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Estimating the effect of climate on agriculture with the productive value of agricultural land

Estimando el efecto del clima en la agricultura con el valor productivo de la tierra agrícola

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Abstract

Objective: the Ricardian model, in which market land values are modeled as a function of climate, has been estimated extensively in the context of developing countries where its core assumptions are likely to fail due to missing or incomplete markets. This article proposes a new measure of land valuation that better reflects agricultural productivity in such contexts: the Productive Value of Agricultural Land (PVAL).
Methodology: a three-step empirical strategy is applied to data from a survey of Mexican rural households. The first step is the estimation of an agricultural production function. In the second step, parameter estimates are used to calculate PVAL. In the third step, PVAL is used as the dependent variable in a Ricardian regression.
Results: suggests that PVAL increases with more precipitation and decreases with by extreme heat. When the Ricardian regression is estimated using market land values, the positive effect of precipitation is underestimated and the effect of extreme heat on land productivity is null.
Limitations: omitted variables bias could still influence the Ricardian estimates obtained using PVAL.
Originality: a novel version of the Ricardian model is estimated, one that does not rely on market values of land.
Conclusions: failing to account for the market setting of agricultural producers, particularly in developing countries, may lead to an underestimation of the effects of climate change in agricultural productivity.
Key Words: climate change, adaptation, agriculture, Ricardian model.
JEL Classification: Q15, Q24, Q54, Q56.

Resumen

Objetivo: el modelo Ricardiano, en el cual el valor de mercado de la tierra se modela como una función del clima, ha sido estimado extensivamente en el contexto de países en desarrollo en donde sus supuestos clave podrían no sostenerse debido a mercados ausentes o incompletos. Este artículo propone una nueva medida de valuación de la tierra que refleja mejor la productividad agrícola en tales contextos: el Valor Productivo de la Tierra Agrícola (VPTA).
Metodología: una estrategia empírica de tres pasos se aplica a datos de una encuesta a hogares rurales en México. En el primer paso se estima una función de producción agrícola. En el segundo paso, los parámetros estimados se utilizan para calcular el VPTA. En el tercer paso, el VPTA se utiliza como variable dependiente en una regresión Ricardiana.
Resultados: sugieren que el VPTA aumenta con la precipitación y disminuye con el calor extremo. Cuando la regresión Ricardiana se estima utilizando valores de mercado de la tierra, el efecto positivo de la precipitación se subestima y el efecto del calor extremo en la productividad agrícola es nulo.
Limitaciones: el sesgo por variables omitidas aún podría influenciar las estimaciones Ricardianas obtenidas con el VPTA.
Originalidad: se estima una nueva versión del modelo Ricardiano que no se basa en valores de mercado de la tierra.
Conclusiones: el no tomar en cuenta el contexto de mercado de los productores agrícolas, particularmente en países en desarrollo, podría derivar en una subestimación del efecto del cambio climático en la productividad agrícola.
Palabras clave: cambio climático, adaptación, agricultura, modelo Ricardiano.
Clasificación JEL: Q15, Q24, Q54, Q56.

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Introduction

Climate change may increase global temperatures by as much as 2.7°C by 2100 under an intermediate scenario of GHG emissions (IPCC, 2023). Such an increase might have important productivity consequences in agricultural systems around the world. The agriculture of developing countries is expected to be the most affected due to the already warm temperatures in which they produce and their low capacity to adapt (Mendelsohn and Massetti, 2017; Lybbert and Sumner, 2012). Yet, the empirical evidence available is likely to underestimate the negative effects of climate change in developing countries because current models overstate their potential for adaptation (Hertel and Lobell, 2014).

One such model is the Ricardian approach (Mendelsohn et al., 1994), which exploits cross-sectional variation of land values and climate to approximate the welfare consequences of climate change. Under certain assumptions, the Ricardian model is said to account for the adaptation of farmers in the long run. When the market for land is perfectly competitive and farmers maximize profits unconstrainedly, market land values reflect the productivity of land and the capacity of farmers to adapt in the long run. However, such a setting is rarely seen in the developing world where access to credit is typically heterogeneous with a big proportion of small, poor farmers facing credit constraints (Eswaran and Kotwal, 1986; Carter, 1988). Isolation (Taylor and Adelman, 2003), uncertainty in land tenure (Feder and Nishio 1998) and violent conflicts (Ibáñez and Querubin, 2004; CMDPHD, 2018) might also prevent well-functioning land markets. In these settings, the market valuation of land typically used in Ricardian studies, is not the appropriate measure to quantify the effects of climate change on agriculture as it might overestimate their ability to adapt.

The possibility of omitted variable bias has also undermined the reliability of the Ricardian results (Deschenes and Greenstone, 2007; Ortiz-Bobea, 2020). Market land values can be influenced by unobserved on-farm characteristics and off-farm pressures to convert agricultural land to new uses such as urbanization and housing, confounding the true relationship between climate and agricultural productivity. While recent studies have tried to solve this identification issue in the context of the US or other developed countries (Severen et al., 2018; Ortiz-Bobea, 2020; Bareille and Shakir, 2023), little attention has been paid to the plausibility of the core assumptions of the Ricardian approach in developing countries and the implications they might have on the climate change welfare effects derived from it.

In this paper, I implement a novel version of the Ricardian approach that relies on a shadow measure of land valuation that I call the Productive Value of Agricultural Land (PVAL). PVAL is structurally uncovered from the estimation of an agricultural production function and, as a result it only reflects farm productivity, reducing concerns about omitted variable bias. Its estimation is derived from the first order condition in the profit maximization program of a household. As a result, it also internalizes the shadow components of land valuation associated with the markets of land and credit reflecting more properly the market setting in which farmers make decisions.

The empirical application of this paper focuses on the case of Mexico, a country in which the level of competitiveness so far achieved in agricultural land markets is unclear and where access to credit is limited. In 1992, Mexico initiated a land reform that sought to strengthen the individual property rights of agricultural producers through a process of certification. Before 1992, land was held under *ejido* ownership, a type of collective property in which individual farmers were not allowed to sell, rent, or collateralize their plots. The land reform ended these restrictions and created a legal mechanism to convert *ejido* land to full private property (de Janvry et al., 2014; de Janvry et al., 2015). As of 2023, 96.0% of *ejido* agricultural land has been certified with only 6.0% transitioning to private property (RAN, 2023). In addition, land rental markets are not very active with only 6.3% of total agricultural land being rented (INEGI, 2022). As for credit markets, in 2019, 9.4% of the farms apply for a loan while only 8.4% secured it (INEGI, 2019).

This paper relies on a three-step empirical strategy applied to household data from Mexico's National Rural Household Survey (ENHRUM). The first step is the estimation of an agricultural production function. In the second step, the estimated input elasticities are used to calculate PVAL using the first order condition of the profit maximization problem of the farmer. In the third step, I use PVAL as the dependent variable in a new version of the Ricardian model. Results are compared with a Ricardian estimation that relies on self-reported market land values instead. In these regressions, the non-linear effect of temperature on land productivity is captured by transforming temperature into growing degree days (GDD) and harmful degree days (HDD).

There are four main findings. First, estimates of PVAL are on average, 33.0% larger than self-reported land values. Market land values underestimate land productivity in all regions of Mexico except the Center, where urbanization pressures are high. Second, when estimating a Ricardian regression using PVAL as the dependent variable, it is found that extreme heat is detrimental for land productivity, i.e. an additional HDD reduces PVAL by 1.5%, on average. Results also reveal a concave and robust relationship between precipitation and land productivity with precipitation increases being beneficial, i.e. a 1mm increase in precipitation increases PVAL by 0.15%. When market land values are used instead, results show no significant effects of harmful temperatures and a smaller increase in market valuation resulting from precipitation increases (a 1mm increase in precipitation increases market land values by only 0.07%). Thirdly, access to formal credit significantly increases land productivity only when PVAL is used. Market land values do not seem to internalize the shadow component of agricultural productivity associated with the credit constraints faced by farmers. Fourth, PVAL does not seem to be affected by the urbanization and housing pressures affecting market land values which increase the closer the farm is to a city.

In Mexico, under a medium GHG emissions scenario, annual mean temperature is expected to increase by 1.5°C by midcentury. This increase might be accompanied with an increase in the number of high heat days (those with maximum temperature>35°C) to above 20 days per month during summer. At the same time, annual total precipitation is expected to decrease by 3.4% (TWBG, 2023). The Ricardian estimates of this paper suggest that the negative effect that extreme heat may have on future agricultural productivity may not be captured when market land values are used. Similarly, the negative effect of less precipitation in future agricultural productivity would be underestimated if marked land values are used. This result is explained by the fact that PVAL and market land values capitalize climate in different ways. PVAL reflects agricultural productivity and internalizes the market setting faced by agricultural producers. Market land values do not. When making projections of the potential effect that climate change may have on agricultural productivity it is important to do it using estimates that correctly reflect land productivity in a context of constrained production, otherwise, the conclusions and the policy recommendations derived may be misleading.

The organization of this paper is as follows. The first section provides a review of the existing approaches and some thoughts on the suitability of their application in the context of developing countries. In the second section, I use a profit maximization setting to show the implications of the Ricardian analysis when the assumptions of competitive and complete markets for land and capital do not hold. In the third section, I lay out the empirical strategy to estimate PVAL and the agricultural data used. In the fourth section, I estimate a version of the Ricardian equation that utilizes PVAL as the dependent variable and present the results and their robustness. The final section provides some conclusions and implications for existing and future work relying on the Ricardian approach.

Existing approaches

In the Ricardian model, farmers are assumed to maximize profits in a context of complete and perfectly competitive markets. With perfect competition in land markets, the market rental price of one unit of land, v, will be set equal to the profit π^* that such unit of land will generate (Mendelsohn et al., 1993). Land values then reflect the present value of future land rents or, equivalently, future farm profits. If the interest rate on capital is the same for all farmers, then:

$$Land\ Value = \sum_{t=1}^{\infty} \frac{\pi^*}{(1+r)^t} = \sum_{t=1}^{\infty} \frac{v}{(1+r)^t} = \frac{v}{r} \quad (1)$$

where t stands for time and *r* is the market interest rate. By relying on cross-sectional variation of farm prices, the Ricardian approach accounts for all the possible forms of adaptations that a profit maximizing farmer would undertake in response to climate change. Given climate, farmers will choose the crop or activity that generates the highest value of π^*. Farmers will then optimize input usage within the chosen activity. Consequently, the Ricardian approach relies on land values to draw conclusions about how exogenous changes in climate affect farm productivity. Typically, this relationship is estimated using an equation of the form:

$$Land\ Value_c = \alpha + f(\overline{W_c}) + X_c^{'}\beta + \varepsilon_c \quad (2)$$

where $\bar{W}$ represents climate normals (three-decade averages of climatological variables, generally, temperature and precipitation) at every location *c* (i.e., counties). $\bar{W}$ is generally estimated from historical meteorological records of temperatures and precipitation for relevant time windows usually associated to growing periods. A set of other relevant determinants of land values, X, is also included. Welfare impacts from different climate change scenarios can then be inferred from the parameter estimates obtained in **Equation 2**.

The Ricardian model proposed in the mid 1990's has been applied extensively. In the US, a first application was provided by Mendelsohn et al. (1994) with subsequent developments aiming to improve upon this seminal work (Schlenker et al., 2005; Schlenker et al., 2006). Econometrically, the cross-sectional nature of the Ricardian approach is its greatest disadvantage. If there exist unobserved factors correlated with climate and land valuation, then, the Ricardian estimates will be affected by omitted variable bias (Mendelsohn and Massetti, 2017). Such unobserved factors could be soil quality, a farmer's idiosyncratic ability and nonfarm influences such as the option value to convert land to a new use (as with urbanization). To reduce the threat of omitted variables, the usual strategy has been the inclusion of a large set of plot or household characteristics. However, some studies have found that even after controlling for such characteristics, the Ricardian estimates are not stable over time and that such instability is likely due to factors affecting land valuation that remain omitted (Deschênes and Greenstone, 2007; Ortiz-Bobea, 2020).

The panel data approach (Deschênes and Greenstone, 2007), solves the identification issues of the Ricardian approach by regressing agricultural outcomes on weather and individual fixed effects. However, by relying on weather, the panel data approach estimates something that is different from the long run effect of climate. Specifically, short run adaptations to fluctuations in weather can differ from long run adaptations to climate change (Fisher et al., 2009; Fisher et al., 2012; Deschênes and Greenstone, 2012; Auffhammer, 2022). In spite of this potential shortcoming, the panel approach has attracted significant attention. Some of the empirical applications relying on panel data include Burke and Emerick (2016), Schlenker and Roberts (2009) and Ortiz-Bobea and Just (2013) for the US, Welch et al. (2010) for Asia, Gammans et al. (2017) for France and Moore and Lobell (2014) for Europe, Guiteras (2009) for India and Lobell et al. (2011) for a global analysis. The application of the panel data approach in developing countries has been more limited mainly because long panel data sets on agricultural outcomes at a sufficiently disaggregated scale are often not available (Burke et al., 2016). In such contexts, cross-sectional data is more likely to be available. Not surprisingly, the implementation of the Ricardian approach in developing countries has been prolific. Some countries and regions for which Ricardian estimates exist are Mexico (Mendelsohn et al., 2010; Galindo et al., 2015), Sri Lanka (Seo at al. 2005), Brazil and India (Sanghi and Mendelsohn, 2008), Latin America (Seo and Mendelsohn, 2008a and 2008b), Africa (Kurukulasuriya and Mendelsohn, 2008) and Asia (Mendelshon, 2014).

Efforts to address the omitted variables bias critique to the Ricardian approach are still ongoing. In the context of the US, Ortiz-Bobea (2020) estimates a Ricardian equation using agricultural land rents as the dependent variable. According to the author, this strategy circumvents the effect of nonfarm influences because land rents better reflect agricultural productivity and do not capitalize the opportunity costs of alternative land uses. When comparing his results with a traditional Ricardian equation that relies on market land values, the author concludes that the estimated effect of climate change in US agriculture is actually not distinguishable from zero which is in sharp contrast with the large negative effects found with Ricardian models that use market land values. In a more recent contribution, Bareille and Chakir (2023) estimate a version of the Ricardian approach based on repeated land sales data from France in which plot fixed effects are included in the regression while climate is allowed to vary between sales. The authors argue that the inclusion of plot fixed effects is the only way to remove the bias associated with omitted factors affecting land valuation. This analysis combines the advantages of both, the cross-sectional approach, by still using land values and climate, and the panel approach, by controlling for confounding omitted variables with plot fixed effects. Their results suggest higher positive impacts of climate change in French agriculture compared to traditional Ricardian estimates. Yet, both of these applications are focused on two developed countries, the USA and France, where the assumptions of perfectly competitive markets for land are likely to hold. These contributions, however, pay no attention to the plausibility of such assumptions in the context of developing countries. In addition, both studies rely on decades-long data on land values or land transactions, which is hard to get in the developing world.

Market land values will reflect the true valuation of land only when the markets for land and credit are well-functioning. Perfect competition in the land market will make profits equate the rental value of land. A complete market for capital allows farmers to access any amount of working capital that they require in order to initiate and continue the production process. This, however, is not the case in many developing countries. Empirical evidence shows that land titling increases land values and farm investments (Feder and Nishio 1998). Uncertainty in land tenure introduces a component of risk to future farm profits not likely to be captured by market land values. Violent conflicts and forced displacements make it impossible for a farmer to have certainty about land tenure and the value of land holdings (Ibáñez and Querubin, 2004; CMDPHD, 2018). Isolated villages poorly integrated with regional or national markets might not fit the assumption of perfectly competitive input markets if local markets for some inputs, including land, do not exist (Taylor and Adelman, 2003).

Agrarian economies in developing countries typically have limited access to credit due to the inability of farmers to provide collateral. Often, the amount of land that farmers own represents their most valuable possession. Whenever access to credit is associated to land holdings, small farmers might remain constrained or not have access to capital at all (Eswaran and Kotwal, 1986; Carter, 1988). Because of heterogeneous access to capital, farmers are unlikely to bear the costs of adaptation to climate change homogenously. Credit constraints preventing adaptation might have important consequences on who is able or not to adapt. In the context of incomplete or missing markets, market land values might not reflect the true productive value of agricultural land and the true ability of farmers to adapt, an issue explored in detail with the theoretical model presented in the next section.

Land valuation in the context of missing and incomplete markets

To illustrate the fact that market land values do not reflect land productivity in the presence of credit and land constraints, consider a household (i) that engages in agricultural production using land (T_i), labor (L_i), and intermediate inputs (I_i) (i.e. fertilizers, pesticides). Agricultural output is given by $Q(T_i, L_i, I_i; A)$ which is assumed to be increasing, twice continuously differentiable and quasi-concave. A is a productivity parameter. Output and inputs are all traded using market prices. The household is also endowed with an amount of land $\bar{T}_i$.

When renting land, hiring labor and purchasing intermediate inputs, the household is subject to a working capital constraint B_i that is equal to the amount of credit for which it is eligible based on the amount of collateral that it can offer.[1] For simplicity, let us abstract away from the potential endogeneity of access to credit and assume that the credit amount B_i is exogenously determined.[2]

The household seeks to maximize profits from agriculture by solving the following problem[3]:

$$\max_{T_i, L_i, I_i} p_Q Q(T_i, L_i, I_i; A) - \upsilon(T_i - \overline{T}_i) - p_L L_i - p_I I_i - rB_i \tag{3}$$

s.t.

$$\upsilon(T_i - \overline{T}_i) + p_L L_i + p_I I_i \leq B_i$$

where p_Q, v, p_L and p_I are the market prices of output, land, labor and intermediate inputs respectively. The household repays the loan at the interest rate r. When $v(T_i - \bar{T}_i)$ is positive, the household rents land in and this expenditure tightens the credit constraint as it uses liquidity. Conversely, when $v(T_i - \bar{T}_i)$ is negative, the household rents land out and the cash generated relaxes the constraint as it creates liquidity (Sadoulet and de Janvry, 1995). Let λ_i be the Lagrange multiplier associated with the credit constraint. The First Order Condition (FOC) with respect to T_i is given

1 In less-developed agrarian economies, land holdings are typically the most valuable asset in a household's portfolio. Thus, access to credit in such economies is heavily determined by a household's ability to collateralize its land and by the size of its land endowment (Carter, 1994; Eswaran and Kotwal, 1986). If access to credit is linked to the size of land holdings, then B_i would be an increasing function of $\bar{T}_i$ and as long as land endowments are heterogeneous across households, access to credit will also be heterogeneous.

2 Results are qualitatively similar if we explicitly model B_i as a function of $\bar{T}_i$.

3 The theoretical results of this section are qualitatively similar if households are modeled as consumers. Assume for example, that households derive utility from the consumption of market goods, self-produced agricultural goods and leisure. Assume also that the market for labor is perfectly competitive and that credit constraints still exist. In this setting, households would maximize utility subject to an income constraint equal to the sum of agricultural profits and any other exogenous income given to the household. In this case, the first order condition with respect to land will still have a shadow component associated with the shadow price of credit and the marginal utility of income.

by:

$$p_Q \frac{\partial Q}{\partial T_i} = \upsilon(1+\lambda_i) \tag{4}$$

The price used by the household to optimally determine land use is a shadow rental price that is household specific and a function of the shadow price of credit, λ_i, and the market rental value of land v. As a result, in the presence of credit constraints the market rental value of land does not entirely reflect its full opportunity cost. **Equation 4** clearly differs from the Ricardian result. Whenever credit constraints are present, the shadow rental value of land will differ from the market rental price. The Ricardian assumption stated in **Equation 1** will result from profit maximization only when the credit constraint is not binding (i.e. $\lambda_i = 0$).

When the market for land is missing, the household cannot rent land in or out, v is equal to zero and the household cannot devote an amount of land larger than its land endowment to agricultural production. The profit maximization program becomes:

$$\max_{T_i, L_i, I_i} p_Q Q(T_i, L_i, I_i; A) - p_L L_i - p_I I_i - rB_i \tag{5}$$

s.t.

$$p_L L_i + p_I I_i \leq B_i$$
$$T_i \leq \overline{T}_i$$

Let μ_i be the Lagrange multiplier associated with the land constraint. When the market for land is missing the shadow rental value of land is given by:

$$p_Q \frac{\partial Q}{\partial T_i} = \mu_i \tag{6}$$

In turn, the shadow rental price of land is household specific and the opportunity cost of land is given by a shadow measure only known to the farmer.

Equation 4 and **Equation 6** illustrate that in the presence of credits constraints and/or when the market for land is missing, the marginal value of an additional unit of land is not necessarily equal to an exogenous price determined in a competitive market. Depending on the market setting, this value could be a combination of market and shadow valuations. When the market for land exists and no credit constraints affect the decision making of the farmer, then, the market value of land, v, tells us all we need to know about its productivity. However, if credit constraints are present, the marginal value of an additional unit of land is higher due to the increased productivity caused by accessing an additional unit of credit. This is the shadow price of credit λ_i, and the market rental price of land fails to internalize it. Finally, if a market for land does not exist, farmland productivity is endogenously determined and given by the shadow price of land, μ_i.

Market measures of land productivity might lead to erroneous conclusions as they might omit other important determinants of land productivity, particularly in developing countries where farmers are expected to face different types of constraints. To investigate the effects of climate change on long-run farm productivity one must use a measure that genuinely reflects it, free of other non-agricultural confounders affecting its market valuation and inclusive of the market setting directly affecting agricultural productivity. If access to credit boosts productivity, then the shadow price of credit λ_i should be part of its productive value. In the absence of a competitive market for land, the shadow rental price of land μ_i should be interpreted as its productive value. Such a measure is what I have defined as PVAL. Although not directly observed, PVAL can be inferred from the left-hand side of **Equation 4** or **Equation 6**. The next section outlines the empirical strategy to estimate it and the results obtained.

PVAL estimation

Empirical strategy

The first step of the empirical strategy of this paper is to estimate PVAL. The shadow rental price of land given by the right-hand side of **Equation 4**, and **Equation 6** is not observed as the idiosyncratic component of land valuation is only known to the farmer. However, regardless of the market setting faced by the farmer, the left-hand side of the FOC is always the same. The marginal value of an additional unit of land should always equate the shadow rental price of land and it is possible to approximate it by estimating an agricultural production function. I assume a Cobb-Douglas production function of the form:

$$G_{it} = A_{it} T_{it}^{\beta_1} L_{it}^{\beta_2} I_{it}^{\beta_3} \tag{7}$$

where G_{it} represents gross output value of household i at time t. As before, T_{it}, L_{it} and I_{it} represent land, labor and intermediate inputs. Taking natural logs of **Equation 7** results in the familiar linear production function:

$$\ln G_{it} = \beta_0 + \beta_1 \ln T_{it} + \beta_2 \ln L_{it} + \beta_3 \ln I_{it} + q_{it} + \eta_t + \varepsilon_{it} \tag{8}$$

where the productivity parameter A_{it} has been decomposed in β_0, the mean efficiency level common to all households, q_{it}, a productivity parameter that represents unobserved household-specific characteristics such as the managerial ability of the farmer and, η_t, a productivity shock common to all households within a time period t. ε_{it}, is an i.i.d. error component composed of unexpected shocks to agricultural productivity.

The correlation between input levels and unobserved productivity factors generates an endogeneity issue. Inputs levels in agricultural production are not independently chosen but are rather determined by the characteristics of the firm including the unobserved factor q_{it}. Panel estimates of **Equation 8** would generate unbiased estimates of the structural parameters of the production function if we are willing to assume that q_{it} is time-invariant. Recent theoretical developments have moved away from such an assumption and treat the idiosyncratic unobserved productivity as time-variant. Of particular relevance for this empirical application are the works of Olley and Pakes (OP, 1996) and Levinson and Petrin (LP, 2003). OP use the firm's investment decisions to proxy for unobserved productivity shocks. LP favors the use of intermediate inputs as proxies arguing that in some settings the proportion of observations with zero investment is high enough to cast doubts on the validity of the assumptions made by OP. This is particularly true for the case of agriculture where investment decisions are not observed on a frequent basis. The preferred results of this empirical application are derived using LP. For comparison purposes, estimates using standard OLS and panel techniques are also provided.[4]

Having estimated the structural parameters of the production function, PVAL is recovered from the capitalization of the shadow rental value of land. **Equation 4** and **Equation 6** state that regardless of the market setting, the shadow rental value of land will always equate to the marginal value of land given by the left-hand side of the equations. Taking the first derivative of **Equation 7** with respect to T and using r to capitalize it we have:

$$PVAL_{it} = \frac{\widehat{\beta}_1 \left[e^{(\widehat{\beta}_0 + \widehat{q}_{it} + \widehat{\eta}_t)} T_{it}^{\widehat{\beta}_1} L_{it}^{\widehat{\beta}_2} + I_{it}^{\widehat{\beta}_3} \right]}{r T_{it}} * \widehat{\varphi} \tag{9}$$

where $\hat{\varphi} = \frac{1}{N} \sum_{n=1}^{N} \exp(\hat{\varepsilon}_n)$, with N equal to the total number of observations in the sample and $\hat{\varepsilon}_n$ equal to the estimated residual from **Equation 8**. $\hat{\varphi}$ is the Duan smearing transformation factor, a correction needed to account for the fact that $E[ln(G)] \neq ln[E(G)]$, (Duan, 1983).[5] As opposed

4 The interested reader could refer to Van Beveren (2012) for a comprehensive survey of this and other available methodologies on the matter.

5 When ε_i follows a normal distribution with $E[\varepsilon_i] = 0$ and $Var[\varepsilon_i] = \sigma^2$, it can be shown that $E[\hat{\varphi}] = e^{\frac{\sigma^2}{2}}$

to the market valuation of land, PVAL is the household's reservation price of land that internalizes the market settings faced by the farmers. It is also uncovered from the structural estimation of a functional form that synthetizes the way in which agricultural inputs are transformed in agricultural output thus reflecting only agricultural productivity.

Data

ENHRUM is a nationally representative panel of Mexican households located in 80 villages with fewer than 2,500 inhabitants and across 14 states. It provides information for the 2002 and 2007 cropping seasons and a complete characterization of the agricultural activities of rural households including total output value and input use and detailed information on socio-demographics, plot characteristics (size, ownership regime, self-reported market land values, access to irrigation, etc.) and access to credit (formal and informal).

Table 1 reports the summary statistics of the variables used to fit the agricultural production function. The sample is composed of 720 agricultural households, 182 present in the 2002 round, 154 present in the 2007 round and 384 present in both rounds of the survey. The pooled sample is composed of 1,104 observations. Agricultural variables in this table represent the aggregated values of every crop grown by the household.[6] For example, in 2002, the average output value per hectare (ha) of $9,540.8 includes the market value of all crops grown by the household (staples, non-staples, annuals, perennials) in the Spring-Summer and Fall-Winter cropping seasons. Double cropping has been mentioned in the literature as a potential way of adaptation to climate change (Seifert and Lobell, 2015). Thus, it is important to account for it when valuing land productivity. Between 2002 and 2007, average output value per hectare increased by 18%.

Average land in production amounts to 4.6 has on average. Total labor is defined as the sum of family and hired labor from the beginning of the production process before planting and up to harvest, and the pooled sample reflects an average of 65.2 days of total labor per ha. We observe an increase of 23% in total labor usage from 2002 to 2007. The cost of intermediate inputs is defined as the sum of seed, fertilizer, manure and pesticide purchases. It also includes the rent of agricultural machinery (i.e. tractors, harvesters, yuntas, etc).[7] On average, households spent $4,984.5 per ha on the purchase of intermediate inputs. Finally, average agricultural value added (output value minus the cost of intermediate inputs) is equal to $4,556.3 per ha and between 2002 and 2007 it increased by 50%.

Results

Table 2 reports the parameter estimates of the agricultural production function. OLS, fixed effects and LP estimates of **Equation 8** are presented in columns (1), (2) and (3) respectively. In OLS and fixed effect, standard errors are clustered at the household level. In LP standard errors are derived using 50 bootstrap replications. In all three specifications, it is found that increases in

However, in many settings, the true distribution of the error term is unknown. Duan's (1983) general result suggests that in such cases, the smearing correction factor can be estimated with the mean exponentiated residual from the model.

6 Production for self-consumption was valued using average market prices calculated at the village level. When market prices for a particular crop were not found at the village level, average market prices were calculated at the state, region and national levels, in that order.

7 The 2002 round of the survey recorded the total machinery-hours used in the production process. Unfortunately, this is not the case in the 2007 round, which only recorded machinery rent expenditures. Ideally, one would treat this form of capital as an additional factor of production in the estimation of an agricultural production function. The unavailability of a physical measure of machinery in both rounds and the high frequency of zero expenditures in the sample makes it necessary to treat machinery expenditures as an intermediate input.

labor and land lead to increases in agricultural value, i.e. all estimated elasticities are positive and statistically significant at the 5% level. Failing to control for unobserved idiosyncratic productivity leads to an overestimation of the magnitude and significance of the elasticity of intermediate inputs, i.e. the OLS estimate is larger compared to the fixed effects and LP estimates. This result indicates that, while all three inputs are potentially correlated with q_{it}, the correlation between intermediate input usage and q_{it} is likely to be the highest.[8] In the event of unexpected productivity shocks, farmers have more flexibility to adjust the use of intermediate inputs compared to land or labor which may have been already committed in the production process. Thus, the omission of q_{it} artificially inflates the parameter estimate of intermediate inputs. In fact, according to the LP estimates (column (3)), the estimated elasticity of intermediate inputs is not statistically significant. Finally, the LP estimates indicate that the hypothesis of constant returns to scale cannot be rejected.

PVAL estimates are obtained from substituting the parameter estimates of column (3) of **Table 2** into **Equation 9**. The interest rate used for the capitalization of PVAL is 4.61% which corresponds to the return of a Mexican treasury bond on June, 2012 (Banxico, 2023). PVAL and self-reported land values are both available for only 727 observations. **Table 3** reports summary statistics and the paired t-test for the difference of these two measures. In the pooled sample, the average PVAL per hectare is \$100,202.8. This value is 33% higher than the mean self-reported land value of \$75,597.3 and the difference is statistically significant. On average, PVAL estimates are significantly larger than self-reported land values in the southern and northern regions. For example, the Northwest displays an average PVAL estimate that is 245.0% higher than the average self-reported land value. Between 2002 and 2007, average self-reported land values increased by 54% while average PVAL increased by only 10%. This result indicates that the rapid increase in self-reported land values is possibly associated to off-farm factors not related to agricultural productivity.

The overall correlation between observed land valuation and the PVAL estimates is only 0.173. Thus, there is little agreement between what households report as market land values and the actual productive value of their plots. Self-reported land values could be affected by measurement error but its magnitude is unknown since there is not an official source of market land values that could be used as comparison. Alternatively, households might report an estimation of the market value of their land but not its shadow components. As detailed before, in the presence of credit constraints, there is an additional component in a household's reservation price for land, the shadow price of credit. If this is true, then **Table 3** provides evidence that such credit constraints are present and economically important, particularly at the regional level. Other empirical findings have also highlighted the economic importance of shadow prices to explain agricultural labor supply responses (Skoufias, 1995) and crop valuation (Arslan and Taylor, 2009).

Ricardian estimation

Empirical strategy

The final step of the empirical application of this paper is the estimation of a version of the Ricardian equation that has PVAL as the dependent variable. To estimate the effect of climate change on land productivity, I use the pooled sample of PVAL estimates (1,104 obs) to estimate the following specification:

$$\ln PVAL_{ivt} = \alpha + \theta_1 GDD_{vt} + \theta_2 HDD_{vt} + \theta_3 P_{vt} + \theta_4 P_{vt}^2 + S_{vt}^{'}\gamma + X_{it}^{'}\phi + \tau_r + \eta_t + \epsilon_{it} \tag{10}$$

8 This hypothesis is corroborated when looking at the actual correlations of the input variables and the estimated $\hat{q}_{it}$ from column (3). Such correlations are 0.027, 0.047 and 0.185 for land, labor and intermediate inputs, respectively.

where the natural logarithm of PVAL of household i in village v at time t is expressed as a function of the following climate variables at the village level: Growing Degree Days (GDD), Harmful Degree Days (HDD), precipitation (P) and precipitation squared (P^2). S_{vt} is a vector of soil types at the village level and X_{it} is a vector of household characteristics. Regional (τ_r) and time (η_t) fixed effects are also included to control for unobserved time-invariant determinants of land productivity common to all households within the same region and during the same year. Versions of **Equation 10** with region-by-year fixed effects are also estimated to control for the possibility that such unobserved determinants are time-varying.

As long as there is correlation between climate and other unobserved determinants of agricultural productivity not included in the regression, the Ricardian estimation could still be biased. However, PVAL only reflects land productivity which greatly reduces concerns about omitted factors polluting land market valuation. Also, PVAL internalizes the market setting in which farmers make decisions and is thus a better representation of land valuation in places where markets are less likely to function perfectly. For comparison purposes, **Equation 10** is also estimated using self-reported land values.

Data

Household data

Table 4 reports summary statistics on the household characteristics included in the estimation of **Equation 10**. There is not much evidence of competitive and complete markets for land and credit. Only 30% of households have predominantly private ownership over their plots[9] with the rest still being under the *ejido* figure. Only 10% of the households participate in land rental markets while an additional 14% engage in informal mechanisms such as borrowing and crop-sharing. Only 8% of households had access to formal credit while an additional 19% had credit from informal sources. Finally, only 27% of the households use irrigation. The table also indicates that rural households in the sample rely heavily on government transfers (from PROCAMPO and PROGRESA) and that household heads in rural Mexico have low levels of education.

Climate and soil data

Daily weather data for 5,422 weather stations were obtained from the meteorological service repository CLICOM[10] which provides information on daily precipitation, maximum and minimum temperatures that date as far back as 1920. Entry and exit are observed for many weather stations, and as a result, daily weather data are missing for the dates in which a station did not exist or did not operate. Missing data are a common issue when using information from weather stations and could introduce a bias in parameter estimates (Auffhammer et al., 2013). To minimize the potential effects of missing data, I restrict the sample of eligible weather stations to those with at least 75% of daily information for the period of 1972 to 2007. This period is long enough to cover 30 years before each round of ENHRUM. After this exclusion, I am left with information from 1,713 stations for precipitation and 1,510 stations for temperature. This procedure keeps the set of stations used to calculate each climate variable constant ensuring that its resulting variation is not caused by changes in station coverage (Auffhammer et al., 2013).

I define weather w, in village v at time t as the weighted average of weather in the 5 nearest weather stations:

$$w_{vt} = \frac{\sum_{t=1}^{5} \alpha_n w_{nt}}{\sum_{t=1}^{5} \alpha_n} \tag{11}$$

[9] At least 50% of all of the household's plots have these characteristics.

[10] Weather station data retrieved from http://clicom-mex.cicese.mx/.

with $\alpha_n = \frac{1}{\sqrt{d_n}}$, where d_n stands for distance of weather station n to each village v. Weights are normalized so that their sum over all stations in a village sum to 1. On average, the 5 closest weather stations used to interpolate precipitation and temperature are located at a distance of 36km and 39km, respectively. A map showing the location of villages and weather stations is provided in **Figure 1**.

Following Jessoe et al. (2018), I predict missing data by regressing weather in the closest station, on weather of the remaining 4 stations assigned to the village. I use the predicted values from this regression to fill in missing values. Weather at time t in station n will remain missing if it is also missing in at least 1 of the other 4 stations. To fill in the remaining missing observations, this regression is repeated while dropping the most distant station in each iteration until there are no more stations to predict weather (i.e. after weather in the closest weather station is regressed on weather of the second closest station). This process is subsequently applied to the second, third, fourth and fifth closest stations. The number of predicted missing observations varies by village, however, on average, it represents about 10.0% of the total number of observations.[11] After completing the interpolation procedure, weighted averages of temperature and precipitation were successfully obtained for about 98.0% of the sample days.[12]

The calculation of climate variables relies on daily weather information for the 30 years preceding each survey round. That is, I use information from the period of 1972-2001 to represent climate in 2002 and information from the period of 1977-2006 to represent climate in 2007. PVAL is estimated from an agricultural production function that aggregates all the different crops grown by the households over the whole year. Consequently, the main Ricardian specification of this paper associates PVAL with measures of annual climate.

The climate measure for annual precipitation is calculated as the 30-year average of yearly accumulated precipitation for each of the two periods previously defined. With regards to temperature, the simple calculation of annual or seasonal averages would not take advantage of the rich daily variability in temperature observed in weather station data. Moreover, plant growth does not benefit from heat over the whole temperature range. Above and below certain thresholds, temperatures might be harmful for plant health. To capture the importance of optimal growing conditions and extreme temperatures, I transform daily observations of temperature into Growing Degree Days (GDD) and Harmful Degree Days (HDD) adopting the 8-32°C range used in related literature (Schlenker et al., 2006; Schlenker and Roberts, 2009; Jessoe et al., 2018). Daily temperature T was calculated as the average of daily maximum and minimum temperatures and converted to GDD and HDD using the following definitions:

$$GDD(T) = \begin{cases} 0 & \text{if } T \leq 8 \\ T-8 & \text{if } 8 < T \leq 32 \\ 24 & \text{if } T > 32 \end{cases} \tag{12}$$

$$HDD(T) = T - 32 \qquad \text{if } T \geq 32 \tag{13}$$

Climate measures of GDD and HDD are constructed by calculating a 30-year average in each period. **Table 5** presents summary statistics of the climate variables. The Southeast region of Mexico displays the highest average annual pre-

[11] The interpolation of weather to every village uses the information of 5 weather stations. Between January 1st, 1972 and December 31, 2007 there are 13,149 days giving a total of 65,745 observations.

[12] There are 13,149 days in the sample period which gives a total of 1,051,920 sample days for the 80 ENHRUM villages.

cipitation while the mostly-semiarid northern regions have the lowest levels. On average, the Southeast is the hottest region but the Northwest has comparable average temperatures. HDD are highly concentrated in the Northwest. Overall, the difference between climate in 2002 and 2007 is minimal.

When estimating the Ricardian equation, one might be worried that the climate variability observed in the sample might not be enough to estimate the effects of climate on agricultural productivity after conditioning on different sets of location and time fixed effects. An a priori evaluation of the residual variability on climate shows that the inclusion of state and state-by-year fixed effect soaks up a large fraction of the variation in climate, (see **Table A.1**). It is important to consider this residual variation when deciding the level of location fixed effects to be included in the regression. On one hand, we want to control as flexibly as possible for unobserved time-invariant and time-varying factors potentially correlated with agricultural productivity. On the other hand, we also want the residual variation in climate left after the inclusion of such location and time fixed effects to be sufficiently large so that results are still informative of the effect of climate on agricultural productivity. Taking this into account, the estimation of **Equation 10** only controls for region and year fixed effects. A robustness test using region-by-year fixed effects is also provided.

Soil data for each village were obtained from FAO's Digital Soil Map of the World (FAO, 2007). Using each village's location, the class of dominant soil was extracted and then grouped into the following 15 major soil types: Acrisols, Cambisols, Rendzinas, Gleysols, Phaozems, Litosols, Fluvisols, Kastanozems, Luvisols, Nitosols, Regosols, Andosols, Vertisols, Xerosols and Yermosols.

Results

Results obtained from the estimation of **Equation 10** are reported in **Table 6**. The dependent variable in column (1) is the natural logarithm of the estimated PVAL while in column (2) the natural logarithm of self-reported land values is used instead. In columns (3) and (4) region-by-year fixed effects are included in lieu of region and year fixed effects. **Table 6** only reports results for relevant variables but other controls include the variables in **Table 4** and 14 categories of major soil types. Standard errors are clustered at the village level which accounts for the potential heteroscedasticity arising from the fact that the dependent variable is estimated (Lewis and Linzer, 2005; Auffhammer, 2022).

Extreme temperatures (HDD) have a large negative and statistically significant effect on PVAL. A one-unit increase in HDD decreases agricultural productivity by 1.5%. This result is consistent with Jessoe et al., (2018) who find that extreme temperatures affect local employment choices using the same dataset. GDD have the expected sign in all specifications but do not achieve statistical significance. Self-reported market land values fail to capitalize the effect of good or bad growing conditions, i.e. the coefficients on GDD and HDD have the expected direction but are not statistically significant.[13] All of the regressions document a concave and statistically significant relationship between precipitation and agricultural productivity. The middle section of **Table 6** displays the implied optimal level of precipitation (P^*) and the marginal effect when evaluated at its sample mean ($\bar{P}$). According to the PVAL specifications, the optimal level of accumulated precipitation is found around 2,050mm. Self-reported land values place this level at around 1,580mm. Also, all of the marginal effects are po-

[13] These results also highlight the importance of exploiting daily variation in temperature when estimating its effects on agricultural productivity. Estimate relying on average temperatures might fail to identify the negative effects of extreme temperatures on agricultural productivity (see **Table A.2**).

sitive and statistically significant. Results using PVAL indicate that a 1mm increase in precipitation increases agricultural productivity by 0.15%, or approximately $150 Mexican pesos relative to the average estimated PVAL (see **Table 3**). When using market land values, the marginal effect is 0.07%, which is equivalent to $53 Mexican pesos relative to the average market land value observed in the sample (see **Table 3**). Thus, market land values underestimate the positive effect that more precipitation has on agricultural productivity.[14]

Access to formal credit has a positive and statistically significant effect on agricultural productivity only when PVAL is used. This result suggests the existence of binding credit constrains in rural Mexico. Access to credit boosts productivity and self-reported land values do not capitalize the marginal gain associated to an additional unit of working land.[15] Access to irrigation is positive and statistically significant in all specifications but the estimated coefficient is higher when PVAL is used, meaning that the productivity returns to irrigation are higher than its capitalization on land valuation. Also, factors like urbanization and housing affect self-reported market land values but not PVAL. The coefficient on the distance to the nearest city is negative and significant in columns (2) and (4). The closer the village is to an urban center, the higher its market land value. PVAL is unaffected by the proximity to a city which suggest that off-farm factors affecting land valuation do not affect PVAL.

Surprisingly, private ownership does not increase agricultural productivity or market land values. A possible explanation of this result is that the process of transitioning from *ejido* to private ownership in Mexico has been slow which has prevented land consolidation and the investments incentives associated with it (de Janvry et al., 2015; Binder, 2015). Thus, in practice, private land in small agricultural communities, such as the villages in our sample, might not be much different from *ejido* land in terms of productivity or market valuation. Finally, smaller farms (as measured by the amount of land in production) have a larger productive or market values per unit of land, a result consistent with findings from the development literature (Kagin et al., 2016).

Robustness

In **Table 6**, PVAL measures and self-reported land values are regressed on annual measures of climate. The rationale is that PVAL is estimated using information from the two cropping seasons throughout the year. Double cropping could be, by itself, a form of adaptation to climate change. Similarly, market land values are expected to capitalize the full flow of annual profits when farmed in one or in both seasons. However, agricultural production in Mexico is highly concentrated in the Spring-Summer season (55.3% of the total farmed land in 2007; SIAP, 2023). In columns (1) and (2) of **Table 7**, the annual climate variables

14 Ricardian estimates for Mexico have been previously reported by Mendelsohn et al. (2010) and Galindo et al. (2015). However, the results of this paper are not directly comparable with their results due to different methodological approaches, particularly with regard to the construction of the temperature and precipitation variables. Specifically, they express land values (Mendelsohn et al., 2010) or agricultural net revenues (Galindo et al., 2015) as a quadratic function of quarterly temperature and precipitation. In this paper, temperature is transformed into GDD and HDD. Then, PVAL and market land values are expressed as a function of GDD, HDD and (quadratic) precipitation accumulated over the whole cropping season year. Both studies document negative effects of marginal increases in annual temperature and precipitation. The estimated negative effect of precipitation is mainly explained by increases in winter and fall precipitation that are detrimental for land valuation or profitability.

15 This result, however, should be interpreted with caution as access to credit may be determined by agricultural productivity and agricultural productivity could also be determined by having access to credit. This endogeneity, potentially arising from simultaneity, could bias the estimated parameters. **Table A.3** (in the Appendix) shows that the exclusion of the variable identifying access to formal credit does not fundamentally change the main results, which suggest that the potential endogeneity of access to credit might not be a large issue in the working sample.

have been substituted with seasonal climate variables constructed using weather information for the months of March to September, the period officially considered as the Spring-Summer season in Mexico (SADER, 2017). Results are qualitatively similar to those reported in **Table 6**.

The main findings of **Table 6** are also robust to the exclusion of precipitation from the Ricardian equation (columns (3) and (4) in **Table 7**) proving that the result is not due to correlation among the climate variables.

Conclusions

In this paper, I propose a novel version of the Ricardian approach that relies on a shadow valuation of land recovered from the estimation of an agricultural production function. This measure, that I call the productive value of agricultural land, or PVAL, internalizes any shadow components associated with the constraints that farmers face, reflecting more properly the market setting in which farmers make decisions. Also, this measure purely reflects land productivity and is thus free of the other factors polluting market land values that have prompted the omitted variable bias criticism raised around the Ricardian model. I argue that the use of this shadow measure as the dependent variable in a Ricardian estimation leads to more accurate estimates of the relationship between climate and land productivity, particularly in settings where markets are not perfectly competitive.

When the proposed approach is applied to data of rural households in Mexico, I find that indeed, when using PVAL, the relationship between climate and agricultural productivity is stronger and more precisely estimated. Specifically, extremely high temperatures decrease land productivity while more precipitation increases it. Market land values fail to capitalize the negative effects of extreme temperatures and underestimate the positive effect of more precipitation. Altogether, the findings of this article suggest that in settings where markets are incomplete, the use of market land values to represent long-run farm productivity in the Ricardian approach may lead to an underestimation of the effect that climate change may have on agriculture.

The Ricardian approach continues to be a useful tool to get insights about the potential effects of climate change on agricultural productivity but future researchers considering implementing it should also pay attention to the market setting of the context in which it is going to be applied. In a developing country setting, it is important to estimate those losses with a methodology that rightfully captures land productivity in the context of constrained production, particularly if public policies promoting adaptation in developing countries will be designed based on such estimations.

The methodology that I propose in this paper addresses an issue so far ignored in the application of the Ricardian approach: non-competitive markets. It also addresses the issue of omitted factors polluting the Ricardian estimates by relying on a shadow valuation of land that only reflects agricultural productivity. Yet, there are still several caveats that apply to this analysis. First, omitted variables could still affect the Ricardian estimates based on PVAL, particularly those affecting farm productivity and not accounted for in the estimation of the production function. Second, the implementation of the Ricardian approach using PVAL relies on getting unbiased estimates of the parameters governing the agricultural production function, which is only plausible when panel data is available for such purpose. As a result, the implementation of the approach proposed in this paper might be limited in settings where panel data does not exist. Finally, the panel I use in this paper is only two-years long. The shortness of my data prevents me from including fixed effects more geographically disaggregated such as at the state, village or household levels. The residual varelationship between climate and agricultural productivity could vanish, either using PVAL or market land values. This highlights the enormous advantage of having access to long data sets when estimating the Ricardian approach.

Table 1
Summary statistics of agricultural variables

p.55

Variable	Pooled Sample (N = 1,104) Mean	sd	2002 (N = 566) Mean	sd	2007 (N = 538) Mean	sd
Output value (pesos per ha)	9,540.8	19,833.6	8,770.5	19,606.3	10,351.3	20,056.3
Land in production (has)	4.6	6.8	5.3	7.6	3.8	5.6
Labor (days per ha)	65.2	216.6	58.6	234.8	72.2	195.5
Intermediate inputs (pesos per ha)	4,984.5	23,867.3	5,107.9	30,863.4	4,854.7	12,954.1
Value added (pesos per ha)	4,556.3	26,629.8	3,662.6	32,579.8	5,496.5	18,386.9

Note: Monetary values are expressed in real pesos of June 2012.

Table 2
Production function parameter estimates

p.55

p.56

	(1) OLS	(2) Fixed effects	(3) Levinson and Petrin
$\ln\left(labor\right)\left(days\right)\left(L_{it}\right)$	0.228*** (0.036)	0.245*** (0.057)	0.196*** (0.038)
$\ln\left(land\right)\left(hectares\right)\left(T_{it}\right)$	0.425*** (0.041)	0.424*** (0.106)	0.489*** (0.202)
$\ln\left(int\,ermediate\ \ inputs\right)\left(pesos\right)\left(L_{it}\right)$	0.427*** (0.030)	0.118* (0.062)	0.264 (0.282)
Year FE	Yes	Yes	Yes
Observations	1,104	1,104	1,104
R-squared	0.436	0.780	–
Constant returns to scale test (p-value)	0.072	0.063	0.662
Number of household		720	

Note: In OLS and fixed effect, standard errors are clustered at the household level. In LP standard errors are derived using 50 bootstrap replications. * p<0.10, ** p<0.05, *** p<0.01.

Table 3
Market land values vs PVAL estimates (pesos per hectare)

p.56
p.60

		Self-reported		PVAL		Diff.	
	N	Mean	sd	Mean	sd	Mean	sd
a) Pooled							
National	727	75,597.3	121,041.8	100,202.8	201,624.8	-24,605.5***	216,459.6
Southeast	189	40,680.2	73,157.7	50,859.9	72,693.5	-10,179.7*	81,314.5
Center	276	108,177.9	142,258.0	103,704.3	205,878.7	4,473.6	241,480.8
Center-west	131	84,942.3	131,110.3	104,887.1	154,368.8	-19,944.9	162,905.3
Northwest	50	97,228.2	139,590.9	335,317.4	441,723.0	-238,089.1***	451,087.6
Northeast	81	17,589.3	23,710.5	50,696.6	98,523.1	-33,107.3***	97,260.1
b) 2002							
National	418	61,492.4	105,349.9	96,033.2	207,590.3	-34,540.8***	213,421.9
Southeast	121	38,128.0	78,312.4	56,417.7	84,492.6	-18,289.7**	91,829.3
Center	148	85,780.5	125,308.8	78,690.6	153,278.4	7,089.9	189,123.3
Center-west	79	65,794.8	86,634.6	98,484.5	162,360.3	-32,689.8**	129,947.4
Northwest	29	91,766.3	159,375.4	405,498.9	530,380.9	-313,732.6***	543,083.6
Northeast	41	13,068.6	15,614.6	51,935.6	126,012.9	-38,867.0**	122,343.3
c) 2007							
National	309	94,677.7	137,379.6	105,843.2	193,452.7	-11,165.5	220,135.5
Southeast	68	45,221.6	63,252.1	40,970.1	43,432.5	4,251.5	55,855.9
Center	128	134,074.9	156,158.1	132,626.4	251,026.7	1,448.5	291,291.4
Center-west	52	114,031.8	175,805.6	114,614.2	142,358.2	-582.4	202,944.0
Northwest	21	104,770.9	109,891.1	238,400.0	259,252.8	-133,629.1**	256,624.2
Northeast	40	22,223.0	29,319.5	49,426.6	60,180.6	-27,203.5***	63,102.0

Note: The regional distribution of the 14 states of the ENHRUM sample is as follows: a) Southeast: Oaxaca, Veracruz and Yucatán; b) Center: Estado de México, Puebla; c) Midwest: Guanajuato, Nayarit, Zacatecas; d) Northwest: Baja California, Sinaloa, Sonora; e) Northeast: Chihuahua, Durango, Tamaulipas.

Table 4
Summary statistics of household characteristics

p.57
p.59

Variable	Pooled sample (N=1,104) Mean	sd	2002 (N=566) Mean	sd	2007 (N=538) Mean	sd
a) Agriculture						
Private ownership	0.30	0.46	0.31	0.46	0.28	0.45
Rents plots (in or out)	0.10	0.30	0.09	0.29	0.10	0.31
Other land-sharing agreements	0.14	0.34	0.14	0.35	0.13	0.33
Access to irrigation	0.27	0.45	0.28	0.45	0.27	0.44
Received PROCAMPO[1]	0.52	0.50	0.55	0.50	0.48	0.50
Has a tractor	0.11	0.31	0.10	0.30	0.11	0.32
b) Sociodemographics						
Access to formal lending	0.08	0.27	0.08	0.28	0.07	0.25
Access to informal lending	0.19	0.39	0.23	0.42	0.16	0.36
Age of household head (years)	53.36	14.65	51.33	14.68	55.49	14.32
Household head is a male	0.92	0.27	0.92	0.27	0.92	0.27
Household head speaks an indigenous language	0.33	0.47	0.36	0.48	0.31	0.46
Household head's education (years)	3.91	3.32	3.73	3.32	4.09	3.31
Received PROGRESA[2]	0.46	0.50	0.51	0.50	0.40	0.49
c) Geography						
Altitude (meters)	1,323.1	953.2	1,302.1	955.5	1,345.3	951.2
Distance to the nearest city (km)[3]	7.5	8.4	7.6	8.3	7.4	8.4

Notes: 1) PROCAMPO is direct income support program for farmers; 2) PROGRESA is a conditional cash transfer program for poor families; 3) obtained using village information and urban polygons of 2010 National Census (INEGI, 2010). An urban center is defined as a localities with at least 2,500 inhabitants.

Table 5

Summary statistics of climate variables

p.58

		2002				2007			
Region	N	P(mm)	T(°C)	GDD	HDD	P(mm)	T(°C)	GDD	HDD
National	**80**	**867.3**	**20.2**	**4,396.7**	**4.46**	**860.6**	**20.3**	**4,413.7**	**5.37**
Southeast	16	1,406.7	23.8	5,640.8	0.40	1,396.7	23.8	5,646.9	0.51
Center	16	1,238.5	16.1	2,927.4	0.00	1,213.8	16.2	2,937.3	0.00
Mid-west	16	724.7	19.8	4,283.7	0.01	728.9	19.8	4,292.1	0.01
Northwest	16	476.2	22.9	5,345.6	21.6	478.1	23.1	5,435.9	26.01
Northeast	16	490.6	18.3	3,786.2	0.30	485.6	18.4	3,756.5	0.30

Note: Climate variables are calculated using daily information for the 30 years preceding each survey round.

Table 6
Ricardian regressions of PVAL and self-reported land values and annual measures of climate

Variable	(1)	(2)	(3)	(4)
	$\ln(\text{PVAL})$	ln (self-reported)		ln (self-reported)
GDD	0.000015 (0.000130)	0.000091 (0.000133)	0.000009 (0.000132)	0.000089 (0.000133)
HDD	-0.015496* (0.008425)	-0.006339 (0.011063)	-0.015177* (0.007857)	-0.006212 (0.010983)
P	0.003247*** (0.000819)	0.002369** (0.000888)	0.003200*** (0.000833)	0.002324** (0.000894)
P^2	-0.000001** (0.000000)	-0.000001** (0.000000)	-0.000001** (0.000000)	-0.000001** (0.000000)
Land in production (has)	-0.036587*** (0.010666)	-0.024746*** (0.006935)	-0.037262*** (0.010675)	-0.024776*** (0.006969)
Access to irrigation	1.045263*** (0.137444)	0.596464*** (0.128479)	1.037653*** (0.137452)	0.592293*** (0.126221)
Access to formal credit	0.507907*** (0.136567)	0.087750 (0.153970)	0.514732*** (0.136238)	0.092837 (0.155171)
Distance to the nearest city (km)	-0.013498 (0.009325)	-0.044360*** (0.009720)	-0.012945 (0.009580)	-0.044182*** (0.009894)
Private ownership	-0.006149 (0.089106)	-0.033831 (0.100481)	-0.008190 (0.092026)	-0.032750 (0.100469)
P^*	2053.766*** (239.3249)	1577.595*** (220.6674)	2064.083*** (244.5255)	1580.753*** (226.9516)
Marginal effects of P	0.001564*** (0.0003545)	0.0007397* (0.0003866)	0.001549*** (0.0003612)	0.0007289* (0.0003855)
$\overline{P}$	1064.981	1084.998	1064.981	1084.998
Observations	1,104	908	1,104	908
R-squared	0.366	0.476	0.368	0.477
Year and region FE	YES	YES	NO	NO
Region-by-Year FE	NO	NO	YES	YES
Region-by-Year FE	NO	NO	YES	YES

Note: Clustered standard errors at the village level are reported in parentheses. Regressions include all the variables summarized in **Table 4** and fifteen categories of major soil types. The age and indigenous background of the household head have a negative effect on PVAL and are the only sociodemographics with statistical significance. Altitude and soil types are highly significant in all regressions. *p < 0.10, **p < 0.05, ***p < 0.01

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Table 7
Robustness of the results to alternative definitions of climate

Variable	Spring-Summer		Annual with no precipitation	
	(1)	(2)	(3)	(4)
	$\ln(\mathrm{PVAL})$	ln (self-reported)	$\ln(\mathrm{PVAL})$	ln (self-reported)
GDD	-0.000058 (0.000234)	0.000122 (0.000224)	-0.000063 (0.000168)	0.000009 (0.000137)
HDD	-0.012658* (0.007065)	-0.004416 (0.009930)	-0.021385** (0.010202)	-0.012709 (0.013661)
P	0.004451*** (0.001072)	0.003922** (0.001171)		
p^2	-0.000001** (0.000000)	-0.000002** (0.000001)		
Land in production (has)	-0.037333*** (0.010687)	-0.024537*** (0.006837)	-0.040722*** (0.011785)	-0.025221*** (0.007217)
Access to irrigation	1.021737*** (0.135868)	0.585115*** (0.122276)	1.004245*** (0.129600)	0.630144*** (0.131251)
Access to formal credit	0.507237*** (0.134946)	0.087600 (0.152107)	0.521458*** (0.129339)	0.083901 (0.161930)
Distance to the nearest city (km)	-0.010531 (0.009270)	-0.042178*** (0.009541)	-0.015839 (0.011431)	-0.048277*** (0.011281)
Private ownership	-0.015609 (0.09132)	-0.049513 (0.101765)	0.121361 (0.115214)	0.029388 (0.099378)
Observations	1,104	908	1,104	908
R-squared	0.371	0.484	0.336	0.464
Region-by-Year FE	YES	YES	YES	YES

Note: Clustered standard errors at the village level are reported in parentheses. Regressions include all the variables summarized in **Table 4** and fifteen categories of major soil types. Regressions include region-by-year fixed effects. When region and year fixed effects are included separately, results are similar. *p < 0.10, **p < 0.05, ***p < 0.01

Appendix

Table A.1
Residual variation in climate
Number of household-year observations for which predicted climate differs from observed climate by more than

Fixed effects	**(1)**	(2)	**(3)**	(4)	(5)
Panel a) Annual temperature	Mean (sd) = 19.329 (4.545)				
	0.5 °C	1.0 °C	1.5 °C	2.0 °C	2.5 °C
State and Year	745	570	425	336	226
Region and Year	1,030	891	846	667	549
State-by-Year	765	566	433	344	226
Region-by-Year	1,028	896	837	654	556
Panel b) Annual GDD	Mean (sd) = 4,077.1 (1,645.7)				
	100 GDD	200 GDD	300 GDD	400 GDD	500 GDD
State and Year	921	736	671	558	503
Region and Year	1,058	1,030	963	915	878
State-by-Year	908	745	669	558	504
Region-by-Year	1,049	1,031	962	900	878
Panel c) Annual HDD	Mean (sd)=0.676 (4.793)				
	0.5 HDD	1.0 HDD	1.5 HDD	2.0 HDD	2.5 HDD
State and Year	157	74	69	47	47
Region and Year	111	105	100	66	66
State-by-Year	139	71	71	44	44
Region-by-Year	109	105	104	66	66
Panel d) Annual precipitation	Mean (sd) =1,065.0 (639.9)				
	100mm	200mm	300mm	400mm	500mm
State and Year	624	546	417	362	277
Region and Year	924	770	682	566	388
State-by-Year	607	515	423	332	261
Region-by-Year	952	748	695	537	418
N= 1,104					

Note: This table (adapted from Jessoe et al., 2018) reports the extent of the residual variation of climate left after controlling for the different sets of location and time fixed effects listed in the Fixed effects column. Each panel shows the number of observations for which the absolute value of predicted climate differs from observed climate by more than the number in the head of each column. For example, in panel a), the cell at the intersection of the first row and column (1) indicates that after regressing annual temperature on state and year fixed effects, the absolute value of the predicted temperature was at least 0.5°C higher than observed temperature in 745 (out of 1,104) observations. When conditioning on regional and year fixed effects, this number increases to 1,030 or 93% of the total number of observations. The interpretation of columns (2) to (5) and of panels b) to d) is similar.

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Table A.2

Ricardian regressions of PVAL and self-reported land values on temperature and precipitation

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	(1)	(2)	(3)	(4)
Variable	$\ln(\mathrm{PVAL})$	ln (self-reported)	$\ln(\mathrm{PVAL})$	ln (self-reported)
T	0.172177 (0155713)	-0.192224 (0.224604)	0.169660 (0.156898)	-0.196040 (0.222797)
T^2	-0.004543 (0.003783)	0.006128 (0.006328)	-0.004542 (0.003799)	0.006187 (0.006305)
P	0.003481*** (0.000793)	0.002326** (0.000846)	0.003432*** (0.000806)	0.002274** (0.000850)
P^2	-0.000001*** (0.000000)	-0.000001** (0.000000)	-0.000001*** (0.000000)	-0.000001** (0.000000)
Land in production(has)	-0.037308*** (0.009937)	-0.026337*** (0.006985)	-0.037978*** (0.009954)	-0.026342*** (0.007032)
Access to irrigation	1.065637*** (0.139251)	0.577286*** (0.135324)	1.058398*** (0.138817)	0.573114*** (0.133461)
Access to formal credit	0.512982*** (0.135520)	0.090416 (0.153156)	0.520089*** (0.135338)	0.095245 (0.154445)
Distance to the nearest city (km)	-0.011184 (0.008903)	-0.043861*** (0.009812)	-0.010652 (0.009155)	-0.043720*** (0.009983)
Private ownership	-0.021147 (0.085283)	-0.008556 (0.098468)	-0.023141 (0.087786)	-0.007300 (0.098622)
R-squared	0.366	0.478	0.368	0.479
Observations	1,104	908	1,104	908
Year and region FE	YES	YES	NO	NO
Region-by-YearFE	NO	NO	YES	YES

Note: Clustered standard errors at the village level are reported in parentheses. Regressions include all the variables summarized in **Table 4** and fifteen categories of major soil types. *p < 0.10, **p < 0.05, ***p < 0.01

Table A.3
Ricardian regressions of PVAL and self-reported land values omitting access to formal credit

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	(1)	(2)	(3)	(4)
Variable	ln (PVAL)	ln (self-reported)	ln (PVAL)	ln (self-reported)
T	0.000018 (0.000130)	0.000090 (0.000132)	0.000012 (0.000131)	0.000088 (0.000133)
T^2	-0.016279* (0.009319)	-0.006497 (0.011277)	0.015999* (0.008807)	-0.006396 (0.011228)
P	0.003288*** (0.000828)	0.002364*** (0.000888)	0.003236*** (0.000844)	0.002319** (0.000894)
P^2	-0.000001*** (0.000000)	-0.000001** (0.000000)	-0.000001*** (0.000000)	-0.000001** (0.000000)
Land in production(has)	-0.033361*** (0.011090)	-0.024303*** (0.007173)	-0.034017*** (0.011100)	-0.024310*** (0.007198)
Access to irrigation	1.075268*** (0.140288)	0.601832*** (0.127835)	1.067800*** (0.140762)	0.597841*** (0.125673)
Access to formal credit				
Private ownership	-0.027631 (0.086260)	-0.037403 (0.100953)	-0.029948 (0.089211)	-0.036529 (0.100971)
Distance to the nearest city (km)	0.014887 (0.009303)	-0.044604*** (0.009654)	-0.014422 (0.009537)	-0.044455*** (0.009823)
R-squared	0.359	0.476	0.360	0.476
Observations	1,104	908	1,104	908
Year and region FE	YES	YES	NO	NO
Region-by-YearFE	NO	NO	YES	YES

Note: Clustered standard errors at the village level are reported in parentheses. Regressions include all the variables summarized in **Table 4** and fifteen categories of major soil types. * p<0.10, ** p<0.05, *** p<0.01

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Figure 1
Location of ENHRUM villages and weather stations

Note: The map shows the location of the 80 ENHRUM villages and the weather stations used to interpolate weather data to each village. The interpolation is limited to the 5 closest weather stations.

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