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Optimal Crop Choice: Farmer Adaptation to Climate Change*

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Abstract

I use a Mixed Logit model and the most detailed agricultural data publicly available to show how farmers employ land allocation as an adaptation mechanism in the face of a changing environment. The driving forces behind the farmer's land-use choice are differences between the crops available for cultivation as well as the soil, climate, and observable and unobservable (to the econometrician) characteristics of the farm. I present a measure of the effects of climate change on agricultural land value based on a structural model of farmer behavior and a mix of data at the plot, county, state and national levels. Results from most previous research are based on county-level data. The improved resolution of the data used in this paper allows us to test the validity of assumptions made in earlier work. Moreover, results show that substitution across crops depends directly on differences in climate for each plot.

Key Words: Climate Change, Adaptation Costs, Land Rents, Mixed Logit

JEL Classification: Q1, Q2, C5

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1 Introduction

After more than a decade of debate, the scientific community now agrees that climate change is one of the most critical environmental problems to face the planet this century¹. The issue has shifted from a scientific to a political and economic question for which common wisdom indicates severe economic consequences. However, recent economic studies show a small but positive effect.

In general, studies of the effects of climate change on the economy have focused on agriculture as it is the economic activity most likely to quickly reflect the effects of changes in climate. In particular, estimates of economic impacts rely either on the link between climate and agricultural production (agricultural process models²), between climate and land values (Ricardian approach³), or between climate and agricultural profits (profit function approach⁴). These three schools of thought have provided insight on a number of phenomena, the most important of which is that profit-maximizing farmers will change crop and farming practices to adapt to any changes in climate, implying that farmers' decisions are, in fact, relevant for estimating the economic impact of climate change. Prior to this present study, economists based their research on assumptions about how the farmer would make her decisions but they were unable to directly account for them⁵. This paper focuses precisely on the issue of farmer adaptation by relying directly on the link between climate and farmers' adaptive behavior.

There are two main assumptions used in the literature. At one extreme, the "agricultural process models" assume that the farmer is constrained to continue farming the same crop no matter how climate changes. This hypothesis is quite simple in that it suggests that crop yields will change with climate and that farmers will assume whatever profits or losses

¹For example, see Oreskes [23], or National Academy of Science [20].

²Examples of this literature are Adams et al. [4], [2], and [3], Mjelde et al. [19], Reilly et al. [24], Schneider et al. [27], Solow et al. [28], among many.

³See Mendelsohn, Nordhaus and Shaw [16], [17], [18], and Schlenker, Hanneman and Fisher [26].

⁴See Deschenes and Greenstone [7], and Kelly, Kolstad, and Mitchell [11].

⁵One notable exception to this statement is the paper by Kelly, Kolstad and Mitchell [11]. However, their focus is not on adaptation but on adjustment costs.

associated with that yield. Consequently, the researcher only needs to focus on the link between climate and crop yields to obtain quantitative economic predictions. Early studies relied upon this approach and this produced unrealistically high estimates of the possible costs of climate change. More recent research considers these estimates to be upper bounds of the actual costs as it does not consider all the actions farmers can take to ameliorate the effects of climate change on their profits.

At the other extreme, the “Ricardian approach” is based on David Ricardo’s premise that any changes in future profitability of land will be immediately capitalized into the land value. For this school of thought, the main assumption is that farmers can adapt to any changes in climate immediately and effortlessly. The belief is that farmers are keenly aware of the changes in climate and they immediately select those crops as well as practices that are most appropriate to the new climate. This assumption effectively lifts all constraints on the way farmers make their land-use decisions. Estimates produced under this model should be considered a lower bound to the actual cost from climate change as, at least in the short-run, there may be constraints that prevent the farmer from responding to climate changes with the promptness assumed by these researchers.

Between these two extremes we have the “profit function approach”. Here, the belief is that farmers will make decisions that incorporate their views about climate which will, in turn, impact their profits. Short-run considerations can be easily incorporated into the analysis. This model allows researchers to eliminate previous assumptions about farmer behavior and, instead, estimate this behavior directly. However, doing so requires detailed data sets and, thus far, no published study has focused on the effect of climate on farmer decisions.

This paper offers a fourth, or alternative, methodology based directly on the link between climate and farmers’ cropping decisions. I develop a model of choice in which profit-maximizing farmers with heterogeneous plots of land choose the best crop for the given conditions in their location. Estimates from this model are used to infer farmer adaptive

behavior, in the form of changes in land-use patterns, as a response to a change in climate. Taking into account recent econometric advances in Industrial Organization, Public Economics and Environmental Economics, a logical way to improve our understanding of farmer behavior is to use the lowest level of behavioral data available. In this model, consideration is given to decision making for parcels as small as one-acre plots, the smallest decision unit for the farmer, where data are characterized by the discrete choice of the most adequate crop for cultivation. Previous approaches have only considered data at the county level, possibly failing to characterize the farmers' choice at the plot level. This could mislead us in our understanding of farmer's adaptive behavior. To avoid this problem, the model in this paper incorporates recent advances in discrete choice theory that allow us to take advantage of information on a sample of more than 60,000 one-acre plots of land in the United States.

In the model presented in this paper, the farmer makes land-use decisions based on crop prices, average expenses on variable inputs for different crops, as well as soil, climate, and other observable and unobservable (to the econometrician) characteristics of the plot. Given this information, the farmer chooses the cultivar that yields the highest profits for the plot and repeats this process for every plot on her farm. Using a detailed sample of plot characteristics I estimate the share of land dedicated to each crop in each county as a function of plot and crop characteristics. At any aggregation level, be it a farm, county, or state, the distribution of the farmers' decisions and, therefore, the distribution of profits and supply of the different crops can be characterized. By exploiting the panel nature of my data, I am able to identify the parameters that primarily influence farmers' decisions.

I follow the estimation strategy proposed by Berry [5] and Berry, Levinsohn, and Pakes [6] (hereafter BLP) for a type of discrete choice problem in which the distribution of heterogeneity, in this case in the form of plots of different characteristics, determines substitution across crops. Ideas developed in Nevo [21] to introduce actual observations of this heterogeneity in the estimation are also incorporated. As in previous work, the modeling and estimation strategies presented here allow us to estimate the damages (or benefits) due to

climate change on agriculture. Moreover, using this approach it is possible to forecast farmers' decisions at a level of disaggregation not possible with previous approaches. This gives us the opportunity to derive welfare measures at the intra-county level as well as predict the distribution of land uses within counties.

In the next section, I discuss different methods used in the literature to estimate the effects of climate change. Section 3 presents a description of the economic model in this paper as well as a discussion of different empirical specifications for this model. Section 4 includes a description of the estimation procedure and a discussion of the results from preliminary regressions and the full model. Conclusions and closing comments follow in section 5.

2 Measuring the effects of Climate Change

Many of the challenges that scientists encounter when attempting to quantify the magnitude of the impacts of climate change stem from the nature of climate itself. In economic terms, climate is a very complex commodity. As a consumption good, it makes locations like Santa Barbara, California, a prime location for residential communities. As a production input, climate will dictate that the most likely location for producing crops is the Corn Belt and, conversely, it makes Death Valley the last place where one would expect to see large-scale agricultural production. Of course, climate cannot be changed or modified at will, nor can it be moved from one location to another. Moreover, climate is not a commodity that can be traded directly. It is bundled up into goods such as housing, land, or into agricultural products. Thus, to measure the effects of climate on the economy one has to turn to factors that are measurable in markets. The literature then makes use of the fact that climate is a direct input for agricultural production to construct estimates of the economic effects of climate change. This suggests that any changes in climate will affect the market for agricultural goods from the production side. It also gives us several theoretical and empirical

ways in which to approach the problem, which I summarize in the following paragraphs.

Agricultural process models⁶ center on the link between climate and production. Because of their focus on production, in general, they can benefit from precise estimates obtained from physiological or technical models of crop production. Moreover, many of these models include data on crop and input prices that are used to construct measures of welfare changes due to changes in crop yields. Earlier studies severely constrained farmer adaptation mechanisms which produced upward-biased estimates of the effect of climate on agriculture. More recent studies, such as Adams et al. [3] and Reilly et al. [24], have included a wide range of possible adaptation mechanisms for the farmer. Nevertheless, as pointed out in Mendelsohn et al. [16] (hereafter MNS) and Schneider et al. [27], even the most detailed models will miss some of the adaptation opportunities available to farmers.

The Ricardian approach⁷ uses land characteristics, including climate, to explain land values. Here, the main assumption is that land values incorporate all the information about any adaptation that a farmer can undertake. Thus, in the context of this approach, adaptation is assumed to be complete, both in the choice of inputs and outputs. Furthermore, the movement to the new equilibrium after climate has changed is made effortlessly by the farmer. This implies that estimates from Ricardian models should be considered a lower bound of the effects of climate change. Note, however, that it is well known that these types of models are not apt to measure the effects of non-localized, non-marginal changes in the explanatory variables (Freeman [8]). These are exactly the type of changes that would cause farmers to change to a more profitable crop. Additionally, this approach may suffer from severe missing variable bias if some of the determinants of land value are not observed (Freeman [8] and Deschenes and Greenstone [7]).

While the agricultural process models and the Ricardian approach can be considered two extremes in terms of the types of assumptions made on adaptive behavior, the profit function

⁶For a sample of references, see footnote 1.

⁷See Mendelsohn, Nordhaus and Shaw [16], [17], [18], and Schlenker, Hanneman and Fisher [26]. The first application of this approach to the climate change literature appears in MNS. Johnson and Haigh [10] use similar methodology to estimate the effects of potentially modifiable aspects of climate.

approach can relax these assumptions and allows for farmer adaptation to be estimated directly. However, to date, the focus of this literature has not attempted to directly construct measures of farmer adaptation.

For example, Kelly, Kolstad and Mitchell [11] (hereforth KKM) define adaptation as the change in profits that occurs from an equilibrium point before climate change to an equilibrium point after climate change. They recognize that the movement from one equilibrium point to the next may not be immediate and effortless as assumed in the Ricardian approach, and that there may be adjustment costs associated with the transition between equilibria. However, the focus of their analysis is on adjustment cost rather than the process of adaptation.

Also within the context of the profit function approach, Deschenes and Greenstone [7] use presumable random variation in weather across counties to estimate the effects of weather on farm profits. However, they do not include prices in their estimation, so we cannot readily infer farmer behavior from their approach.

The analysis presented in this paper differs from the previous literature in both its focus and its methodology. Much of the previous research has centered its attention on either county-level estimates of either land values or profits and, even though these studies have land use at their core, crop choice does not appear explicitly in these models. In this paper, the land-use decision is explicit both in the modeling of the problem and in its estimation. The main assumption in this paper is that farmers rely on their land-use choices to maximize profits and that climate, as well as more traditional economic measures, can directly affect these decisions. Tables (1) through (4) show evidence of this fact⁸.

Moreover, county-level data may not be appropriate to represent the farmers' crop choice. For example, by examining slope length, a measure of distance to water sources⁹, we are able

⁸Tables (1) and (2) show how the choice of crop varies with average temperature. Results are similar for precipitation. Tables (3) and (4) show the gross value of production, crop price and production costs which will also affect the choice of crop. For example, wheat is very adaptable to different types of climates. However, a farmer will readily substitute to a different crop if higher profits are to be made.

⁹See the data appendix for a more precise definition of slope length.

to see the shortcoming of using such data. Suppose for example, that we have two counties with two distinctive plots of land each. These two counties are, in fact, the same in every aspect except that in county A, one plot has a slope length of 50 feet and the other has a slope length of 100 feet while for county B both plots have a slope length of 75 feet. When we don't observe the internal heterogeneity of counties, we may think that these two counties are actually the same as they both have an average slope length of 75. If both of these counties have a wet climate, slope length is not important for cropping decisions and we do not need to worry about aggregation issues. However, if climate is or becomes dry enough, slope length becomes important as the availability of water will greatly impact the farmers' land-use decisions. In this case, aggregate data will bias our results.

In short, this paper adds to the literature by presenting a model which quantitatively describes the link between climate and farmer decisions, and which accounts for the richness of insight gained by analysis at a geographic level ten to hundred fold more refined than previous work.

3 Framework

There are two factors that determine the farmer's choice, the characteristics of the crops under consideration, which are measured in the form of prices and costs, and the characteristics of the land where the crop will be grown, given in terms of climate, weather, and soil characteristics such as salinity, slope, et cetera. Crop and plot characteristics enter the farmers' decision process by affecting the profits a farmer can get from cultivating a given crop. Given a small change the farmer might find it optimal to continue to grow the same crop and suffer small gains or losses in profits, a large change, on the other hand, may induce the farmer to substitute crops as relative profits will most probably be affected by the change. Therefore, we can determine the potential costs/benefits of climate change for agriculture and derive concrete measures of farmer adaptive behavior in the form of changes in land use

by analyzing the effect of climate on profits.

Let producers participate in perfectly competitive markets for agricultural goods, agricultural inputs and land. Further assume that agricultural output is produced in plots of land of size 1, indexed by $j = 1, \dots, J$. At the plot level, production for output (crop) $i \in \{1, \dots, I\}$ is undertaken according to a well-behaved production function:

$$(1) \quad q_{ij} = f_i(x_{ij}, z_j).$$

This production function depends on expenditures in variable inputs x_{ij} and the availability of exogenously given inputs¹⁰ z_j at plot j , one of which is climate. Note that x_{ij} can vary by output, even within a given site, while z_j is outside the control of the farmer no matter what the farmer decides to plant in the plot.

For output price, p_i , the farmer chooses how much to spend on inputs so to be able to grow crop i in plot j in the most profitable manner. Formally,

$$(2) \quad \begin{aligned} \Pi_{ij}(p_i, z_j) &= \max_{x_{ij}} \{p_i f_i(x_{ij}, z_j) - x_{ij}\} \\ &= q_i(p_i, z_j) p_i - c_i(p_i, z_j) \bar{c}_i. \end{aligned}$$

Assuming an interior solution to the maximization problem above, the optimal amount of output is given by $q_{ij}^* = q_i(p_i, z_j)$ while the profit-maximizing choice of input expenditures is given by $x_{ij}^* = c_i(p_i, z_j) \bar{c}_i$, where \bar{c}_i are the mean cost expenditures for crop i , and $c_i(p_i, z_j)$ is a function that captures how farmers may find it optimal to deviate from that mean because of differences in the plot characteristics. However, because of the constraints imposed by the exogenous availability of z_j , even at the optimal level of variable input expenditures, different crops will have varying degrees of success in a plot. The farmer will choose the crop

¹⁰The vector z_j can include plot attributes as well as characteristics of the decision maker.

that yields the highest profit for the plot,

$$(3) \quad \Pi_{*j}(p, \bar{c}, z_j) = \max \{ \Pi_{1j}(p_1, \bar{c}_1, z_j), \dots, \Pi_{Ij}(p_I, \bar{c}_I, z_j) \},$$

where $p = (p_1, \dots, p_I)$, $\bar{c} = (\bar{c}_1, \dots, \bar{c}_I)$, and subscript $*$ represents the optimal choice of crop and $* \in \{1, \dots, I\}$.

Changes in the current conditions in plot j , measured through changes in z_j , affect crop profits by way of equation (2), as conditions may become more or less favorable for the current choice of crop. Moreover, a large enough change in z_j could affect relative profits perhaps making the current crop less profitable than other alternatives. A profit-maximizing farmer will substitute to the most profitable crop as shown in equation (3).

It is important to emphasize that, even though the farmer has no control over plot characteristics, these characteristics do determinate the farmer's production expenditure decisions as well as the optimal choice of crop. In the next section, I propose an empirical specification that allows us to measure changes in farmers' profits as well as any changes in land-use patterns caused by adaptive behavior undertaken by farmers in response to changes in z_j .

3.1 Empirical Specification

Equations (2) and (3) characterize a discrete choice model in which farmers chose the best crop for their plot of land depending on crop and plot characteristics. Thus, we need to specify a profit function for each crop as well as a representation of the farmer choice of crop in equation (3). Data on the farmers' decisions are available at the county level in the form of shares of land dedicated to each crop. County heterogeneity is observed in the form of data on plot characteristics.

Let farmers, in counties indexed by $f = 1, \dots, F$, choose one of $i = 1, \dots, I$ crops to grow in each plot $j = 1, \dots, J$ during year $t = 1, \dots, T$. Crops are characterized by their

prices, p_{it} , and average costs of production, \bar{c}_{it} . Crop attributes that are unobservable to the econometrician, but known to the farmer are represented by $\alpha_{ift} = \alpha_i + \Delta\alpha_{ift}$, where α_i captures those attributes that do not vary with county or time and $\Delta\alpha_{ift}$ is a county and time specific deviation from α_i .

For the full model specification, let profits for each crop assume the following functional form:

$$(4) \quad \Pi_{ijft}(\cdot) = \alpha_i + \beta^p(z_{jft}, \varphi_{jf}) p_{it} + \beta^c(z_{jft}, \varphi_{jf}) \bar{c}_{it} + \Delta\alpha_{ift} + \varepsilon_{ijft},$$

where ε_{ijft} is a mean-zero stochastic term and $\beta^p(\cdot)$ and $\beta^c(\cdot)$ are productivity parameters for plot j that depend on observed and unobserved plot characteristics, which are denoted by z_{jft} and φ_{jf} respectively. The parameters $\beta^p(\cdot)$ and $\beta^c(\cdot)$ relate directly to $q_i(p_i, z_j)$ and $c_i(p_i, z_j)$ in equation (2). More specifically, for $\beta(z_{jft}, \varphi_{jf}) = (\beta^p(z_{jft}, \varphi_{jf}), \beta^c(z_{jft}, \varphi_{jf}))$, these random coefficients are modeled as

$$(5) \quad \beta(z_{jft}, \varphi_{jf}) = B + \Lambda z_{jft} + \Sigma \varphi_{jf}, \quad \varphi_{jf} \sim N(0, I),$$

where z_{jft} is a $k \times 1$ vector of observed plot characteristics (land characteristics, climate and demographic variables), φ_{jf} captures additional unobserved characteristics of the plot, Λ is a $2 \times k$ matrix of coefficients that measure how productivity vary with plot characteristics, and Σ is a 2×2 diagonal scaling matrix. The elements of Λ and Σ are denoted by λ and σ with the corresponding subscripts. Thus, conditional on z_{jft} , the distribution of the productivity parameters is a multivariate normal with mean $B = (B^p, B^c)$ and a variance to be estimated.

To complete the specification of the supply system, we introduce an outside option that allows the farmer the choice of not growing any of the crops included in the analysis and, thus, allocating land to any other use. Without this allowance, a homogenous price increase

for all crops, relative to other sectors, will not change the quantities supplied.

$$(6) \quad \Pi_{0jft} = \alpha_0 + \lambda_0 z_{jft} + \sigma_0 \varphi_{jf} + \varepsilon_{0jft}.$$

The mean profits of the outside option, α_0 , are not identified without either making more assumptions or normalizing one of the inside land uses. Also, the coefficients λ_0 and σ_0 , elements of Λ and Σ , are not identified separately from coefficients on an individual-specific constant term in equation (4). The standard practice is to set α_0 , λ_0 and σ_0 to zero which is equivalent to normalizing profits to zero for the outside option.

Combining equations (4) and (5) we have

$$(7) \quad \begin{aligned} \Pi_{ijft} (p_{it}, \bar{c}_{it}, z_{jt}, \varphi_j, \Delta\alpha_{ift}|\theta) &= \pi_{ift} + \mu_{ijft} + \varepsilon_{ijft}, \\ \pi_{ift} &= \alpha_i + B^p p_{it} + B^c \bar{c}_{it} + \Delta\alpha_{ift} \\ \mu_{ijft} &= [p_{it}, \bar{c}_{it}]' * (\Lambda z_{jt} + \Sigma \varphi_j), \end{aligned}$$

Thus, equation (7) is our empirical representation of profits, as given in equation (2). Note that this specification of profits is not unlike the restricted generalized McFadden profit function KKM estimate. Here π_{ift} is the mean profits from planting crop i (common to all farmers in county f), and $\mu_{ijft} + \varepsilon_{ijft}$ is a mean-zero heteroscedastic deviation from the mean profits that captures the effects of observed and unobserved land characteristics on the random coefficients. As before, the farmer will produce crop i if:

$$\Pi_{ijft} \geq \Pi_{kjft} \quad \forall k$$

A plot is defined as a vector of observed characteristics, unobserved characteristics and product-specific shocks $(z_{jft}, \varphi_{jf}, \varepsilon_{0jft}, \dots, \varepsilon_{Ijft})$. We can use this vector, then, to implicitly define the set of plot attributes that lead to the choice of crop i . Formally, let A_{jft} be the

set of plot characteristics that results in the choice of crop i :

$$A_{jft} = \{ (z_{jft}, \varphi_{jf}, \varepsilon_{0jft}, \dots, \varepsilon_{Ijft}) \mid \Pi_{ijft} \geq \Pi_{kjft} \quad \forall k = 0, 1, \dots, I \}.$$

Assuming ties occur with zero probability, the market share for the i th crop is just an integral over the mass of plots in region A_{jft} . Under our functional form assumptions on π_{jft} and distributional assumptions on the error term $\mu_{ijft} + \varepsilon_{ijft}$, the probability that a plot is planted with crop i is:

$$(8) \quad \begin{aligned} s_{ift} (z_{.ft}, p_{.t}, \bar{c}_{.t}, \pi_{.ft}; \theta_2) &= \int_{A_{if}} dP(z, \varphi, \varepsilon) \\ &= \int_{A_{if}} dP_\varepsilon(\varepsilon) dP_\varphi(\varphi) dP_z(z), \end{aligned}$$

where the second equality is a consequence of independence assumptions, and where $P_\varepsilon(\cdot)$, $P_\varphi(\cdot)$ and $P_z(\cdot)$ denote distributions functions for ε , φ and z . The distribution of unobserved characteristics plot, $P_\varphi(\cdot)$, is assumed to be a multivariate normal with mean zero and variance matrix to be estimated while $P_z(\cdot)$ is an empirical distribution derived from a large sample of plot data. Thus, equation (8) gives us a measure of the land shares dedicated to each crop as a function of crop, plot characteristics and parameters to be estimated.

To obtain a simpler expression for the land shares, I follow the discrete choice literature and assume that ε is distributed *i.i.d.* extreme value. Under this assumption, our expression for (8) reduces to mixed logit choice probabilities,

$$(9) \quad s_{ift} (z_{.ft}, p_{.t}, \bar{c}_{.t}, \pi_{.ft}; \theta_2) = \int \frac{e^{\pi_{ift}}}{1 + \sum_{k=0}^I e^{\pi_{kft}}} dP_\varphi(\varphi) dP_z(z),$$

which, combined with our observed crop shares S_{ift} , provide us with a way to estimate the model.

3.2 Alternative Distributional Assumptions

Different assumptions on the distributions of z , φ and ε produce different models with distinctive characteristics. If we assume that consumer heterogeneity enters land rents only through ε , which is assumed to be distributed Type I extreme value, then the full model reduces to a multinomial logit. The multinomial logit model has an advantage in its well-known properties and in the fact that the integral in equation (8) can be computed analytically (McFadden [13]). However, through its independence of irrelevant alternatives property (I.I.A.), the multinomial logit model imposes restrictions on the cross-price elasticities that prove to be unrealistic in the farmers' choice of crop. I.I.A. implies that if two crops have similar shares, substitution with a third crop will be the same for the two original crops. However, differences in land characteristics across plots may make this assumption unrealistic. Different crops may require different types of soil or climate to grow successfully. Thus, it is reasonable to think that a farmer is more likely to substitute her current crop for another crop that also does well on her land. Moreover, the fact that the outside share is large relative to all crops implies that, under multinomial logit, substitution to the outside option will be downward biased. Note though that I.I.A. can be relaxed by segmenting the choice into different classes. This approach results in a generalized extreme value model (McFadden [14]). However, even though substitution patterns are less restrictive in these types of models, they still depend on the researcher's *a priori* segmentation of the choice set.

The full model does not impose these restrictions and, in fact, can provide us with an arbitrarily closed approximation to any discrete choice model, including those models discussed above (McFadden and Train [15]). It allows for flexible own-price elasticities that are dependent on the farmers' price/cost sensitivities rather than the choice of functional form. More importantly, in the full model, $\mu_{ijf} + \varepsilon_{ijf}$ depends on crop and plot characteristics in such a way that these characteristics are what drive the farmers' substitution patterns.

The flexibility of the full model comes at a cost, however. The integral in equation (8) cannot be computed analytically without the simplifying assumptions that result in more

restrictive models of farmer behavior. However, the estimation strategy proposed by Berry [5], BLP and Nevo [21], deals with this problem by doing the integration numerically. In addition, their estimation algorithm can account for possible correlation between prices and unobserved product characteristics due to measurement error or endogeneity of prices and costs.

4 Estimation and Data

4.1 Estimation

Market shares as well as price and costs are assumed to be endogenous to the model. However, as shown by BLP, the parameters of the model as defined in equation (7) can be estimated by the Generalized Method of Moments (GMM) to account for the endogeneity problem. Berry [5] and BLP show that the structural error term can be computed as a function of observable variables and the parameters of the model. This observation makes the application of GMM possible in this context. I also follow Nevo [21] in its extension of the BLP procedure to introduce actual observations of plot heterogeneity in the estimation rather than relying solely on parametric assumptions about this heterogeneity. The estimation procedure presented here diverges from these two sources in the choice of instrumental variables and the identifying assumptions that support them. It is also different in that the characteristics and completeness of the data allow us to model unobserved crop characteristics using brand-dummy variables without having to resort to a second estimation step as necessary in Nevo to recover all the parameters of the model [21].

For the estimation of profit functions in general, prices present two particular problems. First, to be consistent with economic theory, we need to take into account the fact that cross-price elasticities have a role in farmers' land-use decisions. This is especially true in the profit function approach¹¹, creating a problem of dimensionality. Even in the most simple

¹¹The Ricardian approach assumes that prices and costs are the same across the entire United States and,

profit function specifications, the number of parameters increases with the squared number of agricultural products under consideration. This problem is even more significant if we use a flexible functional form. In previous studies, this problem was solved by making use of different assumptions about the role of prices in estimation. Deschenes and Greenstone [7] justify leaving prices and cost entirely out of their empirical specification by using a complete set of fixed effects that they assume capture the effects of prices on profits. KKM adopt a flexible functional form and restrict higher order coefficients to zero to make estimation manageable¹².

In the specification above, the dimensionality problem is completely avoided by projecting land uses onto price/cost space. This allows for a parsimonious specification in which price/cost is the relevant space and not the number of crops (agricultural products) we incorporate into the analysis. The second problem with prices is that both p_{it} and \bar{c}_{it} are generally assumed to be endogenous to the model¹³. We follow the Industrial Organization literature and deal with the endogeneity of prices and costs by using a GMM approach¹⁴.

Heterogeneity in the error term presents a second challenge in estimation. Note that the source of this heterogeneity is in the different characteristics of plots both within counties as well as across counties. Previous research, however, uses data at the county level. Thus, it can only effectively deal with differences across counties rather than with county heterogeneity¹⁵. Our assumptions on the error term, together with the use of disaggregated data

therefore, excludes prices and costs from the estimation. (Schlenker et al. [25]).

¹²Their restriction is not rejected at a 95 percent significance level. However, as a consequence of the restrictions they impose, they may lose the flexibility provided by their functional form.

¹³Even if we assume that variable input prices are exogenous, it is likely that costs are not. It is reasonable, then, to assume that production shocks affect the quantity of variable inputs used by farmers and therefore they also affect costs of production. (There is also the problem of not observing government payments, pest problems and other factors that may be correlated with prices and costs). Kelly et al. [11] assume that prices are determined *ex ante*. Under this assumption, endogeneity is not a problem in their analysis.

¹⁴See, for example, Berry [5], Berry et al. [6] and Nevo [21].

¹⁵To deal with this heterogeneity, Mendelsohn et al. [16] and [17] use cropland weights and crop revenue weights. Cropland weights are motivated by the assumption that counties with more cropland will yield a better measure of agricultural land value because non-agricultural influences are minimized. Crop weights give emphasis to those counties that are, in general, more important to total agricultural production. Deschenes et al. use the square root of the share of farmland in each county as a weight under a similar motivation to that of cropland weights. KKM weigh their data by taking into account spatial correlation across counties as well as temporal correlation to improve the efficiency of their estimation. Schlenker et al. [25] incorporate

to characterize different plots of land in a county, account for heterogeneity in the characteristics of plots of land within counties, across counties, and over time. Because of the way heterogeneity is introduced into the model, the integral in our land shares equation no longer has a closed form solution as in the case of the logit model. This integral is approximated numerically. Let $w = (p_{it}, \bar{c}_{it})$,

$$s_{ift}(\cdot; \theta_2) = \frac{1}{ns} \sum_{j=1}^{ns} s_{ijft}$$

$$\approx \frac{1}{ns} \sum_{j=1}^{ns} \frac{\exp \left[\pi_{ift} + \sum_{n=1,2} w_{it}^n (\sigma^n \varphi_{jft}^n + \lambda_1^n z_{1jft}^n + \dots + \lambda_k^n z_{kjft}^n) \right]}{1 + \exp \left[\pi_{ift} + \sum_{m=1}^J w_{it}^m (\sigma^m \varphi_{jft}^m + \lambda_1^m z_{1jft}^m + \dots + \lambda_k^m z_{kjft}^m) \right]},$$

where n indexes the elements in w , and where z_{kjft}^n and φ_{jft}^m are draws from $P_z(\cdot)$ and $P_\varphi(\cdot)$ respectively. Note that we use the assumption that $P_\varepsilon(\cdot)$ is the extreme-value so that ε_{ijft} 's are integrated out analytically.

The only unobservable that is not accounted for in the integration of market shares $s_{ift}(\cdot; \theta_2)$ is the county and crop specific productivity shock $\Delta\alpha_{ift}$, which is the structural error term of the model and can be solved for as a function of the parameters of the model. To proceed with the estimation, I follow BLP and restrict my predicted crop shares $s_{ift}(\cdot)$ to match the actual observed crop shares S_{ift}

$$(10) \quad S_{ift} - s_{ift}(z_{.ft}, p_{.t}, \bar{c}_{.t}, \pi_{.ft}; \theta_2) = 0.$$

Equation (10) implicitly defines π_{ift} , the mean profits from planting crop i , which is observed by all farmers. For the full model, equation (10) can be inverted numerically by using a contraction mapping suggested by BLP where the solution to the problem is the fixed point of the function

both spatial correlation and heteroscedasticity into their weights.

$$(11) \quad \pi^{h+1} = \pi^h + \ln(S_{ift}) - \ln(s_{ift}(z_{.ft}, p_{.t}, \bar{c}_{.t}, \pi^h; \theta_2)),$$

where $h = 0, \dots, H$ are the successive iterations needed for the contraction mapping to converge to an arbitrary tolerance and π^h is an approximation to π . In turn, π can now be used to solve for our structural error term as a function of data and parameters of the model

$$(12) \quad \omega_{ift}(\theta) = \pi_{ift}(\cdot; \theta_2) - (\alpha_i + B^p p_{it} + B^c \bar{c}_{it}) \equiv \Delta\alpha_{ift}.$$

Berry [5] defines the structural error term, $\omega_{ift}(\cdot)$, as a function of the parameters of the model and, therefore, we can use generalized method of moments estimation to deal with the correlation between prices and costs and the error term. This definition of $\omega_{ift}(\cdot)$ leads us to the following moment condition

$$(13) \quad E[Z\omega(\theta^*)] = 0,$$

where θ^* denote the true parameters of the model.

With a suitable choice of instruments given by the matrix Z , the GMM estimate is

$$(14) \quad \hat{\theta} = \arg \min_{\theta} \omega(\theta)' ZA^{-1}Z'\omega(\theta)$$

where A is a consistent estimate of $E[Z'\omega\omega'Z]$. I follow Nevo to estimate the weight matrix A in a two-step procedure. First, A is set equal to $Z'Z$ to compute initial estimates of the parameters. Using these parameters we can obtain a consistent estimate of A that we can use to calculate the final estimates of the model's parameters.

4.2 Identification

The assumption that allows us to identify the model is given in equation (13) and requires a set of exogenous instrumental variables. Following the ideas of Olley and Pakes [22], Levinsohn and Petrin [12] and Akerberg et al. [1] I use the timing of production to determine the appropriate choice of instruments.

Within the context of KKM, the profit function specification presented above is an *ex – post* function that measures profits after weather and all other shocks to production have been realized. However, the crop decision and some variable input decisions are made *ex – ante*, at the beginning of the period before the farmer has observed these shocks. Just as all of the information about the shocks from the previous period is observed, the farmer makes crop and initial variable input allocation decisions for the current period. It is, then, logical to assume that the farmer uses this information to make current decisions. Thus, a natural choice of instruments are lagged weather variables, which, defined as mean-zero random deviations from climate, are correlated with current farmer decisions but should be orthogonal to current county and time specific shocks, $\Delta\alpha_{ift}$.

Using the same timing assumption and following Hausman [9], lagged prices are another potential set of instruments. The identifying assumption is that controlling for crop specific intercepts, α_i , our error term, $\Delta\alpha_{ift}$, is independent across counties but allowed to be correlated over time. Since we observe prices by state, prices in other states are then valid instruments. That is, prices in other states will be correlated due to the common cost component. However, due to the independent assumption on the error term, they will be uncorrelated with county specific productivity shocks. A problem will arise, however, if there is a nation wide shock to the market. Then current prices from other states will not be valid instruments as they will all reflect the same shock. To avoid this possibility, we only use average lagged prices in other states as instruments. The timing assumption on the farmer decisions, assures us the farmers use price information from the previous period to help guide their decisions for the current period.

4.3 Data

The analysis below takes advantage of the most detailed publicly available data on crop prices and costs, land use, weather and land characteristics. Each variable that appears in equation (7) is directly known by the farmers. However, the researcher only has information on the distribution of plot characteristics, through the observation of a sample of plots in each county, and can only observe prices and costs, p_{it} and \bar{c}_{it} , at the state and national levels respectively. Land-use shares for each crop, S_{ift} , are available for every county.

The data covers 2027 non-irrigated rural counties¹⁶ for 1982, 1987, 1992 and 1997 and 8 crops that cover over 60 percent of the harvested area and represent 53 percent of the value of crop production in the U.S.¹⁷. Figure (3) highlights those counties that are included in the analysis. Data on crop shares and plot characteristics come from the 1997 National Resources Inventory (NRI). The NRI is a statistically designed sample of non-federal lands in the United States. It contains data on land use, soils, natural resources and trends for approximately 800,000 points for 1982, 1987, 1992 and 1997. These data include K Factor (erodibility factor), Flood Prone, Sand, Clay, Slope Length and Wetland (see definitions for these terms in the data appendix). For each of these variables, I sample 30 observations that correspond to 30 one-acre plots of land for each county.

The source for weather and climate data is the Spatial Climate Analysis Service at Oregon State University. These are the finest resolution public data for the entire U.S. and are generated using observations from more than 20,000 weather stations in the National Climatic Data Center's Summary of the Month Cooperative Files. Climate is defined as a 30 year average of temperature and precipitation information, up to the year prior to the year in question. Weather is defined as a deviation from this average for each year under

¹⁶Schlenker et al. [26] argue that changes in climate will have different effects on irrigated and non-irrigated counties. As they do, I restrict the sample to non-irrigated (less than 5% of land in farms is irrigated) rural counties. This also avoids the problem of forecasting the availability of water in irrigated counties or having to rely on assumptions about the availability of water for irrigation.

¹⁷These statistics are calculated from the 1997 National Agricultural Statistics Service Crop rankings. Each of these crops, except for oats, is ranked among the top 25 crops in term of value, with corn, soybean, wheat, and cotton among the top 10.

consideration. Data for the months of January, April, July and October are included in the data set, thus, giving us measures of climate and weather for every season of the year.

Price data comes from the National Agricultural Statistics Service (NASS) Agricultural Statistics Data Base. Cost data were extracted from the Commodity Costs and Returns data set from the Economic Research Service. With the exception of price and cost variables, I follow the literature in our choice of right-hand variables for the estimation.

4.4 Results

Estimates for the full model are based on equation (7) and were computed to match the full model's predictions to the observed shares of land allocated to each crop in each county. Heterogeneity enters the model in the form of assumptions on the unobservables, as well as, and more importantly, in the form of observations on plot characteristics. The instrumental variables that help us identify the model are lagged yearly averages for prices in different states and lagged weather variables.

In this section, I present results for three types of specifications: the logit specification for which plot characteristics are introduced as county averages, another logit specification in which I instrument for price and cost and the full model specification as described above. I use the logit estimates to highlight the importance of instrumenting for prices and cost, and to show the importance of heterogeneity in the determination of elasticities of substitution. The full model includes coefficients on the same variables as the logit models. However, for the full model these variables are at the plot level rather than county averages. Two extra coefficients that account for the variance of the unobservable characteristics of the plot are also introduced. The left-hand variable, in all cases, is $\ln(S_{ift}) - \ln(S_{oft})$, where S_{ift} are the observed shares of crop i for the respective county and year, and where S_{oft} is the share for the outside option.

In table (13), I display the results from regressing the left-hand variable on prices, costs and interaction terms corresponding to plot characteristics aggregated at the county level.

The coefficients reported in the price and cost columns correspond to the interaction of price and cost with the variables in each of the rows. Table (14) presents analogous results for the case in which we instrument for cost and price. Note the difference in sign for the price coefficient between these two tables. It highlights the need for instrumenting as, without instruments, the price coefficients takes an unintuitive sign.

Tables (16) and (17) clearly illustrate the need to introduce heterogeneity in the model. Although the signs for the elasticities in both cases are intuitively correct, the substitution patterns they represent are very restrictive. For example, in table (13), an increase in the price of barley would cause both wheat farmers and cotton farmers to substitute to barley in the same proportion implying that both wheat and cotton as both as likely substitutes for barley than any other crop. This can clearly not be the case as most cotton farms will be located in climates adequate to grow barley.

The full model includes instruments for price and cost and it accounts for plot heterogeneity. The coefficient estimates for this model, displayed in table (15), are in general intuitive in sign and show more realistic own and cross-price elasticities than the logit specifications. A surprising result is that soil characteristics do not appear to be significant to the farmer's choice. I presume that effects of soil characteristics on the farmers' crop decision are captured by the mean cost of producing each crop.

The coefficients on price and cost are decomposed into a mean, a standard deviation and parameters that determine the variation that is due to differences in plot characteristics. Note that the mean price and cost coefficient estimates have the correct sign. However, after we account for plot heterogeneity, the price coefficient estimate is not significantly different from zero. This gives some support to Deschenes and Greenstone's [7] decision not to include prices in their estimation. However, the mean cost coefficient is highly significant implying that we cannot ignore the common component of cost for the individual crops. Moreover, even though the price and cost coefficients for the full model have the same sign and similar magnitudes than the same coefficients for the IV logit model, we can now

represent the distribution of these coefficients over different plots (see figures (2) and (3)). It is also important to mention that the standard deviations estimate for the price and cost coefficients, which are included because of the normality assumption on plot unobservables, are not significantly different from zero. This shows that our results are not driven by distributional assumptions on unobserved heterogeneity, but that they are based on our observations of plot characteristics.

As a last point, the elasticity estimates that results from the full model present much more realistic patterns of substitution that are consistent with the pattern shown in table (1). Crops that do well in temperate climates are more likely to be substituted for another crop that does well in a temperate climate. See, for example, that our elasticities indicate that corn and sorghum, both crops that do well in similar types of climate, respond to cross price changes. On the other hand, the table shows, as we would expect, that cotton and barley are not crops farmers are likely to substitute for each other.

5 Conclusions

The work presented in this paper is motivated by our need to better understand the role of climate on farmer adaptive behavior. In general, the main hypothesis in this paper is that climate has an important influence in the farmer's land-use decisions. In particular, I developed a discrete choice model of farmers' land-use decision where farmers optimally choose the crop that yields the highest possible profits, given the characteristics the farmers' land. This model extends on previous literature by giving us a clear depiction of farmers' adaptive behavior on the face of climate change and by allowing us to test our hypothesis. I use a random coefficients Mixed Logit model to estimate an agricultural production system of U.S. crops that includes information of heterogeneous plots of land for 2027 non-irrigated, rural counties. Results show that climate does play a significant part in the farmers' cropping decisions and, thus, it is an important determinant of the distribution of land uses within

counties.

We observe a sample of over 60,000 one-acre plots across the U.S. that allows us to empirically determine the distribution of plot characteristics for every county in the sample. We do not observe the individual choice of crop for each plot of land, however, we do observe crop shares at the county level. This mixture of aggregate and highly disaggregated data gives us a very rich representation of within county heterogeneity which, in turn, allows us to obtain very flexible estimates of crop substitution by farmers. To identify the parameters of this model, we exploit the timing of farmers' decisions, the independence assumption on the productivity shock across different counties, as well as the panel structure of the data.

Preliminary estimates corroborate the need to instrument for prices and costs. Moreover, estimates of own and cross-price elasticities emphasize the need to account for heterogeneity to be able to reasonably portray the behavior of farmers. The full model accounts for this heterogeneity resulting in very realistic patterns of substitution across crops.

References

- [1] Daniel A. Akerberg, Kevin Caves, and Garth Frazer. Structural identification of production functions. *Preliminary*, March 2005.
- [2] R. Adams, K. Bryant, B. McCarl, D. Legler, J. O'Brian, A. Solow, and R. Weiher. Value of improved long-range weather information. *Contemporary Economic Policy*, 13:10–19, 1995.
- [3] R. Adams, B. McCarl, K. Segerson, C. Rosenzweig, K. Bryant, B. Dixon, R. Conner, R. Evenson, and D. Ojima. Economic effects of climate change on US agriculture. In R. Mendelsohn and J. E. Neumann, editors, *The Economic Impact of Climate Change on the United States Economy*, pages 18–54. Cambridge University Press, 1999.
- [4] R. Adams, C. Rozenzweig, R. Peart, J. Ritchie, J. McCarl, D. Glycer, B. Curry, J. Jones, K. Boote, and L. Allen. Global climate change and US agriculture. *Nature*, 345:219–224, May 1990.
- [5] S. Berry. Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics*, 25:242–262, 1994.
- [6] S. Berry, J. Levinsohn, and A. Pakes. Automobile Prices in Market Equilibrium. *Econometrica*, 63(4):841–890, July 1995.
- [7] O. Deschenes and M. Greenstone. The Economic Impacts of Climate Change: Evidence from Agricultural Profits and Random Fluctuations in Weather. *Department of Economics, University of California Santa Barbara*, Working Paper.
- [8] A. Myrick Freeman III. *The Measurement of Environmental and Resource Values: Theory and Methods*. Resources for the Future, 2nd edition, 2003.
- [9] J. Hausman. Valuation of new goods under perfect and imperfect competition. In T. Bresnahan and R. Gordon, editors, *The Economics of New Goods, Studies in Income and Wealth*, volume 58. National Bureau of Economic Research, Chicago, 1996.
- [10] S. Johnson and P. A. Haigh. Agricultural land price differentials and their relationship to potentially modifiable aspects of the climate. *Review of Economics and Statistics*, 52:173–181, 1970.
- [11] D. Kelly, C. Kolstad, and G. Mitchell. Adjustment Costs from Environmental Change. *Journal of Environmental Economics and Management*, Forthcoming.
- [12] J. Levinsohn and A. Petrin. Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, Forthcoming.
- [13] D. McFadden. Econometric models of probabilistic choice. In C. Manski and D. McFadden, editors, *Structural Analysis of Discrete Data*, pages 198–272. MIT Press, 1981.
- [14] D. McFadden. Modeling the choice of residential location. In A. Karlqvist et al, editor, *Spatial Interaction Theory and Planning Models*. North-Holland, 1981.

- [15] D. McFadden and K. Train. Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5):447–470, 2000.
- [16] R. Mendelsohn, W. Nordhaus, and D. Shaw. The impact of global warming on agriculture: A ricardian analysis. *American Economic Review*, 84(4):753–771, 1994.
- [17] R. Mendelsohn, W. Nordhaus, and D. Shaw. Climate impacts on aggregate farm value: Accounting for adaptation. *Agricultural and Forest Meteorology*, 80:55–66, 1996.
- [18] R. Mendelsohn, W. Nordhaus, and D. Shaw. The impact of climate variation on US agriculture. In R. Mendelsohn and J. Neumann, editors, *The Economic Impact of Climate Change on the United States Economy*, pages 55–74. Cambridge University Press, 1999.
- [19] J. Mjelde, H. Hill, and J. Griffiths. A review of current evidence on climate forecasts and their economic effects in agriculture. ENSOnomics: The agricultural economics of climate and climate forecasting. *The American Journal of Agricultural Economics*, 80(5):1089–1096, 1998.
- [20] National Academy of Sciences. Joint Science Academies’ Statement: Global Response to Climate Change, June 2005.
- [21] A. Nevo. Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica*, 69:307–342, 2001.
- [22] S. Olley and A. Pakes. The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64:1263–1295, 1996.
- [23] N. Oreskes. BEYOND THE IVORY TOWER: The Scientific Consensus on Climate Change. *Science*, 306(5702):1686, December 2004.
- [24] J. Reilly, F. Tubiello, B. McCarl, D. Abler, R. Darwin, K. Fuglie, S. Hollinger, C. Izaurralde, S. Jagtap, J. Jones, L. Mearns, D. Ojima, E. Paul, K. Paustian, S. Riha, N. Rosenberg, and C. Rozenzweig. US agriculture and climate change: New results. *Climatic Change*, 57:43–69, 2003.
- [25] W. Schlenker, M. Hanemann, and A. Fisher. The impact of global warming on u.s. agriculture: An econometric analysis. *Working Paper*, 2003.
- [26] W. Schlenker, M. Hanemann, and A. Fisher. Will u.s. agriculture really benefit from global warming? accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1):395–406, 2005.
- [27] S. Schneider, W. Esterling, and L. Mearns. Adaptation: Sensitivity to natural variability, agent assumptions and dynamic climate changes. *Climatic Change*, 45:203–221, 2000.
- [28] A. Solow, R. Adams, K. Bryant, D. Legler, J. O’Brien, B. McCarl, W. Nayda, and R. Weiher. The value of improved ENSO prediction to US agriculture. *Climatic Change*, 39:47–60, 1998.

A Data

A.1 Definitions

- Soil definitions adopted from: 1997 National Resources Inventory Data CD, Revised December 2000

K factor: An erodibility factor which quantifies the susceptibility of soil particles to detachment and movement by water. This factor is used in the Universal soil loss equation (USLE) to calculate soil loss by water.

Flood Prone: Indicator variable that indexes whether a plot is prone to flooding.

Sand: Indicator variable that indexes whether a plot or a portion of a plot falls on salt flats.

Clay: Indicator variable that indexes plots with soil with high clay content.

Slope length: The distance from the point of origin of overland flow to the point where either the slope gradient decreases enough that deposition begins, or the runoff water enters a well-defined channel that may be part of a drainage network or a constructed channel. For the NRI, length of slope is taken through the sample point.

Wetland: Lands transitional between terrestrial and aquatic systems where the water table is usually at or near the surface or the land is covered by shallow water. For purposes of this classification wetlands must have one or more of the following three attributes: (1) at least periodically, the land supports predominantly hydrophytes; (2) the substrate is predominantly undrained hydric soil; and (3) the substrate is nonsoil and is saturated with water or covered by shallow water at some time during the growing season of each year. (Cowardin, L. M., V. Carter, F. C. Golet, E. T. LaRoe. 1979. Classification of wetlands and deepwater habitats of the United States. FWS/OBS-79/31. U.S. Department of the Interior, Fish and Wildlife Service.)

Climate: Climate is defined as a 30 year averages of observed mean temperatures and precipitation for the months of January, April, July, and October up to the year prior to the year in question. For example, for plot j , let z_{jT}^c be our our climate measure for July temperature for year T and W_{jT} be our observation of July temperature for year T . Then

$$z_{jT}^c = \frac{1}{30} \sum_{t=T-31}^{T-1} W_{jt}.$$

Weather: Weather is define as a standardized deviation from climate. Continuing with our example above, let z_{jT}^w be our our climate measure for July temperature for plot j in year T . Then,

$$z_{jT}^w = \frac{W_{jT} - z_{jT}^c}{\sqrt{\frac{1}{30-1} \sum_{t=T-31}^{T-1} (W_{jt} - z_{jT}^c)^2}}$$

B Tables and Figures

TABLE 1: AVERAGE ANNUAL TEMPERATURE VS LAND SHARES (1982)

T	Barley	Corn	Cotton	Oats	Peanuts	Sorghum	Soybeans	Wheat	Outshare
0	2.05	1.03	0.00	0.94	0.00	0.01	0.22	11.57	84.17
5	0.53	14.78	0.00	1.75	0.00	0.26	7.02	4.48	71.17
10	0.06	9.32	0.02	0.16	0.02	1.25	8.20	5.36	75.61
15	0.02	1.80	1.71	0.29	0.39	0.78	4.80	3.28	86.92

TABLE 2: AVERAGE ANNUAL TEMPERATURE VS AGRICULTURAL LAND VALUES AND REVENUE (1982)

T	Land Value	Revenue/Acre	Count
0	580	36	125
5	995	63	577
10	995	70	731
15	820	53	594

TABLE 3: CROP MEANS (1982)ⁱ

	Gross Value of Production	Crop Price	Production Costs ⁱⁱ
Barley	113.7101	2.136108	34.53
Corn	251.6061	2.672432	47.77
Cotton	338.1091	0.581288	75.43
Oats	90.1687	1.756379	35.45
Peanut	651.7157	0.25149	77.66
Sorghum	232.079	8.056527	37.52
Soybean	162.1327	4.077879	34.56
Wheat	114.1433	5.607918	29.15

ⁱ Gross Value of Production and Production Costs are measured in dollars per acre

ⁱⁱ Includes estimated hired and non hired labor expenses as well as capital expenses

TABLE 4: CROP MEANS (ALL YEARS)ⁱ

	Gross Value of Production	Crop Price	Production Costs ⁱⁱ
Barley	114.0585	2.0503	38.6025
Corn	248.0933	2.3809	66.5250
Cotton	379.4199	0.5982	113.9850
Oats	92.5216	1.6502	40.7175
Peanut	690.1418	0.2781	143.1500
Sorghum	233.5588	7.7913	51.7500
Soybean	184.3621	3.6587	48.5675
Wheat	125.3334	5.8351	31.0250

ⁱ Gross Value of Production and Production Costs are measured in dollars per acre

ⁱⁱ Includes estimated hired and non hired labor expenses as well as capital expenses

TABLE 5: SUMMARY STATISTICS FOR CROP DATA

	Mean	Standard Deviation	Median	Max	Min
Price	3.0304	2.5152	2.1800	10.9000	0.2340
Production Costs	66.7900	45.5420	46.9900	238.3400	26.4500

TABLE 6: AVERAGE PERCENT LAND IN EACH CROP BY COUNTY BY YEAR

	1982	1987	1992	1997
Barley	0.304	0.330	0.286	0.243
Corn	8.162	7.339	7.616	7.328
Cotton	0.507	0.515	0.568	0.692
Oats	0.699	0.559	0.379	0.272
Peanuts	0.122	0.119	0.141	0.127
Sorghum	0.755	0.635	0.570	0.481
Soybeans	6.377	6.244	5.790	6.407
Wheat	4.884	4.027	3.928	3.673
outshare	78.188	80.233	80.722	80.777

TABLE 7: CLIMATE MEANS BY YEAR

	1982	1987	1992	1997
Climate - January Temp	-0.8313	-1.2355	-0.9775	-0.7942
Climate - January Precip	68.8455	67.1068	68.5847	70.4353
Climate - April Temp	12.3550	12.2215	12.2840	12.1487
Climate - April Precip	88.2673	88.6364	86.0388	85.8967
Climate - July Temp	23.9999	23.9175	23.9942	23.9447
Climate - July Precip	97.3834	97.8729	96.1980	98.7156
Climate - October Temp	13.4032	13.4060	13.2888	13.1630
Climate - October Precip	66.8854	74.0315	72.3692	76.6938

TABLE 8: SUMMARY STATISTICS FOR CLIMATE DATA

	Mean	Standard Deviation	Median	Max	Min
Climate - January Temp	-1.1838	6.7777	-0.9565	21.0790	-18.5440
Climate - January Precip	66.5820	52.7030	58.1100	1105.0000	4.2927
Climate - April Temp	12.0790	4.8483	12.3430	25.1410	-8.6318
Climate - April Precip	85.1570	32.2980	86.4540	516.8600	2.1720
Climate - July Temp	23.8810	3.2531	24.3010	34.9280	6.7957
Climate - July Precip	95.1170	35.5370	99.4420	258.5000	0.0023
Climate - October Temp	13.1760	4.1415	13.2290	26.8050	-2.0682
Climate - October Precip	71.3850	26.5870	73.1450	586.7100	1.9983

TABLE 9: SOIL MEANS BY YEAR

	1982	1987	1992	1997
K Factor	0.2691	0.2691	0.2691	0.2691
Flood Prone	0.0894	0.0894	0.0894	0.0894
Sand	0.0979	0.0979	0.0979	0.0979
Clay	0.1744	0.1744	0.1744	0.1744
Salt	0.0021	0.0021	0.0021	0.0021
Slope Length	75.1069	74.1968	73.4031	72.0652
Wetland	0.0585	0.0585	0.0585	0.0585

TABLE 10: SOIL DATA

	Mean	Standard Deviation	Median	Max	Min
K Factor	0.2691	0.1133	0.2800	0.6400	0.0000
Flood Prone	0.0894	0.2854	0	1	0
Sand	0.0979	0.2971	0	1	0
Clay	0.1744	0.3795	0	1	0
Salt	0.0021	0.0462	0	1	0
Slope Length	73.6930	132.7100	0.0000	3000.0000	0.0000
Wetland	0.0585	0.2347	0	1	0
Irrigated	0.2691	0.1133	0.2800	0.6400	0.0000

TABLE 11: WEATHER MEANS BY YEAR

	1982	1987	1992	1997
Weather - January Temp	-0.8720	0.4601	0.7832	-0.0638
Weather - January Precip	0.8527	0.0047	-0.0012	0.2808
Weather - April Temp	-1.1936	0.1005	-0.3342	-1.5121
Weather - April Precip	-0.2194	-0.6637	-0.3193	0.1002
Weather - July Temp	0.0327	0.5005	-0.9520	-0.0165
Weather - July Precip	0.1542	0.0086	0.8791	-0.1924
Weather - October Temp	-0.0527	-1.2637	-0.2524	0.0870
Weather - October Precip	0.2000	-0.8625	-0.4638	-0.0336

TABLE 12: CLIMATE MEANS BY YEAR

	1982	1987	1992	1997
Climate - January Temp	-0.8313	-1.2355	-0.9775	-0.7942
Climate - January Precip	68.8455	67.1068	68.5847	70.4353
Climate - April Temp	12.3550	12.2215	12.2840	12.1487
Climate - April Precip	88.2673	88.6364	86.0388	85.8967
Climate - July Temp	23.9999	23.9175	23.9942	23.9447
Climate - July Precip	97.3834	97.8729	96.1980	98.7156
Climate - October Temp	13.4032	13.4060	13.2888	13.1630
Climate - October Precip	66.8854	74.0315	72.3692	76.6938

TABLE 13: OLS COEFFICIENT ESTIMATES

Interaction	Price	Cost
	-1.2688 -(14.1910)	-0.1087 -(14.7150)
Soil - K Factor	0.5886 (7.7384)	0.0158 (2.9494)
Soil - Flood Prone	-0.0725 -(1.8495)	-0.0018 -(0.6554)
Soil - Sand	0.0878 (3.8172)	0.0030 (2.1470)
Soil - Clay	0.0943 (5.9815)	0.0074 (5.9355)
Soil - Slope Length	0.0006 (11.2640)	0.0001 (20.1530)
Soil - Wetland	0.0672 (1.5697)	-0.0039 -(1.5426)
Climate - January Temp	0.0013 (0.4833)	-0.0059 -(27.1750)
Climate - January Precip	0.0007 (3.4960)	0.0000 (2.0625)
Climate - April Temp	-0.0191 -(2.6785)	-0.0020 -(3.5481)
Climate - April Precip	-0.0008 -(3.0315)	0.0000 (1.4230)
Climate - July Temp	0.0595 (11.0200)	-0.0027 -(6.1954)
Climate - July Precip	-0.0011 -(6.9462)	0.0002 (15.6610)
Climate - October Temp	-0.0093 -(1.0318)	0.0119 (17.6710)
Climate - October Precip	-0.0009 -(3.9531)	-0.0001 -(6.2063)
Weather - January Temp	-0.0075 -(1.1953)	0.0019 (3.5646)
Weather - January Precip	0.0082 (2.3165)	-0.0012 -(4.5551)
Weather - April Temp	-0.0002 -(0.0435)	-0.0049 -(11.5110)
Weather - April Precip	0.0049 (1.3820)	-0.0004 -(1.6183)
Weather - July Temp	-0.0033 -(0.6911)	0.0032 (9.6797)
Weather - July Precip	0.0069 (1.8970)	0.0015 (5.6999)
Weather - October Temp	-0.0105 -(2.0926)	0.0023 (6.2304)
Weather - October Precip	0.0062 (1.6389)	-0.0022 -(7.2616)

Results in this table are based on 20,214 observations. The data set includes four years of data for 2027 counties and 9 crops. Observations with zero land allocated for a crop where dropped. Aggregate measures of plot characteristics are used in the estimation. t-scores in parenthesis.

TABLE 14: COEFFICIENT ESTIMATES FOR IV

	Price	Cost
	0.2132 (4.1604)	-0.0094 -(5.7609)
Soil - K Factor	0.9166 (7.7003)	0.0274 (3.2841)
Soil - Flood Prone	-0.0594 -(0.9175)	-0.0013 -(0.2932)
Soil - Sand	0.1287 (3.4201)	0.0049 (2.0939)
Soil - Clay	0.1593 (6.3323)	0.0104 (5.5302)
Soil - Slope Length	1.7393 (6.2842)	-0.1820 -(6.3425)
Soil - Wetland	0.0864 (1.2815)	-0.0094 -(2.3389)
Climate - January Temp	-0.0245 -(6.1796)	-0.0059 -(19.0450)
Climate - January Precip	0.0008 (2.5344)	0.0001 (2.0275)
Climate - April Temp	-0.0243 -(2.1680)	-0.0012 -(1.3985)
Climate - April Precip	-0.0008 -(1.9653)	0.0000 (0.2191)
Climate - July Temp	0.0351 (3.8690)	-0.0022 -(3.2813)
Climate - July Precip	-0.0010 -(3.9535)	0.0001 (6.7092)
Climate - October Temp	0.0317 (2.2804)	0.0113 (11.3100)
Climate - October Precip	-0.0019 -(5.0521)	-0.0001 -(2.3715)
Weather - January Temp	0.0021 (0.2149)	0.0025 (3.2406)
Weather - January Precip	0.0116 (2.0263)	-0.0012 -(2.8489)
Weather - April Temp	-0.0090 -(0.9729)	-0.0036 -(5.2169)
Weather - April Precip	0.0277 (4.2144)	-0.0021 -(4.9454)
Weather - July Temp	-0.0300 -(3.9430)	0.0041 (7.9932)
Weather - July Precip	0.0276 (5.1913)	0.0003 (0.8586)
Weather - October Temp	0.0260 (3.0049)	0.0007 (1.1937)
Weather - October Precip	-0.0062 -(1.0886)	-0.0020 -(4.6244)

Results in this table are based on 20,214 observations. The data set includes four years of data for 2027 counties and 9 crops. Observations with zero land allocated for a crop where dropped. Aggregate measures of plot characteristics are used in the estimation. t-scores in parenthesis.

TABLE 15: COEFFICIENT ESTIMATES FOR THE FULL MODEL

	Price	Cost
Mean	0.1236 (0.6704)	-0.0204 -(4.0040)
Standard Deviation	-0.0041 -(0.0209)	-0.0004 -(0.0330)
Soil - K Factor	-0.5221 -(0.5834)	0.0683 (1.2124)
Soil - Flood Prone	-0.3632 -(0.7680)	0.0059 (0.2906)
Soil - Sand	-0.5606 -(1.7396)	0.0249 (1.5123)
Soil - Clay	0.0249 (0.1160)	0.0081 (0.4739)
Soil - Slope Length	0.0010 (1.9122)	0.0000 -(0.1021)
Soil - Wetland	-0.9339 -(1.2274)	0.0397 (2.3428)
Climate - January Temp	-0.1091 -(2.8944)	-0.0004 -(0.1261)
Climate - January Precip	0.0121 (4.6369)	-0.0010 -(4.7220)
Climate - April Temp	0.1397 (2.1470)	-0.0135 -(2.7752)
Climate - April Precip	-0.0099 -(3.2532)	0.0007 (3.1040)
Climate - July Temp	-0.0628 -(1.0069)	0.0018 (0.3810)
Climate - July Precip	-0.0002 -(0.1152)	0.0003 (2.8237)
Climate - October Temp	0.0387 (0.3713)	0.0144 (1.8510)
Climate - October Precip	0.0014 (0.5480)	-0.0002 -(1.0774)
Weather - January Temp	-0.3289 -(5.0857)	0.0300 (6.8897)
Weather - January Precip	-0.0584 -(1.8016)	0.0056 (2.4316)
Weather - April Temp	0.1290 (2.3044)	-0.0145 -(3.5053)
Weather - April Precip	0.0016 (0.0310)	-0.0037 -(1.1317)
Weather - July Temp	-0.0833 -(1.6073)	0.0088 (2.4993)
Weather - July Precip	0.0017 (0.0375)	0.0028 (0.9059)
Weather - October Temp	-0.0380 -(0.7842)	0.0058 (1.6657)
Weather - October Precip	-0.0790 -(2.3457)	0.0067 (2.5819)

Results in this table are based on 20,214 observations for four years of data for 2027 counties and 9 crops. Observations with zero land allocated for a crop were dropped. 30 draws from each plot characteristics are used per county. t-scores in parenthesis.

TABLE 16: LOGIT OLS: MEDIAN OWN AND CROSS-PRICE ELASTICITIES

	Barley	Corn	Cotton	Oats	Peanuts	Sorghum	Soybeans	Wheat
Barley	8.681300	-2.384600	-1.196000	-0.255970	-0.353610	-1.982300	-5.081600	-4.720100
Corn	-0.424790	13.658000	-1.196000	-0.255970	-0.353610	-1.982300	-5.081600	-4.720100
Cotton	-0.424790	-2.384600	4.364400	-0.255970	-0.353610	-1.982300	-5.081600	-4.720100
Oats	-0.424790	-2.384600	-1.196000	6.879800	-0.353610	-1.982300	-5.081600	-4.720100
Peanuts	-0.424790	-2.384600	-1.196000	-0.255970	2.577600	-1.982300	-5.081600	-4.720100
Sorghum	-0.424790	-2.384600	-1.196000	-0.255970	-0.353610	76.858000	-5.081600	-4.720100
Soybeans	-0.424790	-2.384600	-1.196000	-0.255970	-0.353610	-1.982300	19.479000	-4.720100
Wheat	-0.424790	-2.384600	-1.196000	-0.255970	-0.353610	-1.982300	-5.081600	37.721000

Percent change in market share of row i given a percent change in price of column j

TABLE 17: LOGIT IV: MEDIAN OWN AND CROSS-PRICE ELASTICITIES

	Barley	Corn	Cotton	Oats	Peanuts	Sorghum	Soybeans	Wheat
Barley	0.272910	-0.002409	-0.000041	-0.000231	-0.052662	-0.000130	-0.002610	-0.002166
Corn	-0.000027	0.258650	-0.000041	-0.000231	-0.052662	-0.000130	-0.002610	-0.002166
Cotton	-0.000027	-0.002409	0.107550	-0.000231	-0.052662	-0.000130	-0.002610	-0.002166
Oats	-0.000027	-0.002409	-0.000041	0.239260	-0.052662	-0.000130	-0.002610	-0.002166
Peanuts	-0.000027	-0.002409	-0.000041	-0.000231	0.001202	-0.000130	-0.002610	-0.002166
Sorghum	-0.000027	-0.002409	-0.000041	-0.000231	-0.052662	0.447120	-0.002610	-0.002166
Soybeans	-0.000027	-0.002409	-0.000041	-0.000231	-0.052662	-0.000130	0.321800	-0.002166
Wheat	-0.000027	-0.002409	-0.000041	-0.000231	-0.052662	-0.000130	-0.002610	0.659790

Percent change in market share of row i given a percent change in price of column j

TABLE 18: FULL MODEL: MEDIAN OWN AND CROSS-PRICE ELASTICITIES

	Barley	Corn	Cotton	Oats	Peanuts	Sorghum	Soybeans	Wheat
Barley	6.76900	-0.52699	-0.03176	-0.03219	-0.00417	-0.04243	-0.42962	-0.27551
Corn	-0.02577	7.21760	-0.04825	-0.03913	-0.00723	-0.05162	-0.46463	-0.30896
Cotton	-0.00731	-0.20551	1.97180	-0.01103	-0.00879	-0.00827	-0.07791	-0.04163
Oats	-0.01579	-0.42258	-0.03039	5.48240	-0.00446	-0.03528	-0.32877	-0.21288
Peanuts	-0.00333	-0.09727	-0.01731	-0.00515	0.92778	-0.00385	-0.03323	-0.01806
Sorghum	-0.07321	-1.94480	-0.07703	-0.12712	-0.00519	25.63900	-2.08750	-2.05180
Soybeans	-0.03811	-0.95634	-0.04889	-0.05945	-0.00469	-0.09460	11.32000	-0.61270
Wheat	-0.05487	-1.47900	-0.05704	-0.09446	-0.00406	-0.19708	-1.50890	18.27400

Percent change in market share of row i given a percent change in price of column j

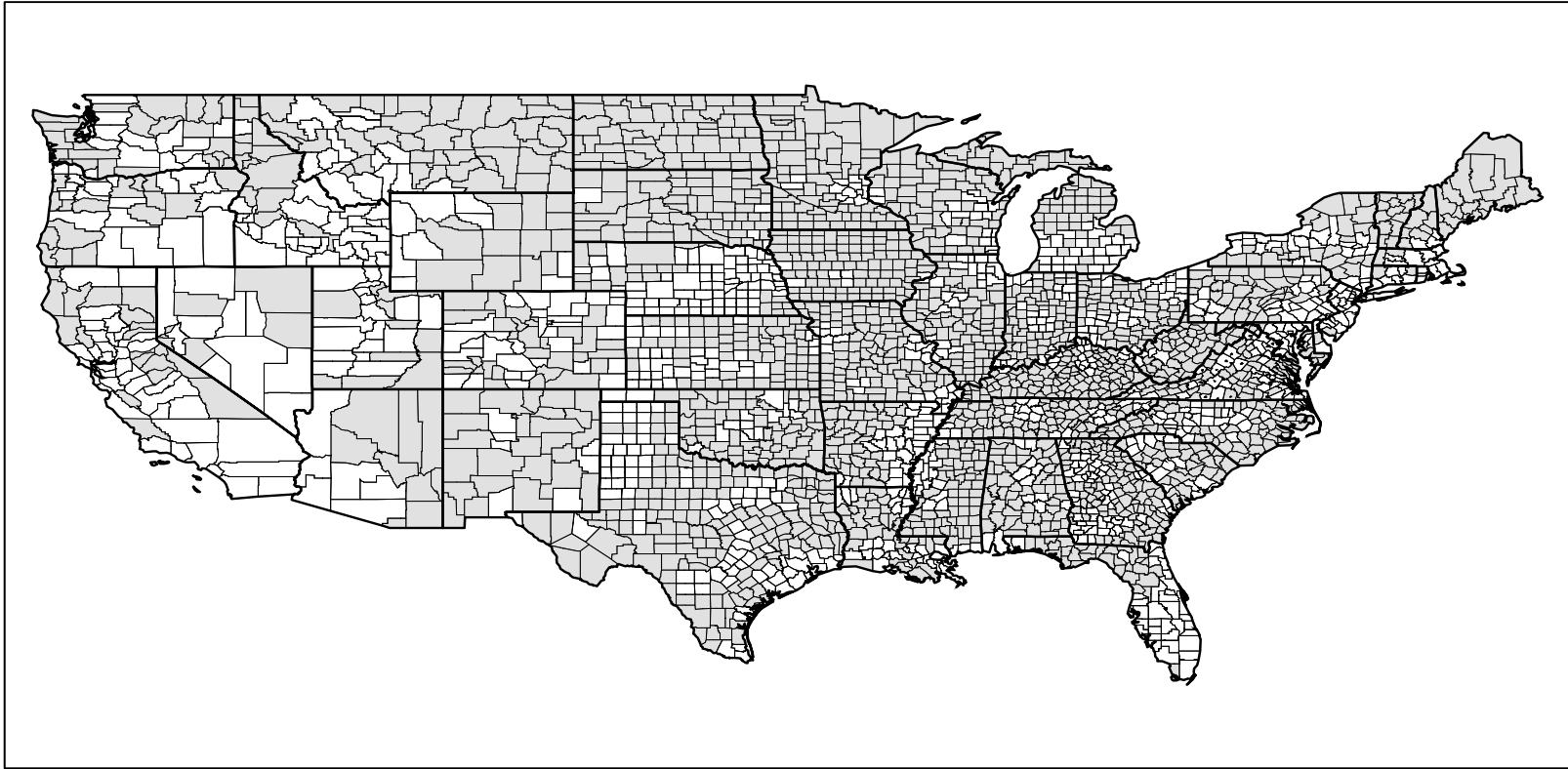


FIGURE 1: SELECTED COUNTIES (2027 NON-IRRIGATED RURAL COUNTIES FOR 1982, 1987, 1992, AND 1997).

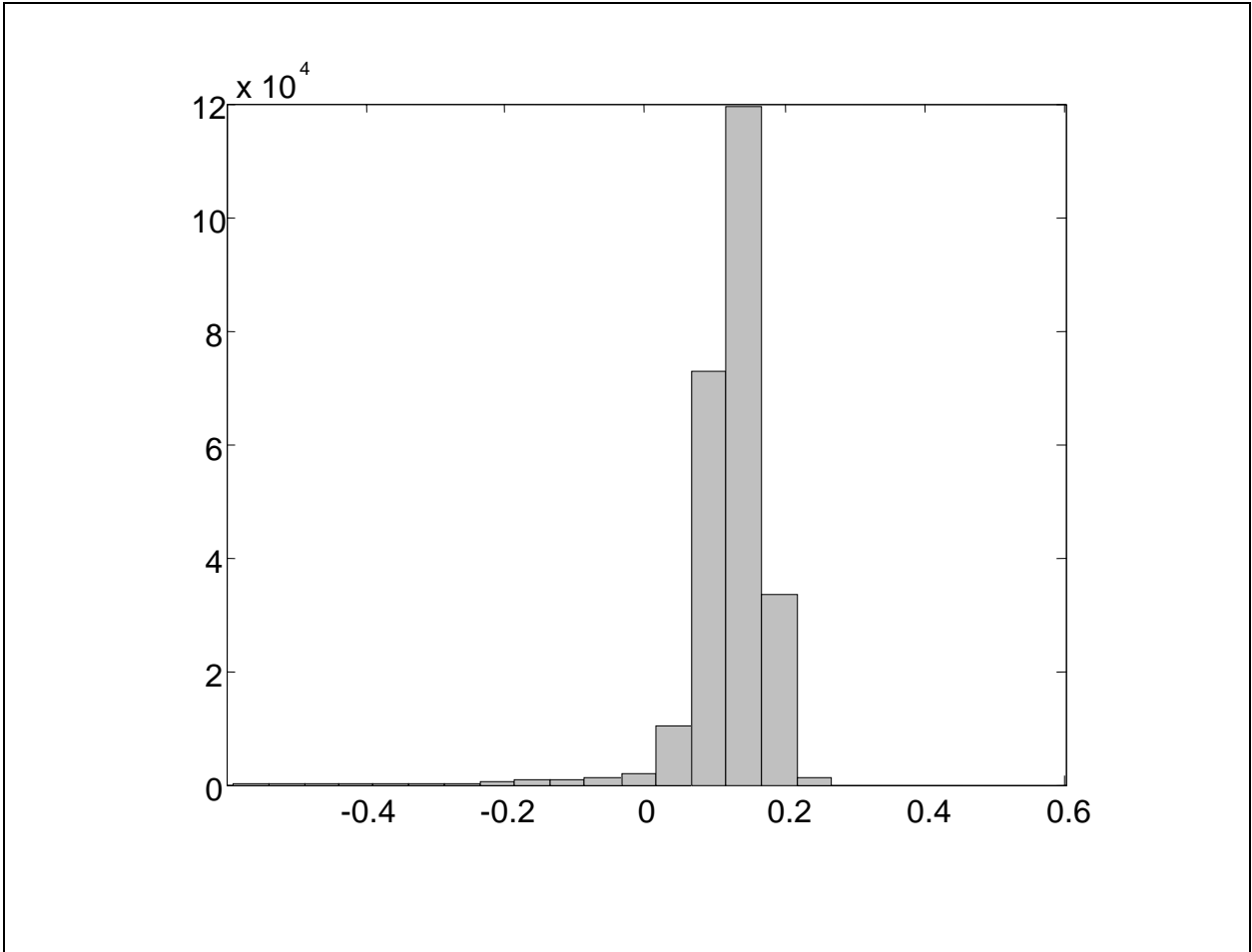


FIGURE 2: FREQUENCY DISTRIBUTION OF THE PRICE COEFFICIENT (BASED ON TABLE XV).

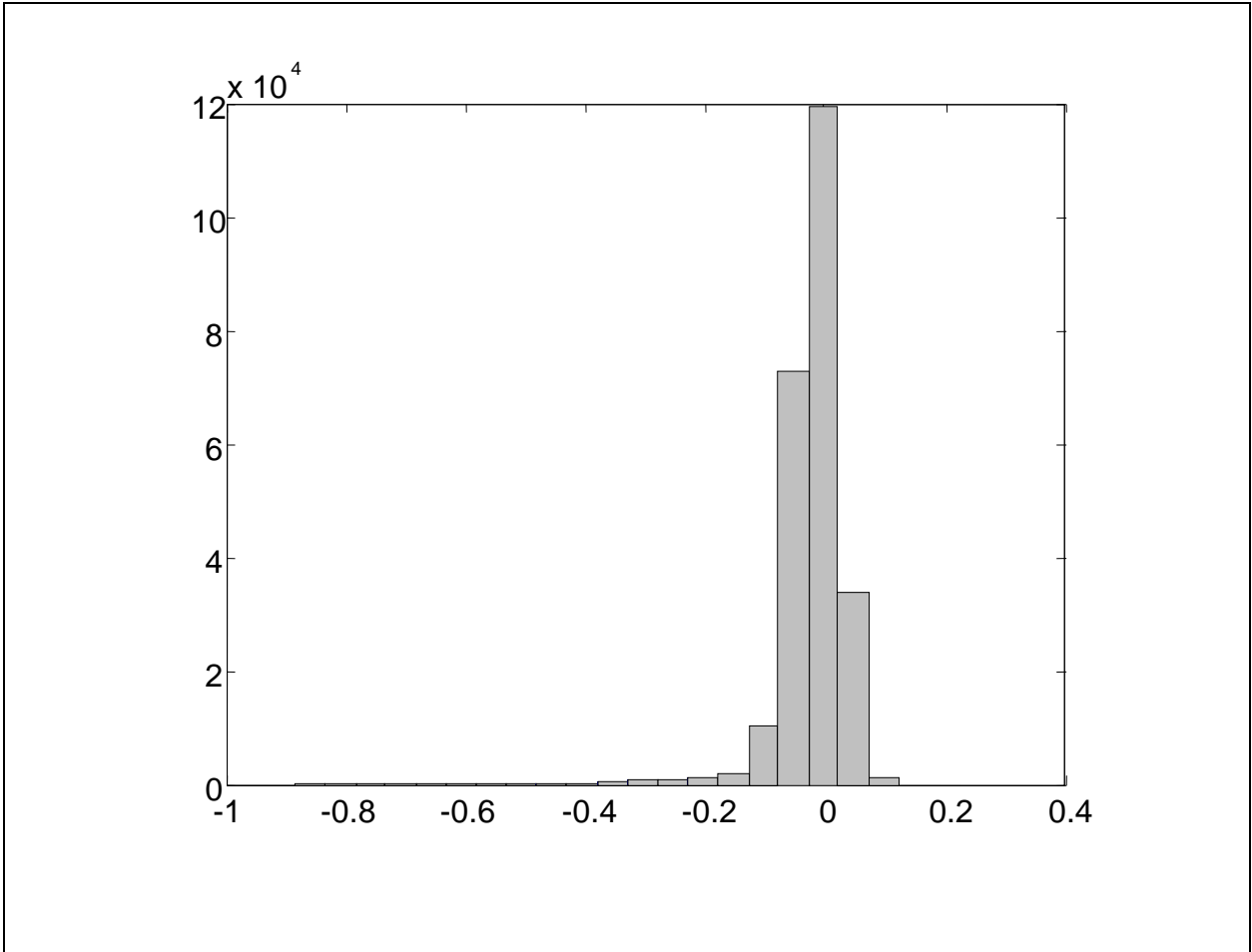


FIGURE 3: FREQUENCY DISTRIBUTION OF THE COST COEFFICIENT (BASED ON TABLE XV).