered at the municipality level. Standard errors for the quantile regressions are bootstrapped with 500 repetitions. Marginal effects are computed at the mean values of all the variables in each region.

Table V. Marginal Effect of Warming on the Distribution of the Log Land Value

Temperature Decile	Interquantiles of Log Land Value					
	0.1 - 0.9	0.01 - 0.99	0.01 - 0.1	0.1 - 0.5	0.5 - 0.9	0.9 - 0.99
	(1)	(2)	(3)	(4)	(5)	(6)
Decile 1 (16.8 °C)	0.01	0.29	0.35	-0.07	0.08	-0.06
Decile 2 (18.0 °C)	0.00	0.35	0.40	-0.07	0.08	-0.05
Decile 3 (18.9 °C)	0.02	0.42	0.46	-0.06	0.08	-0.04
Decile 4 (19.6 °C)	0.02	0.48	0.50	-0.06	0.08	-0.04
Decile 5 (20.6 °C)	0.06	0.63	0.62	-0.04	0.10	-0.05
Decile 6 (21.8 °C)	0.04	0.74	0.73	-0.06	0.09	-0.02
Decile 7 (22.9 °C)	0.04	0.83	0.82	-0.06	0.09	-0.02
Decile 8 (23.9 °C)	0.03	0.89	0.88	-0.06	0.09	-0.01
Decile 9 (25.3 °C)	0.06	1.03	0.98	-0.03	0.08	0.00
Decile 10 (26.6 °C)	0.05	1.05	0.98	-0.05	0.10	0.02

Table VI. Robustness Analysis of the Ricardian Model with Census Data

	Ricardian Quantile (τ = 0.5)			OLS					OLS with State Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Temperature variables:											
Temp summer	-0.905***	-0.902***	-0.751***	-1.209***	-1.340***	-0.710**	-1.209***	-1.209***	-0.401	-0.22	-0.448**
Temp summer squared	0.0165***	0.0183***	0.0116***	0.0232***	0.0273***	0.0130**	0.0232***	0.0232***	0.00905*	0.00	0.0108**
Temp winter	0.635***	0.639***	0.660***	0.778***	0.852***	0.757***	0.778***	0.778***	0.375***	0.358***	0.440***
Temp winter squared	-0.0156***	-0.0166***	-0.0161***	-0.0199***	-0.0224***	-0.0198***	-0.0199***	-0.0199***	-0.0104***	-0.0102***	-0.0120***
Temp summer x Distance to port	-0.402***	-0.339***		-0.191	-0.0748	0.0793	-0.191**	-0.191	0.00873		0.109
Temp summer x Income per capita	-3.365	-6.096**		-5.567**	-8.584***	-0.548	-5.567***	-5.567	-6.549***		-7.943***
Temp winter x Distance to port	0.158***	0.181***		0.148**	0.171***	0.0521	0.148***	0.148	0.0797		0.0197
Temp winter x Income per capita	0.0192	1.834		1.428	2.396*	0.773	1.428**	1.428	3.557***		3.997***
Marginal effect of warming:											
Brazil	-0.20	-0.12	-0.13	-0.18	-0.15	-0.10	-0.18	-0.18	-0.03	0.00	0.00
Decile 1 (16.8° C)	-0.13	-0.05	-0.02	-0.10	-0.06	0.06	-0.10	-0.10	0.03	0.08	0.07
Decile 10 (26.6° C)	-0.31	-0.24	-0.30	-0.31	-0.28	-0.31	-0.31	-0.31	-0.12	-0.13	-0.10
Number of Farms	468,596	1,388,208	468,596	468,596	1,388,208	229,803	468,596	468,596	468,596	472,902	1,388,208
R2				0.256	0.286	0.207	0.256	0.256	0.273	0.264	0.309

Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of land value. Only the coefficients for the temperature variables are presented. All the regressions include a full set of controls. Standard errors are clustered at the municipality level, except for models (8) and (12), clustered at the microregion level, and model (7), clustered at the census block level. Standard errors for the quantile regressions are bootstrapped with 500 repetitions for the commercial farm sample and with 200 repetitions for the largest sample (column (2)).

Appendix A – Description of Variables, Maps, and Additional Binscatter Plots

A1. Description of Variables

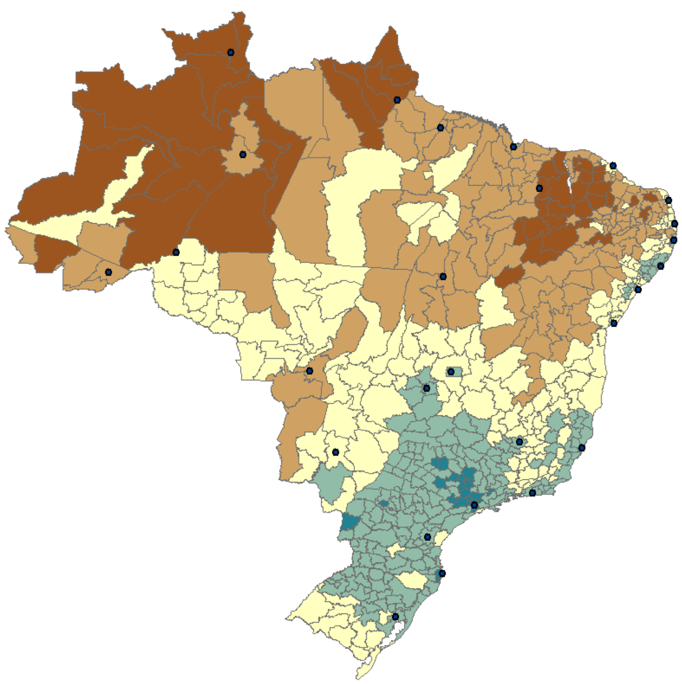
Variable	**Description / Unit**	**Data Source / Level**
Land value	Total land value in 2006 Reals	Agr. Census / farm
Farm size	Total area of farm in hectares	Agr. Census / farm
Water source	1 if farm has spring	Agr. Census / farm
River	1 if farm has river or stream	Agr. Census / farm
Lake	1 if farm has a lake	Agr. Census / farm
Pop. density	Population density – people / sq. km	Pop Census / municipality
Inc. per capita	Income per capita – R$1,000 / people	Pop Census / municipality
Elevation avg.	Average elevation for municipality	Embrapa / municipality
Elevation sdt.	Elevation standard deviation	Embrapa / municipality
Distance to port	Distance to port in Km	GIS / census block
Distance to city	Distance to capital in Km	GIS / census block
Climate:		
Temp summer	Average summer temperature in degree Celsius (Nov, Dec, Jan)	Willmott and Matsuura / census block
Temp winter	Average winter temperature in degree Celsius (Jun, Jul, Aug)	Willmott and Matsuura / census block
Prec summer	Average summer precipitation in millimeters (Nov, Dec, Jan)	Willmott and Matsuura / census block
Prec winter	Average winter precipitation in millimeters (Jun, Jul, Aug)	Willmott and Matsuura / census block

Latitude	Latitude degrees	GIS / census block
Soil:		
Clay	Share of clay in soil at municipality	Embrapa / municipality
sand	Share of sand in soil at municipality	Embrapa / municipality
silt	Share of silt in soil at municipality	Embrapa / municipality
ph_h2o	Soil pH index	Embrapa / municipality
Organic matter	Organic matter content index	Embrapa / municipality
nitrogen	Nitrogen content index	Embrapa / municipality
total2o3	Alumina content index	Embrapa / municipality
totfe2o3	Iron oxide content index	Embrapa / municipality
totsio2	Silicon oxide content index	Embrapa / municipality

A2. Geographical regions in Brazil and cross-sectional variation in land values in 2006

Geographical regions of Brazil:

Cross-sectional variation in land values in 2006:



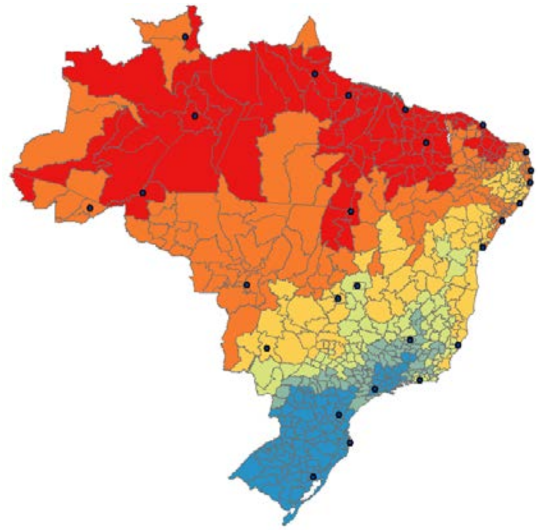
Scale unit is standard deviation from average land value: Brown <-1.5; -0.5; 0.5; 1.5; >1.5 Blue.

Notes: land values at microregion level based on aggregated census data.

A3. Cross-sectional variation in average temperature and precipitation in Brazil

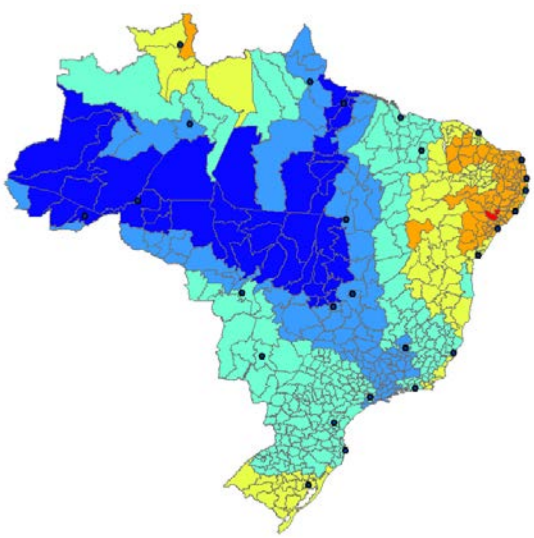
Average Temperature Summer

Average Temperature Winter



Temperature scale in degrees Celsius: Blue < 8; 20; 22; 24; 26; >26 Red

Average Precipitation Summer

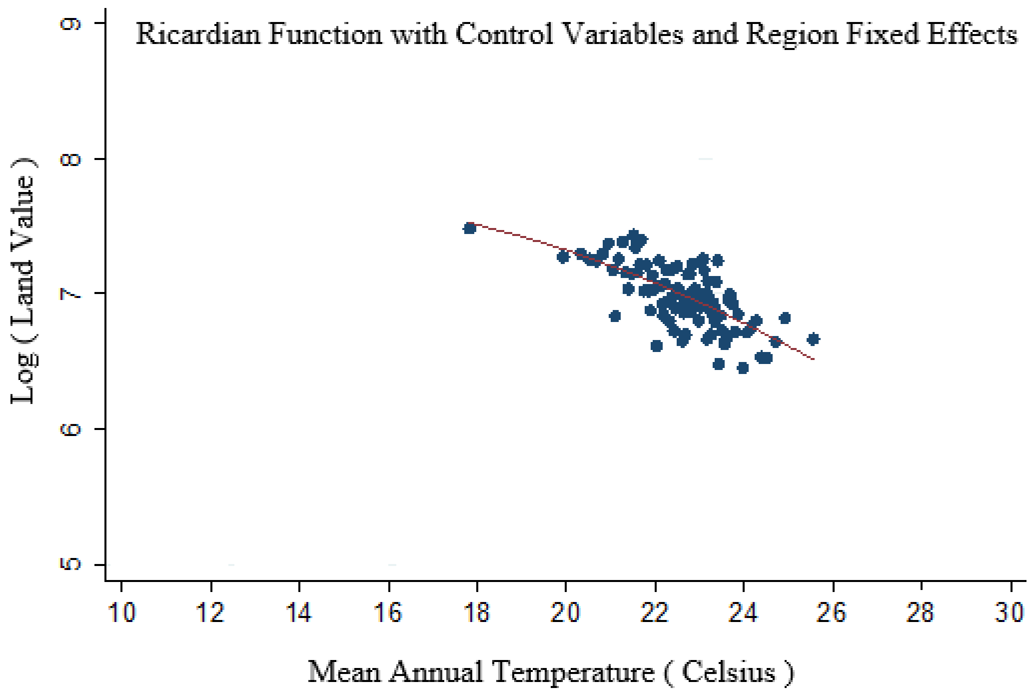


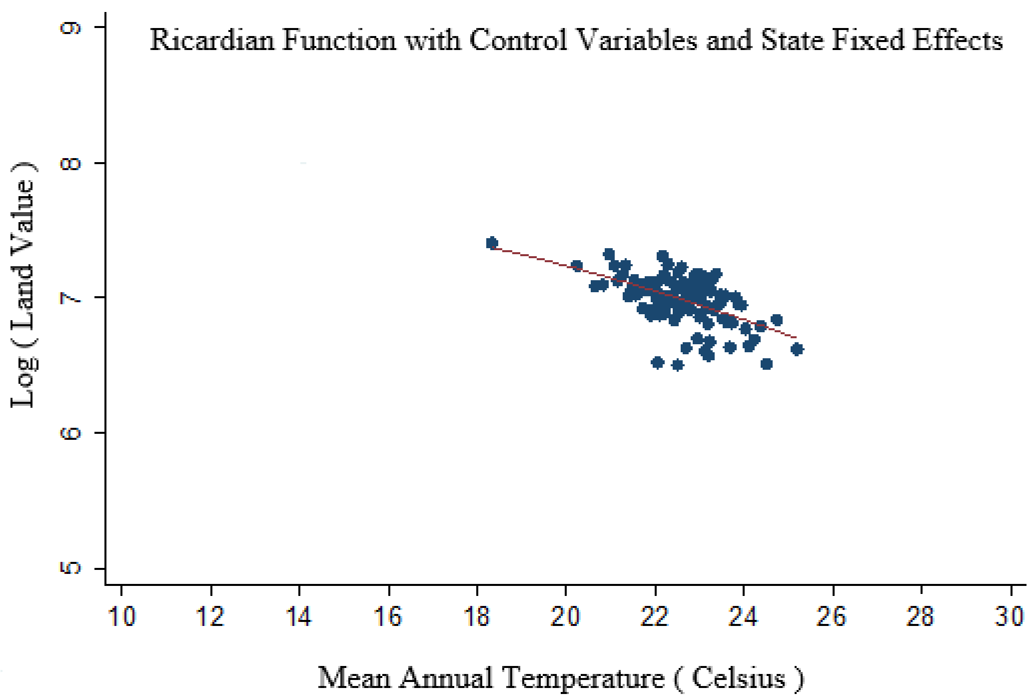
Average Precipitation Winter

Precipitation scale in millimeters: Red <40; 80; 140; 200; 240; >240 Blue

Notes: summer is modeled as January, February, and March. Winter is June, July, and August. Red represents warm or dry and blue represents cold or wet in the scales above. Climate data at microregion level from Embrapa (Fortes, 2012), average for 1960-1990 period.

A4. Non-parametric Ricardian Functions with Fixed Effects





Notes: Binscatter plots with census data. Plots with state and region fixed effects are similar.

Appendix B – Ricardian Quantile Regression Coefficients - Complete Version of Table III

	Quantile Regression Estimates					OLS
	0.01	0.1	0.5	0.9	0.99	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Temp summer	-3.078***	-1.560***	-0.905***	-0.754***	-1.042***	-1.209***
Temp summer squared	0.0453***	0.0317***	0.0165***	0.0136***	0.0179***	0.0232***
Temp winter	2.451***	0.867***	0.635***	0.530***	0.561***	0.778***
Temp winter squared	-0.0559***	-0.0230***	-0.0156***	-0.0126***	-0.0121***	-0.0199***
Prec summer	-3.366***	-0.749***	-0.740***	-0.483***	-0.530***	-0.833***
Prec summer squared	0.00184	0.000961	-0.00155	0.00298	-0.000107	0.00408*
Prec winter	0.129	0.149	-0.0622	-0.0672	-0.136	-0.0478
Prec winter squared	0.0731***	0.00211	-0.0167***	-0.000815	0.00153	0.00506
Temp x Prec summer	0.00143***	0.000334***	0.000311***	0.000160***	0.000209***	0.000322***
Temp x Prec winter	-0.000288***	-6.06e-05	0.000101***	6.03e-05**	9.40e-05**	2.92e-05
Latitude	-0.0680***	-0.0725***	-0.0879***	-0.0636***	-0.0393***	-0.0769***
Total2o3	0.0158	0.0164	0.00755	-0.00533	-0.0128	0.00347
Totfe2o3	0.0152	0.0129***	0.0195***	0.0128***	0.0100**	0.0157***
Totsio2	-0.0156	-0.0137	-0.0114**	0.00245	0.0170***	-0.00755
Clay	2.254**	3.488***	3.336***	3.321***	2.438***	3.476***
Sand	2.630***	2.545***	2.323***	2.231***	2.156***	2.441***
Log ph_h2o	-2.026***	0.855***	0.102	-0.0682	0.276	-0.00932
Organic matter	0.0464	0.0943***	0.0380***	0.0515***	0.116***	0.0578***
Nitrogen	0.843	-1.198**	-0.597***	-0.727***	-0.938**	-0.650***
Distance to city	6.361	10.20***	7.558***	5.174**	0.539	6.533***
Distance to port	-21.51**	-6.586	5.768**	5.077	1.903	0.719
Elevation - mean	0.0382*	0.0387***	0.0379***	0.0325***	0.0211*	0.0359***
Elevation - std dev	-0.00340***	-0.00300***	-0.00349***	-0.00125***	0.000128	-0.00285***
River	-0.0923**	0.0658***	0.0102	0.00912	-0.0114	0.0185*
Lake	-0.0450	-0.0332	0.0313***	0.0756***	0.195***	0.0187*
Water source	0.00930	0.0314	0.00114	-0.000285	0.0165	0.0160
Pop density	-27.78**	0.136	-1.147	-2.303	1.807	-2.929
Income per capita	315.8*	150.7**	95.33*	12.36	87.86	122.8***
Log farm size	0.552	-0.425***	-0.140*	-0.0823	-0.0314	-0.145*
Temp summer x Distance to city	0.226	-0.237	-0.216**	-0.176*	0.0350	-0.159
Temp summer x Distance to port	0.586	0.0429	-0.402***	-0.355**	-0.0453	-0.191
Temp summer x Pop density	1.483**	0.127	0.177	0.435	0.353	0.287
Temp summer x Income per capita	-6.793	-6.418*	-3.365	-2.171	-4.972	-5.567**
Temp summer x Log farm size	-0.0125	0.00159	-0.00331	-0.00187	-0.00368	-0.00571
Temp winter x Distance to city	-0.592***	-0.205***	-0.0897**	-0.0257	-0.0417	-0.113**
Temp winter x Distance to port	0.339*	0.240**	0.158***	0.130**	-0.0909	0.148**
Temp winter x Pop density	-0.434	-0.151	-0.125	-0.321	-0.417*	-0.181*
Temp winter x Income per capita	-8.217*	0.948	0.0192	3.352*	3.193	1.428
Temp winter x Log farm size	-0.0387***	0.00131	0.00303	-0.00225	-0.00560***	0.00254
	24.85**	13.52***	10.60***	11.38***	15.68***	13.36***
Observations	468,596	468,596	468,596	468,596	468,596	468,596
R2						0.256

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the municipality level.

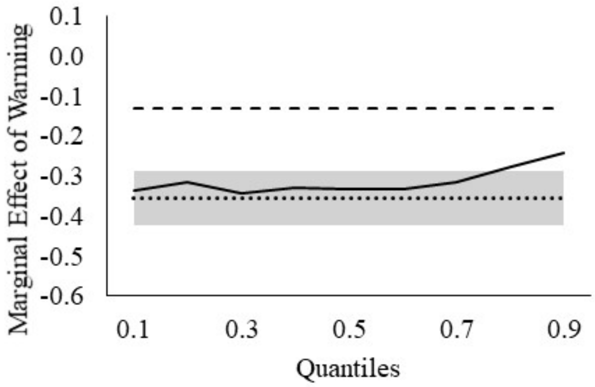
Appendix C – Interquantile Regression Coefficients - Complete Version of Table IV

	Interquantiles					
	0.1 - 0.9	0.01 - 0.99	0.01 - 0.1	0.1 - 0.5	0.5 - 0.9	0.9 - 0.99
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Temp summer	0.807***	2.036***	1.518***	0.655***	0.152**	-0.289*
Temp summer squared	-0.0181***	-0.0274**	-0.0136	-0.0153***	-0.00283**	0.00431
Temp winter	-0.337***	-1.889***	-1.584***	-0.232***	-0.105***	0.0313
Temp winter squared	0.0104***	0.0438***	0.0329***	0.00734***	0.00304***	0.000466
Prec summer	0.266***	2.836***	2.617***	0.00849	0.257***	-0.0473
Prec summer squared	0.00202	-0.00195	-0.000880	-0.00251**	0.00453***	-0.00309
Prec winter	-0.217***	-0.264*	0.0206	-0.212***	-0.00491	-0.0684
Prec winter squared	-0.00292	-0.0716***	-0.0710***	-0.0188***	0.0159***	0.00235
Temp x Prec summer	-0.000174***	-0.00122***	-0.00109***	-2.27e-05	-0.000151***	4.98e-05
Temp x Prec winter	0.000121***	0.000382***	0.000227***	0.000161***	-4.05e-05***	3.38e-05**
Latitude	0.00895***	0.0287**	-0.00455	-0.0153***	0.0243***	0.0243***
Total2o3	-0.0218***	-0.0286**	0.000667	-0.00890***	-0.0129***	-0.00752*
Totfe2o3	-0.000155	-0.00517	-0.00229	0.00660***	-0.00675***	-0.00273
Totsio2	0.0161***	0.0326***	0.00192	0.00223	0.0139***	0.0145***
Clay	-0.166	0.185	1.234**	-0.151	-0.0150	-0.883***
Sand	-0.314***	-0.474	-0.0848	-0.222**	-0.0927**	-0.0748
Log ph_h2o	-0.924***	2.303***	2.882***	-0.753***	-0.171***	0.345**
Organic matter	-0.0428***	0.0700***	0.0478**	-0.0562***	0.0135***	0.0650***
Nitrogen	0.470***	-1.781***	-2.041***	0.600***	-0.130***	-0.211
Distance to city	-5.031***	-5.822*	3.843	-2.646***	-2.385***	-4.635***
Distance to port	11.66***	23.41***	14.92***	12.35***	-0.691	-3.174**
Elevation - mean	-0.00628*	-0.0171	0.000566	-0.000821	-0.00546***	-0.0114**
Elevation - std dev	0.00175***	0.00352***	0.000396	-0.000496***	0.00225***	0.00138***
River	-0.0567***	0.0809**	0.158***	-0.0556***	-0.00104	-0.0205
Lake	0.109***	0.240***	0.0118	0.0645***	0.0443***	0.119***
Water source	-0.0317**	0.00722	0.0221	-0.0303**	-0.00142	0.0168
Pop density	-2.439	29.58***	27.91***	-1.283	-1.156	4.109
Income per capita	-138.3***	-227.9*	-165.1	-55.37***	-82.98***	75.50**
Log farm size	0.343***	-0.584**	-0.977***	0.285***	0.0581***	0.0509
Temp summer x Distance to city	0.0617	-0.191	-0.463***	0.0211	0.0406**	0.211***
Temp summer x Distance to port	-0.398***	-0.632**	-0.543**	-0.445***	0.0466*	0.310***
Temp summer x Pop density	0.308***	-1.129***	-1.356***	0.0506	0.258***	-0.0815
Temp summer x Income per capita	4.247***	1.821	0.375	3.053***	1.194*	-2.801
Temp summer x Log farm size	-0.00346	0.00879	0.0141	-0.00490**	0.00145	-0.00181
Temp winter x Distance to city	0.179***	0.551***	0.387***	0.115***	0.0640***	-0.0159
Temp winter x Distance to port	-0.110***	-0.430***	-0.0987	-0.0820**	-0.0284***	-0.220***
Temp winter x Pop density	-0.170***	0.0167	0.283***	0.0253	-0.196***	-0.0961
Temp winter x Income per capita	2.403***	11.41***	9.165***	-0.929**	3.332***	-0.158
Temp winter x Log farm size	-0.00356***	0.0331***	0.0400***	0.00172	-0.00528***	-0.00335***
	-2.139	-9.168	-11.32*	-2.926**	0.788	4.296**
Observations	468,596	468,596	468,596	468,596	468,596	468,596

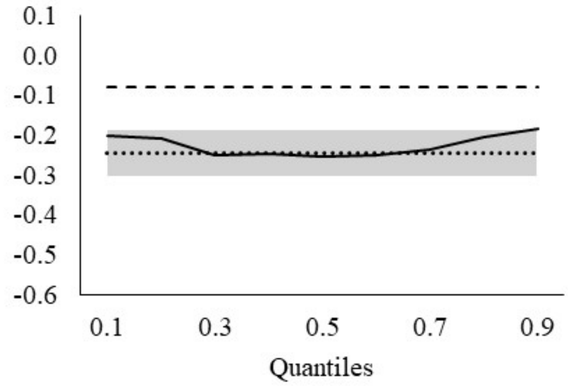
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the municipality level. Standard errors for the quantile regressions are bootstrapped with 500 repetitions.

Appendix D – Marginal Effects of Warming for Six Regions of Brazil

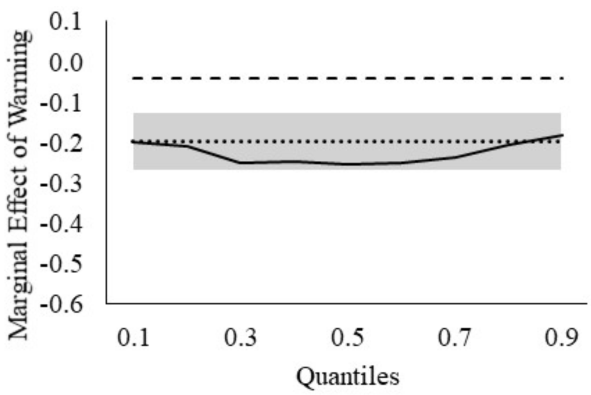
A. North



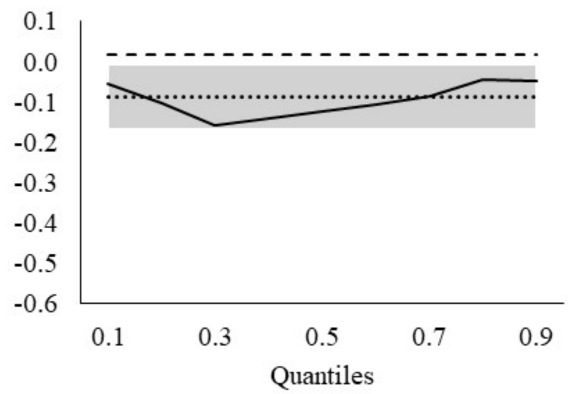
B. Northeast



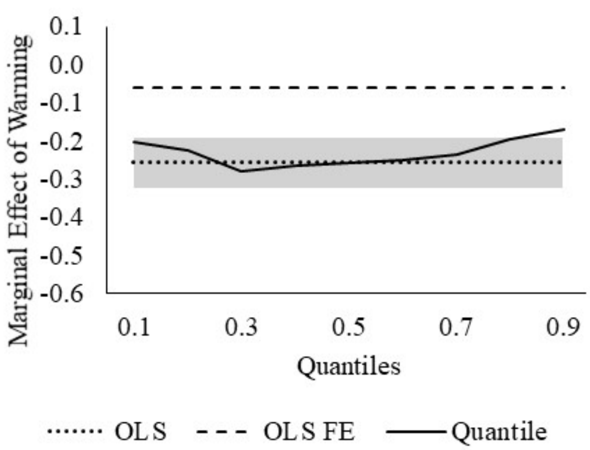
C. Southeast



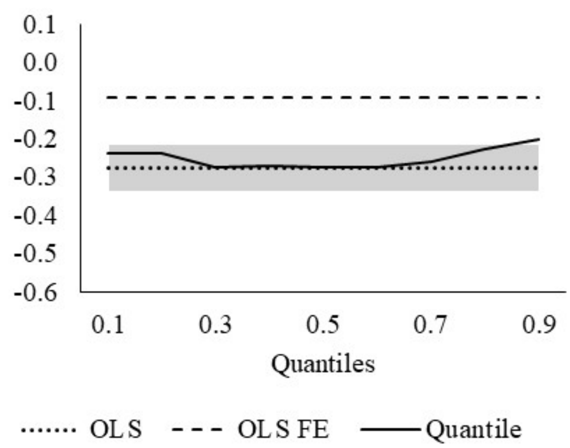
D. South



E. Midwest



F. MATOPIBA



Appendix E – Robustness Analysis of the Ricardian Model - Complete Version of Table VI

	Ricardian Quantile (τ = 0.5)			OLS	
	(1)	(2)	(3)	(4)	(5)
Temp summer	-0.905***	-0.902***	-0.751***	-1.209***	-1.340***
Temp summer squared	0.0165***	0.0183***	0.0116***	0.0232***	0.0273***
Temp winter	0.635***	0.639***	0.660***	0.778***	0.852***
Temp winter squared	-0.0156***	-0.0166***	-0.0161***	-0.0199***	-0.0224***
Prec summer	-0.740***	-0.484***	-0.418***	-0.833***	-0.712***
Prec summer sq.	-0.00155	-0.00315	-0.00549**	0.00408*	0.00123
Prec winter	-0.0622	0.104	0.0720	-0.0478	0.116*
Prec winter sq.	-0.0167***	-0.0216***	-0.0172***	0.00506	0.00276
Temp x Prec summer	0.000311***	0.000233***	0.000204***	0.000322***	0.000306***
Temp x Prec winter	0.000101***	4.40e-05*	5.26e-05**	2.92e-05	-3.83e-05
Latitude	-0.0879***	-0.0768***	-0.0794***	-0.0769***	-0.0674***
Total2o3	0.00755	0.00528	0.0123**	0.00347	0.000753
Totfe2o3	0.0195***	0.0212***	0.0199***	0.0157***	0.0184***
Totsio2	-0.0114**	-0.00993**	-0.0150***	-0.00755	-0.00716
Clay	3.336***	3.728***	3.287***	3.476***	4.106***
Sand	2.323***	2.734***	2.321***	2.441***	2.961***
Log ph_h2o	0.102	0.266*	0.287	-0.00932	0.0734
Organic matter	0.0380***	0.0442***	0.0324***	0.0578***	0.0583***
Nitrogen	-0.597***	-0.460**	-0.444**	-0.650***	-0.434**
Distance to city	7.558***	8.367***	0.527***	6.533***	8.297***
Distance to port	5.768**	4.103*	-0.645***	0.719	-2.229
Elevation - mean	0.0379***	0.0327***	0.0298***	0.0359***	0.0229***
Elevation - std dev	-0.00349***	-0.00347***	-0.00346***	-0.00285***	-0.00293***
River	0.0102	-0.00379	0.0112	0.0185*	0.00285
Lake	0.0313***	0.0286***	0.0296***	0.0187*	0.0154
Water source	0.00114	0.00299	0.00296	0.0160	0.0291***
Pop density	-1.147	-3.062	0.724***	-2.929	-3.792
Income per capita	95.33*	128.7**	17.07***	122.8***	176.3***
Log farm size	-0.140*	-0.355***	-0.164***	-0.145*	-0.274***
Temp summer x Distance to city	-0.216**	-0.335***		-0.159	-0.324***
Temp summer x Distance to port	-0.402***	-0.339***		-0.191	-0.0748
Temp summer x Pop density	0.177	0.267		0.287	0.305
Temp summer x Income per capita	-3.365	-6.096**		-5.567**	-8.584***
Temp summer x Log farm size	-0.00331	0.00907**		-0.00571	0.00337
Temp winter x Distance to city	-0.0897**	-0.00776		-0.113**	-0.0268
Temp winter x Distance to port	0.158***	0.181***		0.148**	0.171***
Temp winter x Pop density	-0.125	-0.138		-0.181*	-0.160*
Temp winter x Income per capita	0.0192	1.834		1.428	2.396*
Temp winter x Log farm size	0.00303	-0.00297*		0.00254	-0.00423**
Constant	10.60***	8.980***	8.952***	13.36***	12.98***
Number of Farms	468,596	1,388,208	468,596	468,596	1,388,208
R2				0.256	0.286

Appendix E – Robustness Analysis of the Ricardian Model - Complete Version of Table VI

	OLS			OLS with State Fixed Effects		
	(6)	(7)	(8)	(9)	(10)	(11)
Temp summer	-0.710**	-1.209***	-1.209***	-0.401	-0.22	-0.448**
Temp summer squared	0.0130**	0.0232***	0.0232***	0.00905*	0.00	0.0108**
Temp winter	0.757***	0.778***	0.778***	0.375***	0.358***	0.440***
Temp winter squared	-0.0198***	-0.0199***	-0.0199***	-0.0104***	-0.0102***	-0.0120***
Prec summer	-0.572***	-0.833***	-0.833***	-0.125	0.08	-0.0836
Prec summer sq.	0.00298	0.00408***	0.00408	-0.00249	0.00	0.000374
Prec winter	0.105	-0.0478	-0.0478	-0.0281	0.02	0.0561
Prec winter sq.	0.0130**	0.00506	0.00506	0.00616	0.00	0.00365
Temp x Prec summer	0.000210***	0.000322***	0.000322***	7.18e-05	0.00	4.35e-05
Temp x Prec winter	-4.92e-05	2.92e-05	2.92e-05	5.66e-07	0.00	-2.58e-05
Latitude	-0.0782***	-0.0769***	-0.0769***	-0.0416***	-0.0398***	-0.0460***
Total2o3	0.00694	0.00347	0.00347	0.00750	0.0160***	0.00523
Totfe2o3	0.00996***	0.0157***	0.0157***	0.0114***	0.0124***	0.0146***
Totsio2	-0.00246	-0.00755**	-0.00755	-0.00298	-0.00908*	0.00345
Clay	3.491***	3.476***	3.476***	1.833***	1.662***	2.272***
Sand	2.402***	2.441***	2.441***	1.247***	1.217***	1.799***
Log ph_h2o	0.0931	-0.00932	-0.00932	-0.136	0.07	-0.0138
Organic matter	0.0476***	0.0578***	0.0578***	0.0593***	0.0561***	0.0606***
Nitrogen	-0.716***	-0.650***	-0.650*	-0.716***	-0.676***	-0.600***
Distance to city	3.999**	6.533***	6.533**	5.663***	0.13	6.340***
Distance to port	-3.369	0.719	0.719	-2.522	-0.724***	-3.574
Elevation - mean	0.0360***	0.0359***	0.0359***	0.0217***	0.0175**	0.0150**
Elevation - std dev	-0.00311***	-0.00285***	-0.00285***	-0.00194***	-0.00192***	-0.00196***
River	0.0412***	0.0185**	0.0185	0.0126	0.01	-0.00230
Lake	-0.00941	0.0187**	0.0187	0.0215**	0.02	0.0274***
Water source	0.0648***	0.0160*	0.0160	0.00657	0.00	0.0126
Pop density	-4.368	-2.929	-2.929	0.537	0.000323***	1.236
Income per capita	16.31	122.8***	122.8*	111.7**	0.0229***	136.6***
Log farm size	0.0712	-0.145***	-0.145	-0.360***	-0.200***	-0.464***
Temp summer x Distance to city	-0.0336	-0.159**	-0.159	-0.186**		-0.282***
Temp summer x Distance to port	0.0793	-0.191**	-0.191	0.00873		0.109
Temp summer x Pop density	0.324	0.287**	0.287	0.0522		0.0117
Temp summer x Income per capita	-0.548	-5.567***	-5.567	-6.549***		-7.943***
Temp summer x Log farm size	-0.0248***	-0.00571**	-0.00571	0.00775*		0.0146***
Temp winter x Distance to city	-0.132**	-0.113***	-0.113	-0.0506		0.0181
Temp winter x Distance to port	0.0521	0.148***	0.148	0.0797		0.0197
Temp winter x Pop density	-0.149	-0.181***	-0.181	-0.0721		-0.0553
Temp winter x Income per capita	0.773	1.428**	1.428	3.557***		3.997***
Temp winter x Log farm size	0.0172***	0.00254*	0.00254	-0.00268		-0.00806***
Constant	7.138**	13.36***	13.36***	7.759***	5.488*	6.741***
Number of Farms	229,803	468,596	468,596	468,596	472,902	1,388,208
R2	0.207	0.256	0.256	0.273	0.264	0.309

Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of land value. Only the coefficients for the temperature variables are presented. All the regressions include a full set of controls. Standard errors are clustered at the municipality level, except for models (8) and (12), clustered at the microregion level, and model (7), clustered at the census block level. Standard errors for the quantile regressions are bootstrapped with 500 repetitions for the commercial farm sample and with 200 repetitions for the largest sample (column (2)).