Adjustment Costs from Environmental Change[*]

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Abstract

The paper is concerned with the case whereby the distribution of a firm's productivity shocks changes without the knowledge of the firm. Over time the firm learns about the nature and extent of the change in the distribution of the shock and adjusts, incurring adjustment costs in the process. The long run loss in profits ($\pm$) due to the shift in the distribution we term the equilibrium response. The transitory loss in profits, incurred while the firm is learning about the distribution shift, is termed the adjustment cost. The theory is then applied to the problem of measuring adjustment costs in the face of imperfectly observed climate change in agriculture. The empirical part of the paper involves estimating a restricted profit function for agricultural land in a five-state region of the Midwest US as a function of prices, land characteristics, actual weather realizations and expected weather. We then simulate the effect of an unobserved climate shock, where learning about the climate shock is by observing the weather and updating prior knowledge using Bayes Rule. We find adjustment costs to climate change are 1.4% of annual land rents.

Keywords: Adjustment Costs, Adaptation, Climate Change, Learning, Uncertainty.

1 INTRODUCTION

Climate change is clearly one of today's leading global environmental problems, brought on by an increase in atmospheric levels of carbon dioxide and other greenhouse gases. Climate change may manifest itself in many ways, including changes in average temperature and precipitation, variability of weather (such as more frequent hurricanes), and sea levels.[1]

One of the most important issues in the climate change debate is the quantification and monetization of the market and non-market impacts (damages) from a change in the climate. Most quantitative estimates of damages are modest, which tends to contradict the intuition of many that a significant change in the climate must have very serious consequences.[2]

Early damage studies measured the short-run response from climate change: if temperatures rise rapidly, what are the losses to a sector (eg, agriculture), assuming the sector has no time (or inclination) to change practices and adapt?[3] Assuming away adaptive actions is known as the "dumb farmer" assumption.[4] This was the norm for estimates of damage in the late 1980's and early 1990's.

Recognizing the inappropriateness of assuming away agent adaptive response to climate change, other authors have assumed agents have time to react and adapt to climate change. This implicitly quantifies the long-run impact from climate change, for instance after farmers adapt to the changed climate and after coastal areas adapt to newly defined shorelines. In fact, in the long-run, climate change could have a positive effect, at least on certain sectors and regions. Adaptation

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[1] There is an enormous literature on climate change and climate policy. There are also many reviews of this literature; see for example, Kolstad and Toman [20] for an overview and references to other sources.

[2] For instance, in a review of damage estimates, the United Nations Intergovernmental Panel on Climate Change (IPCC) found market and nonmarket damage from climate change in the US to be from 14 to 139 billion dollars a year [30], which is modest in a 10 trillion dollar economy. In fact, an inability to clearly identify dramatic monetary losses from climate change is a major dividing issue between economists and non-economists in the climate change debate.

[3] A non-agricultural example is if the sea-level rises, what are the costs incurred by flooded cities and other coastal lands, assuming no adaptive actions?

[4] The term "dumb farmer" has been attributed to Rosenberg [37] by Schneider et al. [43], who also discuss the "smart farmer," the "clairvoyant farmer," and the "genius farmer." See also [24] and [35].

is now recognized as an important factor in moderating potential impacts of climate change, a factor which must be incorporated into estimates of damage.[5]

A third issue, which has received very little attention in the literature (and which is the subject of this paper), concerns the path from short-run to long-run – the adjustment process with associated adjustment costs. When a shock occurs, agents cannot instantly adapt. More precisely, adjustment costs are the extra costs incurred relative to the (counterfactual) case of instantly adapting to changed circumstances.[6]

The nature of adjustment costs can most easily be understood in the context of a firm subject to a one time price shock for one of its inputs. The literature on the theory of the firm subject to price shocks (beginning with Lucas [21] and nicely summarized in Berndt et al. [4]), distinguishes between short-run response, long-run response and the additional costs of adjusting from the short run to the long-run. After the price shock, if the firm makes no attempts to adjust inputs, it will suffer the maximal profit loss. However, the firm can adapt, changing production technique, moderating the loss in profit. But the firm may not be able to adjust its inputs quickly – capital for instance takes time to replace. Additional losses will occur, compared to the case of complete flexibility and ability to instantly respond to the shock. These extra costs are termed "adjustment costs."

An analogous process occurs with climate change, though instead of a price shock we have a technology shock – the change in climate. When the climate changes, maximal profit loss occurs if the firm makes no changes in its production techniques; i.e., remains a "dumb farmer." This loss

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[5] Adaptation has been the subject of a number of papers. See the discussion of adaptation in the National Academy of Sciences [29] study on climate change as well as the special issue of Climatic Change devoted to this subject (April 2000). Schimmelpfennig et al. [39] have addressed adaptation in agriculture. See also the recent IPCC volume on the subject, [22].

[6] For instance, costs of adjusting to an unexpected sea level rise exist. Buildings and infrastructure must be abandoned and reconstructed. This is a problem of fixed capital, capital that cannot easily be moved, modified or adjusted. The slower the adjustment need be, the lower the cost. In other sectors of the economy, capital fixity is less of an issue; for instance, in agriculture, if the climate changes, crops can be relatively easily changed and the amount of capital that is made obsolete is probably minimal.

can be moderated by adaptation, reducing the profit loss. Agents are slowed in their ability to instantly adapt to the changed climate for two reasons: input (eg, capital) fixity and incomplete knowledge of the climate change. In this paper, we focus on the later source of adjustment costs.

There are two purposes of this paper. One is to provide a theoretical structure for viewing adjustment in the context of environmental change, specifically climate change. The second is to apply this theoretical structure and measure adjustment costs; in particular, we consider agriculture and examine the costs of adjustment in US agriculture in the Midwest, a relatively homogenous region agriculturally.

In this paper, the inability to instantly adjust to a changed climate arises because the economic agent (think of a farmer) does not perfectly observe the climate change: the farmer only slowly realizes that the climate has changed. The farmer forms her subjective assessment of what weather might be for the coming year based on currently available information (IPCC predictions and historical weather). Given this structure, we simulate how a farmer would react to an unobserved change in the climate (ie, the distribution of weather). The farmer would initially think she is seeing unusual weather, only slowly updating her estimate of the true climate. Eventually she learns the true nature of the change in the climate; in the meantime, her production decisions are suboptimal (relative to perfect information) and thus her profits suffer, generating adjustment costs.

To implement this concept of adjustment costs, we first econometrically estimate how US farm profit is influenced by a variety of factors, including realized weather and expectations about weather. Expectations are assumed to be derived from observing past weather. We then simulate how farmers would respond to a change in climate (mean temperature and precipitation). We consider two cases, one where the farmer is fully informed of the change in the climate and another where the farmer only realizes the climate has changed by observing unusual weather and slowly

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updating her prior on the climate. The difference in profits for these two cases is the adjustment cost.

We argue that adjustment costs are likely to be quantitatively important for many cases of environmental change. Environmental change results in many winners and losers, which tend to cancel each other out. But adjustment costs are a cost to everyone, regardless of whether or not eventually environmental change is a benefit or a cost.

Indeed, we show that incomplete knowledge of the climate can indeed lead to a loss in profits. We examine agriculture in the Midwest using data from the 1976-97 period, and then simulate what might happen over a century from gradual unobserved climate change.[7] Although we find that this change in climate eventually increases annual expected profits by 3.7%, the net present value of adjustment costs is 1.4% of annual land rents. In absolute net present value terms, in our sample climate change results in a long run gain of $0.54 billion but adjustment costs of $0.24 billion, for a net gain of $0.30 billion.

2 BACKGROUND

If farmers know the climate has changed, how do they respond in the long-run and what is the effect on welfare? We call the *equilibrium response* the profits or welfare under environmental change under full information less profits or welfare with no environmental change. The equilibrium response includes any adaptation that economic agents may make to the environmental change. Understanding the transition to a different climate is somewhat more subtle. Under our assumption that all inputs are variable,[8] we may denote the *adjustment cost* the profits or welfare under full information about environmental change, less profits or welfare when environmental

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[7]We assume the climate change scenario is randomly drawn from a normal distribution whose parameters are determined from information given in the IPCC Third Assessment Report [49]. Other scenarios result in larger (up to 7.6%) adjustment costs.

[8]As noted in the Introduction, adjustment costs may arise from factory quasi-fixity as well as incomplete information. The focus of this paper is on incomplete information only.

change occurs under current (incomplete) information. Incomplete information prevents agents from taking advantage of some available adaptations because agents are not perfectly sure of the degree of environmental change and therefore not perfectly sure of what adaptations to use. Presumably, agents are aware of their own uncertainty and can therefore also make use of adaptations that perform well under a variety of circumstances, and yet would not be ideal if the exact nature of the environmental change was known.

The climate change literature already has a plethora of terms for damage and impacts of climate change and it is appropriate to put the terms introduced above – equilibrium response and adjustment costs – into the context of that terminology. The literature typically distinguishes two actions that can and should be taken to limit the climate change problem: mitigation and adaptation.[9] Mitigation, simply put, is action to reduce net emissions of greenhouse gases, thus slowing climate change. Adaptation involves changing behavior and making investments so that the changed climate is not as damaging. Such actions may be taken by individual agents or by governments (see [12]). Adaptation might include the construction of dikes to reduce the effect of sea-level rise or the changing of cropping practices to reflect a changed climate.

Economists would typically assume that adaptation taken by private agents is implicit in computing the net damages from climate change. In fact, the case of no adaptation would be difficult to observe. But, in response to a climate shock, adaptation may take time to implement. Analogous to our approach, Pearce et al. [30] and Schneider and Sarukhan [42] distinguish between transient and equilibrium effects of climate change. The equilibrium effects include all adaptation that is eventually taken; sectorial or societal well-being may be higher or lower after the climate change and after all adaptation has taken place. The transient effects refer to the additional,

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[9]There is already quite a bit of terminology regarding costs and damages from climate change (refer to McCarthy et al. [22] for a discussion). Somewhat surprisingly, there is little precision on the definition of these terms. See the special issue of Climatic Change on adaptation, including [45] and [15], and the volume from the Third Assessment Report of the IPCC [22].

temporary dislocations, as climate moves from one equilibrium climate to another. The key determinant of the cost of adjustment is the rapidity of change. If change is slow, agents have time to adapt, incurring little or no adjustment costs. If change is rapid, adjustment costs may be more significant.

Figure 1 shows a hypothetical economic activity generating value over time, $V(t)$. Climate change is represented as an instantaneous technology shock at $t = t_0$ that reduces the per time period value of the economic activity by $V_0 - V_2$. Over time, adaptation reduces losses. The difference between the long run values, $V_0 - V_1$, is the per period equilibrium response from the climate change. The (total) equilibrium response is the net present value (from $t = t_0$) of the stream of lost value, $V_0 - V_1$. The value of adaptation would be the net present value (from $t = t_0$) of the stream $V_1 - V_2$. The shaded area in the Figure represents the component of damage (undiscounted) associated with the failure to instantly take adaptive actions due to the speed of the shock, the "adjustment costs." The (total) adjustment costs are the net present value (from $t = t_0$) of the stream $V_1 - V(t)$.

Although Figure 1 shows an instantaneous change in the climate, the change could of course be more gradual, in which case the adjustment costs would be lower. In fact, with a very slow and gradual change, the adjustment costs would asymptotically approach zero.

2.1 Adapting to Climate Change in Agriculture

A number of authors consider the effect of climate change on agriculture. Adams et al. [1, 2, 3] Mjelde et al. [28], Reilly et al. [36], Rozenzweig and Parry [38], Schneider et al. [43], and Solow et al. [47] are prominent examples of the use of agricultural process models (including crop growth models) to measure the effect of climate change on crop yields and welfare. Sohngen and Mendelsohn [46] use a process model to study timber. Process models consist generically

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of physiological or technological models of production, often combined with a model of various input and output markets. The models are calibrated generally so that the supply of inputs and outputs and prices in the model closely match the data over a recent period.[10] Process models have become increasingly sophisticated in the range of adaptations allowed. Adams et al. [2] and Reilly et al. [36] are perhaps the most sophisticated, allowing farmers to change decisions about planting dates, crop choice, and some inputs in response to environmental change. However, it is well known [11, 24, 43] that even sophisticated process models may miss some adaptations available to farmers and thus overstate the equilibrium response to climate change.

Ricardian models, such as Mendelsohn et al. [24, 25, 26] and Johnson and Haigh [13] go even further and assume *complete* adaptation, both in crops and input decisions [40, page 1].[11] Figure 2 illustrates this point. Shown in the figure are response curves for multiple uses of land as a function of the climate (simplistically represented by average temperature). These reflect the value of the product of the land (net of non-land costs) after full equilibration to a climate change. The upper locus of points, shown as the heavier line, is the maximum value of the land. Consider a climate change, say from T_1 to T_2. Prior to the change, the value of the land is at point A. When the farmer adapts, changing the crop from wheat to corn, and perhaps other cropping practices, the value of the land ends up at B, for an equilibrium response L_0. If the farmer is unable to switch crops but can adjust other practices, this results in a more significant loss from climate change, as illustrated by the points along the wheat curve in the Figure (such as point C, with corresponding loss L_1). Keeping the crop fixed as well as all other practices of the farmer results in points interior to the crop-specific curve in the figure, such as point D. Hence significant interim

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[10]Agricultural process models are akin to activity analysis models in production. Complete enumeration of all possible technological options is desired; relative prices are used to determine an efficient technology choice (e.g., see [3]).

[11]Yohe et al. [53, 54], Yohe and Marshall [52] use a similar approach for sea level rise. Interestingly, Johnson and Haigh [13] examined the value of climate using a very similar approach, though from the point of view of valuing intentional and supposedly beneficial weather modification.

costs of the climate change may exist, costs that are ultimately eliminated as the farmer adapts to the new climate.

Mendelsohn et al. [24] have measured the differences in land values across the US, inferring that land value differences are due to endowed soil quality and climate. This allows the authors to infer the value of different climates. Using this approach, they infer a very small effect (possibly positive, possibly negative) on US agriculture from climate change.[12] In effect, the Mendelsohn et al papers establish a lower bound on the cost of climate change on agriculture, corresponding to perfect and instantaneous adaptation and equal to what we term the equilibrium response.[13,14]

2.2   Adjusting to Climate Change

The literature on adjustment costs in agriculture from climate change is sparse. Some process model authors have undertaken first steps towards modeling adjustment costs. For example, although it is not studied in detail, one could infer adjustment costs in the timber industry equal to $2.21-4.86 billion by comparing Tables 4 and 5 in Sohngen and Mendelsohn [46]. Uncertainty there is modeled as planting the strand of timber that did best in the previous decade(s). Kaiser et al. [14] and Schneider et al. [43] do a similar procedure for agriculture. These models likely understate adjustment costs as the limited number of endogenous decisions effectively limits the number of suboptimal decisions (relative to perfect information).[15] A similar point is noted in

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[12]The climate change they consider is a uniform 5°F (2.8°C) warming accompanied by a uniform 8% precipitation increase. A similar analysis of Russian agriculture found an output gain from the same amount of climate change [19].

[13]Schlenker et al. [41] have performed a similar analysis on a subset of the US, focusing on non-irrigated land.

[14]There are fewer econometric analyses of the effect of weather on agriculture. Perrin and Smith [31] investigate the effect of weather on several crops in North Carolina and then use results of climate models to estimate the effect on crops of climate change. Hansen [11] estimates the effect of weather and climate on corn yield and then postulates the effect of a change in climate. Some studies in agricultural economics and agronomy focus more directly on the weather effect [17, 48, 51]. These models approach the problem after the production decisions have been made, only considering the effect of actual weather realizations on yield. Typically the weather data is transformed into some measure of deviation from expected weather. The underlying idea is that the effect of normal weather (represented by climatic expectations) is captured in the farmer's cropping practices, but that unusual weather will have an impact of yield.

[15]Clearly, process models with no endogenous decisions must predict adjustment costs equal to zero.

Adams et al. [1, page 18].

Adams et al. [1], Reilly et al. [36], Schneider et al. [43], and Solow et al. [47] compare welfare when decision makers have perfect information about environmental change with welfare when environmental change is unobserved in a process model. For example Reilly et al. [36] find the value of perfect El Nino Southern Oscillation (ENSO) weather information to agriculture to be $453 million. These models overstate adjustment costs, as decision makers are not allowed to learn and adapt, even when environmental change is obvious. In our application below, farmers learn the climate has changed in some dimensions in as little as 20 years.

Ricardian models have the advantage of not needing to model endogenous decision making. However, it is not clear how to model adjustment costs within the Ricardian framework. After an unobserved environmental change, one cannot compare decisions under current information versus perfect information because no decisions are modeled in the Ricardian framework. Yohe et al. [53, 54], Yohe and Marshall [52] attempt to overcome this problem by adding a decision to save or protect structures, with the cost of protecting calibrated (not estimated) as a linear function of the sea level rise. They compare full information about sea level rise, where no structures are lost since none are built that will be lost, with no information about sea level rise, where structures are saved each period if the cost is low enough. Clearly, this model of adjustment costs suffers from the same problems listed above: only one endogenous decision (abandon or save) is allowed, and learning is not modeled.

Several related literatures are relevant. One concerns the rate of adoption of new technologies. As Reilly [33] points out, historically agriculture has been relatively slow to adopt innovation, ranging from new crops to new technologies. Some literature exists on the process of adopting new technology, focusing primarily on learning and incomplete information (e.g. Fischer et al. [9], Ellison and Fudenberg [8]). Farmers start out with a diffuse prior on the usefulness of the

new technology; over time they observe how well (or poorly) others do with the technology and from that experience, revise their priors. Bayesian learning is the starting point for these models although as Fischer et al. [9] point out, Bayesian models tend to overstate learning rates in some cases.

The literature on adjusting the optimal level of capital in response to changed relative prices [44] emphasizes the cost of rapidly adjusting the capital stock. If, for instance, energy prices rise rapidly and call for a substitution of capital for energy in production, this shift cannot be made rapidly. Explicitly recognizing the cost of adjustment makes the path of adjustment of the capital stock the result of an intertemporal trade off between adjustment costs and expenditures on other factors. It would not appear that this literature has much to offer in the agricultural context where capital (other than land) is relatively easy to change over time.[16]

McFadden [23] focuses on how a farmer (or other agent) may change behavior based on un-certainty about climate change (or even weather variability). In essence, if the farmer feels a possibility of climate change exists, he may adopt more robust practices (e.g., irrigation) that perform relatively well over a range of weather or climates, sacrificing a bit relative to the case of perfect knowledge about the weather. Fisher and Rubio [10] similarly find that water storage investments should increase as the variance of precipitation increases.

3 A MODEL OF ADJUSTMENT COSTS

In our method of modeling adjustment costs, agents learn about an unobserved environmental change by observing the weather and updating using Bayes rule. More importantly, we use the Ricardian framework and assume that decision making by farmers under uncertainty is implicit in agricultural profits. Specifically, we show that profits given uncertainty about environmental

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[16]Irrigation capital may be somewhat more difficult to adjust quickly, depending on the nature of the capital.

change in a county with a given climate variance is equivalent to an otherwise similar county with no uncertainty about environmental change but a higher climate variance. Thus in our mind, adjustment costs can be measured as the change in profits from an increase in the climate variance. Thus we not only advance the literature on adjustment costs by allowing for Bayesian learning, but measure adjustment costs without having to directly model decisions of the firm.

3.1 Stochastic Production

We consider a firm that has access to a production technology, where production depends on input choice as well as a stochastic shock. This could be a physical shock to the production technology (which is how we consider it) or a price shock. The timeline is such that first inputs, X_t, are chosen, then the firm learns the realization, W_t, of the random shock W, and finally output, Y_t, is realized. It is important to recognize that X_t includes any and all potential defensive actions that the firm may take in response to a known change in the distribution of W. We let the shock be normally distributed with a possibly time varying mean so that $W_t \sim N(\omega_t, 1/\rho)$.[17] Production is determined by the realized shock only, not expectations:

$$Y_t = f(X_t, W_t). \tag{1}$$

This is an *ex post* production relation in the sense that the realization W_t is determined after input decisions are made. (This is consistent with Pope and Chavas [32]). The firm faces prices for outputs, q_y, and inputs, q_x, which we assume are not uncertain nor affected by the shock.[18]

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[17]The model can easily be extended to other distributions and/or other unknown parameters, as long as the distribution belongs to a conjugate family.

[18]One might expect there to be uncertainty in the price of output, particularly if there is a time lapse between the first period and the ultimate sale of product. Furthermore, one might expect the output price to be correlated with the shock. This latter point may or may not be true. In the case of agriculture, the futures price is the expected price at harvest, which will be correlated with weather over the entire market. Thus the farmer should have expectations about her own weather and market-wide weather. These two may well be uncorrelated. We are ignoring these issues, which amounts to the producer entering into a contract to deliver output (the quantity of which is uncertain) at a agreed-upon price.

We characterize production at two different points in time: prior to resolution of the uncertainty (*ex ante*) and after resolution of the uncertainty (*ex post*) since demand for X_t is an *ex ante* demand and the supply of Y_t is *ex post*.

3.1.1 *Ex ante* Profits, Factor Choice and Output

Let E_x denote the expectation over the random variable x, then expected profits, *ex ante*, are:

$$\Pi^A(\omega_t, \rho) = \max_{X_t} \mathrm{E}_{W_t} \left\{ q_y f(X_t, W_t) - q_x X_t \right\} \tag{2}$$

$$\equiv \max_{X_t} \int_{W_t} \left\{ q_y f(X_t, W_t) - q_x X_t \right\} N(\omega_t, 1/\rho) dW_t.$$

Associated with the profit function in Eqn. (2) is an *ex ante* factor demand equation $X_t = X(\omega_t, 1/\rho)$. For simplicity of notation we suppress the dependence of all functions in this section on prices, q_x and q_y.

3.1.2 *Ex post* Profits and Output

Ex post profits are measured after the shock has been realized:

$$\Pi^P(\omega_t, \rho, W_t) = q_y f(X(\omega_t, \rho), W_t) - q_x X(\omega_t, \rho) \tag{3}$$

The difference between the *ex ante* and *ex post* profit functions is the knowledge of the realization of the random shock. Clearly,

$$\Pi^A(\omega_t, \rho) = \mathrm{E}_{W_t} \left\{ \Pi^P(\omega_t, \rho, W_t) \right\}.$$

3.2 Unanticipated and Unobserved Change in Distribution of Shocks

Now consider the case of an unobserved and unanticipated change in the distribution of the shock. Let Z_t be a vector of exogenous variables which affect the mean of the shock. If ω_t represents the

climate then Z_t could include a constant, a climate trend, and/or variables such as greenhouse gas concentrations.[19] We suppose the mean of the shock is known to evolve according to:

$$\omega_t = \beta' Z_t. \tag{4}$$

We thus allow the mean of the shock to possibly change slowly over time, as is the case with climate change. Hence:

$$W_t = \beta' Z_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, 1/\rho). \tag{5}$$

Here we assume Z_t is observed and uncorrelated with ε_t, whereas changes in β are unobserved.

3.2.1 Equilibrium Response and Adjustment Costs

Suppose in Eqn. (4) that at $t = 0$ there is an unobserved change in β to $\overline{\beta}$. Let b_t be the firm's subjective estimate of the parameters of the distribution of the random shock at any point in time, with b_0 based on the historical record. Each year the realized shock, W_t, is drawn from the distribution $N(\overline{\beta}' Z_t, 1/\rho)$. Assume the producer observes W_t and updates her prior b_t to yield the posterior b_{t+1}. How this updating is done is another question, which we turn to later, but we expect that $\lim_{t\to\infty} b_t = \overline{\beta}$ and that the firm knows that their estimate is not perfect, for example, the firm believes that $\overline{\beta} \sim N(b_t, 1/p_t)$, where p_t is the precision of the firm's beliefs that $b_t = \overline{\beta}$.

The firm's *ex ante* optimization problem under uncertainty is:

$$\Pi^{UA}(b_t, Z_t, \rho, p_t) = \max_{X_t} \mathrm{E}_{\varepsilon, \overline{\beta}} \left\{ q_y f(X_t, W_t) - q_x X_t \right\} \tag{6}$$

$$= \max_{X_t} \int_{\overline{\beta}} \left(\int_{\varepsilon} \left(q_y f(X_t, \overline{\beta}' Z_t + \varepsilon) - q_x X_t \right) N(\overline{\beta}' Z_t, 1/\rho) d\varepsilon \right) N(b_t, 1/p_t) d\overline{\beta},$$

leading to input demand $X^U(b_t, Z_t, \rho, p_t)$, *ex post* profit

$$\Pi^{UP}(b_t, Z_t, \rho, W_t, p_t) = q_y f(X^U(b_t, Z_t, \rho, p_t), W_t) - q_x X^U(b_t, Z_t, \rho, p_t), \tag{7}$$

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[19] For instance, if $Z_t = \begin{bmatrix} 1 & t & h(GHG) \end{bmatrix}'$, then we hypothesize that the mean temperature, ω_t, is a linear function of time and some (possibly complex) function of greenhouse gas concentrations, GHG.

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and output equal to $Y^{UP}(b_t, Z_t, \rho, W_t, p_t)$.

Two losses exist, the adjustment cost due to incomplete knowledge of the new distribution, and the equilibrium response, due to the effect of the changed distribution on production. The per period (expected) equilibrium response is

$$L_{ER}(Z_t, \overline{\beta}) = \Pi^A(\beta' Z_t, \rho) - \Pi^A(\overline{\beta}' Z_t, \rho) \tag{8}$$

$$= \mathrm{E}_{W_t}\left\{\Pi^P(\beta' Z_t, \rho, W_t)\right\} - \mathrm{E}_{W_t}\left\{\Pi^P(\overline{\beta}' Z_t, \rho, W_t)\right\}.$$

Here in the first expectation $W_t \sim N(\beta' Z_t, 1/\rho)$ and the second expectation $W_t \sim N(\overline{\beta}' Z_t, 1/\rho)$. Eqn. (8) indicates how much better or worse off the firm is as a result of the shift in the distribution, leaving aside the question of incomplete information. Notice that the equilibrium response implicitly includes any cost savings from defensive actions (adaptation) the firm might take to mitigate the effects of the change in the distribution. Such actions would constitute a change in the input choice X. By measuring profits as a function of the parameters of the distribution of the shock, we avoid having to specifically measure defensive expenditures. Thus we avoid the problem of overestimating the loss from a shift in the distribution that comes from missing possible adaptations.[20]

The per period (expected) adjustment cost is:

$$L_{ADJ}(Z_t, b_t, \overline{\beta}, p_t, \rho) = \mathrm{E}_{W_t}\left\{\Pi^P(\overline{\beta}' Z_t, \rho, W_t)\right\} - \mathrm{E}_{W_t}\left\{\Pi^{UP}(b_t, Z_t, \rho, W_t, p_t)\right\}. \tag{9}$$

Here in both expectations $W_t \sim N(\overline{\beta}' Z_t, 1/\rho)$. Notice that in Eqn. (9) we measure expected profits under uncertainty as what we expect, given full information, profits of a firm acting under uncertainty to be. Let ϕ be the discount rate; then the total adjustment cost is:

$$NL_{ADJ}(\overline{\beta}) = \sum_t \left(\frac{1}{1+\phi}\right)^t L_{ADJ}(Z_t, b_t, \overline{\beta}, p_t, \rho). \tag{10}$$

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[20]Another way to insure all possible adaptations are included is to use land values rather than profits. One advantage of our approach is that land values sometimes suffer from measurement error since land is illiquid and few parcels of land are sold each year [5, page 38].

Eqn. (9) defines the expected annual loss in profit due to incomplete information, while Eqn. (10) converts a stream of these losses back to the present using the discount rate ϕ.[21] Two sources of adjustment costs exist. First, adjustment costs occur because $b_t \neq \overline{\beta}$, so the firm chooses an input vector which is sub optimal relative to perfect information. Secondly, the firm realizes the estimate of the parameters of the distribution is likely incorrect, so the firm realizes the predicted value of the shock is likely to be less accurate. Thus from the point of view of the firm, the variance of the shock increases due to incomplete information.

It is important to point out that the losses in Eqn. (8) and (9) are not the net welfare losses to the economy since we are focusing on a firm only. We are assuming that these changes are occurring in isolation, that there are no price effects (prices are constant). To extend this to the market, we would have to take into consideration the effect of the shock on prices, the effect of the change in the distribution on prices, but not only for the product in question but other products whose demand depends on the price of substitutes and complements. In a dynamic context, we would have to take into account the effect on technical change. A welfare measure of the consequences of this learning would involve the changes in surplus accruing to all producers and consumers.

3.2.2 A Key Result

An important result of this paper is that weather drawn from an uncertain climate is equivalent (in a distributional sense) to weather drawn from a certain, but more variable, climate. In particular, from Eqn. (4) we have that $W_t \sim N(b_t' Z_t, \sigma^2 + s^2)$, where b is certain and $\sigma^2 = 1/\rho$

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[21] In the Section 5 below, we assume that $\overline{\beta}$ is also unknown to the analyst, in which case expected adjustment costs are equal to $\mathrm{E}[NL_{ADJ}(\overline{\beta})]$.

and $s^2 = Z_t'Z_t/p_t$. Consequently,

$$X^U(b_t, Z_t, \rho, p_t) = X\left(b_t'Z_t, \left(\frac{1}{\rho} + \frac{Z_t'Z_t}{p_t}\right)^{-1}\right), \tag{11}$$

where X^U is defined in the context of Eqn. (6) and X is defined in the context of Eqn. (2). Further:

$$\Pi^{UP}(b_t, Z_t, \rho, W_t, p_t) = \Pi^P(b_t'Z_t, \left(\frac{1}{\rho} + \frac{Z_t'Z_t}{p_t}\right)^{-1}, W_t). \tag{12}$$

Eqns. (11) and (12), while straightforward to derive, represent one of the fundamental insights of the paper. Apparently, the input decisions made by the firm under uncertainty are equivalent to the input decisions made as if the firm were certain the mean of the distribution was $b_t'Z_t$, except for a mean-preserving increase in the variance of the shock. Similarly, *ex post* profits under uncertainty are the *ex post* profits given the mean of the distribution is $b_t'Z_t$ with certainty, except for a mean-preserving increase in the variance of the shock.

The adjustment cost is then

$$L_{ADJ}(b_t, \overline{\beta}, Z_t, \rho, p_t) = \mathrm{E}_{W_t}\left\{\Pi^P(\overline{\beta}'Z_t, \rho, W_t)\right\} - \mathrm{E}_{W_t}\left\{\Pi^P(b_t'Z_t, \left(\frac{1}{\rho} + \frac{Z_t'Z_t}{p_t}\right)^{-1}, W_t)\right\}. \tag{13}$$

Adjustment costs thus stem from two sources. Because $b_t \neq \overline{\beta}$, the firm chooses a sub-optimal X relative to perfect information. Second, the firm knows it's estimate is uncertain, and therefore likely makes more robust input choices, which perform better under a wide variety of potential shocks but which perform less well than input choices specifically tailored to a particular shock. Under reasonable conditions, adjustment costs are increasing in $\left|\overline{\beta} - b_t\right|$ and decreasing in p_t. Further, adjustment costs stemming from an increase in perceived uncertainty occur even if initially b_0 is close to $\overline{\beta}$.

Eqns. (11) and (12) also provide a strategy for estimating adjustment costs. Assume during the period of estimation that no uncertainty exists, so we estimate the effect of changes in the

variance parameter on firm profits, Π^P. Then for a given change in the distribution, we calculate the adjustment cost using Eqn. (13).

3.2.3 Learning

How will b_t evolve over time? In the simplest case, assume that W_t and Z_t are scalars. According to Bayes rule, after observing W_t, the firm continues to believe $\overline{\beta}$ is normally distributed with mean and precision [6]:

$$b_{t+1} = \frac{b_t p_t + \rho W_t Z_t}{p_t + \rho Z_t^2}, \tag{14a}$$

$$p_{t+1} = p_t + \rho Z_t^2. \tag{14b}$$

Let $Z_t = Z$ be non-stochastic. Then in expectation, after T years [6], the updated estimate of the mean is given by

$$b_T - \overline{\beta} = \frac{\left(b_0 - \overline{\beta}\right) p_0}{p_0 + \rho T Z^2}. \tag{15}$$

As $T \to \infty$ the right hand side of Eqn. (15) approaches zero so the learning is consistent. If $b_0 < \overline{\beta}$ (for example if the mean temperature rose) then b_n converges to $\overline{\beta}$ from below. Finally, learning is faster if the variance of W_t is small, so that a change in W_t is more obviously the result of a change in the distribution as opposed to normal variation.

Although the representation of learning using Bayes Rule is the efficient way to process this new information, it is not an altogether satisfactory way of representing learning. In the case of agriculture, anecdotal evidence suggests that some farmers are more myopic, weighing recent information more than is efficient [50, 45]. Secondly, the Bayesian process requires a structural model that includes as many determinants of the observed variable as possible. For instance, Eqn. (14) assumes all information about the distribution of the shocks is known except the mean. If we posit a more complex process responsible for the change in the distribution, we need a

different structural model. A different structural model may give quantitatively different results on learning.

4   ESTIMATION

In implementing the theory of the previous section, we focus on agriculture in a portion of the U.S. Our goal is to estimate an *ex post* profit function, an empirical version of Eqn. (3). The ex post profit function is the primitive that permits us to calculate the equilibrium response (Eqn. 8) and adjustment costs (Eqn. 13). This function specifies profits as a function of input prices, output prices, climate, weather, and other technological factors. In our application, profits will be quasi-rents accruing to fixed factors, primarily land. The US Government reports net farm income, revenue less operating costs, by county; these data represent profits. We restrict attention to a six-state region of the Midwest US, in order to avoid a large degree of heterogeneity that characterizes agriculture in the US.

Some literature exists for guidance in estimating how weather, climate, and other factors affect agricultural output. Several authors [16, 48, 17, 11, 51] estimate yield equations for US corn, typically with county data. This work is useful in identifying the most important factors to use in explaining yield. Mendelsohn et al. [26] estimate an equation determining land value by county as a function of climate and weather, essentially an *ex ante* restricted profit function, Π^A, holding land fixed.

4.1   Econometric Model

The *ex post* profit function depends on two types of variables: prices and non-price factors such as weather, climate, and demographics. Let q represent the vector of prices and s represent the vector of non-price exogenous variables. Because we do not have farm level observations (only county level), we assume farming exhibits constant returns and thus estimate the profit per unit land

(per acre). A generalized McFadden flexible functional form for a profit function with constant returns to scale technology has the form [7]

$$\widehat{\Pi}^P(s, q) = \frac{1}{2}q_1^{-1}\left(q'\Lambda q\right) + \lambda' q + q'\Theta s + \overline{q}\left(s'\Psi s\right) + \overline{q}\left(\theta' s\right), \tag{16}$$

where Λ, Θ, and Ψ are parameter matrices and λ and θ are parameter vectors, all to be estimated; q_1 is a numeraire price, which is an arbitrary linear combination of prices, assumed here to be a simple average. Note that the profit function in Eqn. (16) is homogeneous of degree 1 in prices. Because of the very large number of exogenous variables, which are defined shortly, some restriction in Eqn. (16) was necessary to make the estimation manageable. In particular, we assume Ψ is diagonal.[22]

4.2   Estimation

The characteristics of the data suggest that errors are correlated across both time and space. The temporal autocorrelation comes from two sources. First the exogenous variables include demographic variables that have interpolated values for years between Census years. The interpolation is guided by interim surveys, which provide only estimates of actual income and population. An error in an estimate leads to errors in surrounding years as well. Second, the profit variable uses net income reported by farmers. Most income is attributable to current production, but the presence of long term futures markets and the possibility of temporary on-site storage for some agricultural products means that production in the previous year may affect current income.

Correlation across space may also be present, particularly due to the construction of the weather data. County weather observations are constructed using actual weather observations

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[22]The assumption that Ψ is diagonal simply means we exclude non-price cross-products. It is possible to estimate the model using the full set of cross-products. The number of variables (over 800) is then large relative to the size of the data set. This creates a new problem associated with the temporally and spatially autocorrelated error structure discussed below. The maximum-likelihood approach used to address the error structure relies on asymptotic properties of large data sets, and the data set would not be large relative to over 800 variables. Further, we were unable to reject the hypothesis that Ψ is diagonal at the 95% level, using a likelihood ratio test.

from all nearby weather stations using approximately the procedure of Mendelsohn et al. [24]. An inaccurate observation at a single station affects the data in all nearby counties. The effect is large for nearby counties and small for counties that are more distant, decreasing with the inverse square of the distance.

Finally, counties display considerable variation in size, agricultural output and revenue, and the relative importance of agriculture in the local economy. This may lead to differences in the level of variation for the error terms. The final econometric specification should account for heteroskedasticity in the error terms as well as autocorrelation.

Since the errors are not likely to be independent and identically distributed, OLS regression is not efficient and the estimates of the standard errors for the estimated parameters may be biased. One way to improve estimation is to assume a particular structure for the error terms and estimate the parameters describing that structure and the other parameters at the same time, using maximum likelihood. The resulting estimates are efficient, if the structural assumptions are correct. Here we assume the errors are AR(1), and spatially autocorrelated in a manner that mimics the process of constructing county weather data. Appropriately "lagged" error terms (where the lags are both temporal and spatial) are assumed independent and normally distributed, with the variances of the errors conditional on county specific factors such as county size. Sample selection is not a problem since nearly all counties have some agricultural production.

Consider first the corrections for autocorrelation. For a time period t, the cross-sectional equation of N observations is

$$\widehat{\Pi}_t^P = Q_t \gamma + \zeta_t \tag{17}$$

where Q_t is a vector consisting of all prices, non-price variables, and cross-products and γ is a parameter vector. Spatial autocorrelation implies the error structure

$$\zeta_t = \delta D \zeta_t + \eta_t, \tag{18}$$

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where D is an NxN weighting matrix. We assume the ijth element of D is $1/d_{ij}$, where d_{ij} is the distance in miles between counties i and j and $D_{ii} = 0 \ \forall i$. For distances greater than 500 miles, we assume the weight is zero. In terms of the entire panel (T years)

$$\zeta = \delta \left(I \otimes D \right) \zeta + \eta, \tag{19}$$

where I is the TxT identity matrix. Temporal autocorrelation of η can similarly be represented by

$$\eta = \mu M \eta + v, \tag{20}$$

where $v \sim N(0, \Sigma)$ with Σ diagonal and M is $NTxNT$ and corresponds to an AR(1) process. Combining Eqns. (19) and (20) gives:

$$R\zeta = v, \quad R = (I - \mu M)(I - \delta \left(I \otimes D \right)) \tag{21}$$

We can "pre-whiten" the variables in Eqn. (17) by pre-multiplying by R. Define

$$\Pi^* = R\widehat{\Pi}^P \tag{22a}$$

$$Q^* = RQ \tag{22b}$$

$$\zeta^* = R\zeta, \tag{22c}$$

so that $\zeta_{it}^* \sim N(0, \sigma_{it}^2)$. Errors may be heteroskedastic, so we assume

$$\sigma_{it}^2 = Q_{it}^* \nu \tag{23}$$

where Q_{it}^* is a row of Q^*, and ν is a vector of parameters to be estimated that, when combined with Q_{it}^*, yield the diagonal σ of the covariance matrix ζ^*.

It is straightforward (refer to Mitchell [27]) to write a likelihood function for Eqn. (17), using the whitened data in Eqn. (22) and correcting for heteroskedasticity using Eqn. (23). Estimated parameters include the coefficients γ, ν (heteroskedasticity), and the spatial and temporal auto-correlation terms, δ and μ.

4.3 The Data

A detailed explanation of the data is available online as a supplement to this article through http://www.aere.org/journal/index.html. Here we present an overview. We use annual county observations for the US, 1975-97. Estimation is based on 1976-1997 because of the lagged variables. Table I summarizes the statistical properties of the variables used.

We restrict attention to a 5-state region of the US (Illinois, Iowa, Kansas, Missouri and Nebraska). Although the data are available for the entire US, we have found that agriculture is so varied that it is difficult to estimate a single technology of production for the entire US (Schlenker et al. [41] find a similar result and argue that differences in irrigation requirements are an important reason). We sought a compact, contiguous region with similarities in agriculture. We settled on the following criteria in selecting states: the majority of land is agricultural; the majority of agricultural land is cropland; and each state in the sample is contiguous to at least two other states in the sample. This results in the five state region mentioned above. Although climate and geography vary less across the region than the entire country, the climate change scenario in the next section is well within the range of climates in the data (only one is greater than two standard deviations from the mean in the data, see Table 1).

The endogenous variable in the estimation is profits per acre of land. The data are farm income per acre of agricultural land and are computed as farm revenue less variable production costs. The data are prepared using the Agricultural Census (taken every 5 years), and the "best available county data" during non-census years. Revenues include most Federal subsidies. Our definition of profits as quasi-rents should exclude land rentals. Land rental payments are both a revenue and expense in this data, and are thus excluded as long as the income and expense are in the same county. A final simplification is that we effectively assume owner's labor income is zero for sole proprietorships, by measuring quasi-rents as equal to profits in the case of sole

proprietorships.

The U.S. Department of Agriculture has a monthly index of agriculture prices. Each index represents a specific category of agricultural products. We use the December value for each year. Feed grain and food grain are closely correlated and thus combined into a single index (weighted by the relative levels of output). The result is five output price indices do not vary by county. However, the use of inputs does vary by county. Thus an aggregate input price index is constructed for each county, based on the relative weights of various inputs in each county. This aggregate input price index is used as the numeraire.

Weather for a county is constructed from weather station information [27], following approximately the method of Mendelsohn et al. [24]. Weather is normalized by subtracting the mean of a particular weather variable from the realization of that variable and dividing the difference by the standard error of the variable. Our hypothesis is that the difference between realized weather and mean weather (climate) has an effect on profits separate from climate since one can adjust input decisions in response to climate but not in response to weather. Further, we standardize by dividing by the standard error because our hypothesis is that weather five degree above normal has a bigger effect on profits when normal variation is one degree than when normal variation is five degrees. The weather data that we use are monthly precipitation, precipitation squared, monthly average temperature, and average temperature squared for January, April, July, and October.

For climate, we use most of the first and second moments of the weather for each of the four months assuming weather in one month is independent of weather in another month. These are computed using data from 1930 through the year prior to the year in question. Thus for each month we use a mean precipitation and temperature, a standard error and a covariance between the precipitation and temperature. We ignore uncertainty associated with the estimates of the first and second moments.

We assume soil characteristics are unvarying over the sample period. Time is included to capture neutral technical change. County demographic information is included as a fixed factor since the composition of population and income in a county may affect the availability and quality of capital and labor, and so directly affect the production technology for agriculture. Additionally, the soil variables described above represent an average across an entire county. As land gets transferred from agriculture use to other uses, this alters the quality of the land remaining in agriculture. Income and population affect how much land is used for purposes other than agriculture, and therefore affect the accuracy of the soil characteristics. The observations are interpolated values, using decennial census data and interim surveys, constructed at the county level.

4.4 Estimation and Results

Estimation of Eqn. (17) was accomplished by numerically maximizing the likelihood function. The sample size was 10752 and 80 parameters were estimated. Climate variables are the first and second temperature and precipitation moments, whereas weather are the deviations from these moments. Thus our panel data set exploits cross-sectional variation in profits to estimate climate effects and time series variation to estimate weather effects. Most parameter estimates were highly significant and of intuitively plausible sign. However, because of the difficulty in interpreting the coefficients of the profit function directly, the results are presented here in terms of the effect of individual variables on profits, through the estimated derivative of profits with respect to the variable in question or the corresponding elasticity. In computing these estimates, variables were set to their sample means.

4.4.1   Price Effects

Table II indicates how prices influence profits. Almost all of the price variables affect profits in the expected direction, and the effect is significant at the 99% level. Input price increases plausibly reduce profits whereas most output price increases tend to increase profits. The only exception is grain perhaps because feed grain is both an input and an output.

4.4.2   Climate Effects

Table II indicates how climate (the parameters of the distribution, not the realized weather) influences profits. With the exception of one variable, April temperature standard error, all coefficients are highly significant. Areas which are wetter in the January-April period generate smaller profits; similarly, areas which are wetter in July and October generate larger profits. Areas with higher mean temperatures in April and October have higher profits whereas the reverse is true with regard to expected temperature in January and July. This suggests that a uniform increase in temperature (or precipitation) over the entire year will have a more modest effect since the effect in the different months will tend to cancel one another.

Notice from Figure 2 that we are estimating a second order approximation of what is likely to be a complex, non-differentiable relationship between climate and profits. As the climate changes, the profits change both because the land in it's current use becomes more or less profitable, but also because the optimal use of the land may change. Thus the model offers no prediction of the sign or magnitude of the climate elasticities. By adding the elasticities over the four months, we obtain a positive figure for both precipitation mean and temperature mean: wetter and warmer counties generate higher profits. Finally, some of the covariances are negative so the marginal and elasticity are of opposite signs in this case.

4.4.3 Weather Effects

Since weather is a realization, not an expectation, it is best thought of as a deviation from the expectation, normalized by standard deviation (z-score). A large z-score for January temperature means that the temperature turned out to be higher than expected. Table II indicates how weather influences profits. Generally, weather acts in a similar fashion to climate. However, the sum of the elasticities for temperature over the four months is negative: an increase in temperature of one-percent above average over the year will depress profits. Contrast this to the result for climate: a one-percent increase in expected temperature will increase profits. But this is intuitive. On average, warm is good but if it turns out to be warmer than expected, that is bad.

4.4.4 Other Factors

Table II presents the effect of other factors on profits. The soil characteristics are clearly important, suggesting that omitting them from the regression could have significant consequences. Only irrigation has an insignificant effect. The negative and significant elasticity for land area is somewhat puzzling since county boundaries and thus size are totally arbitrary. The positive and significant time effect indicates substantive technical change over the 21 years of data. Finally, county demographics apparently play an important role. Counties with high per capita income generally have lower profits. Counties with high population have higher profits; as expected, because competition for land for other uses tend to result in only the better quality agricultural land staying in farming.

4.4.5 Error Structure

Table II presents the estimates of the parameters of the covariance matrix. The regression results indicate that autocorrelation is significant, both temporally and spatially. The finding of

spatial autocorrelation is unusual in econometric studies and points out the importance of correct specification for studies using spatial data such as this one.

Little evidence of heteroskedasticity exists across counties. Two variables are included to account for possible heteroskedasticity: county size (available agricultural land) and total climate variance (the sum of all of the climate standard deviation variables). Table II indicates these variables were not significant in determining the variance of the residual term across counties.

5   ADJUSTMENT COSTS FOR CLIMATE CHANGE

The estimated profit function presented in the previous section gives us the information we need to compute adjustment costs. As we have argued here, the adjustment costs are a direct function of the agent's information regarding the true distribution of weather and the speed with which the agent acquires information. In order to compute meaningful adjustment costs, we compute them for a change in the climate commonly used in the literature. We also make the rational expectations assumption that beliefs converge to the actual stochastic process generating the weather.

5.1   The Climate Change Scenario

We focus our attention on the median farmer/county; in other words, we examine an artificial county with the median of each of the exogenous variables as given in Table I. Let $Z_t = [1, t]'$ and $\beta = [\beta_0, \beta_1]'$, where β_0 is an $1x8$ vector of pre-climate-change mean temperatures and rainfalls and β_1 is an $1x8$ vector of zeros.[23] We further assume climate change occurs gradually, in fact linearly over a 100 year period. Thus we let $\overline{\beta}_0 = \beta_0$ and parameterize $\overline{\beta}_1$ so that after 100 years,

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[23]Data is annual. The $1x8$ vector consists of monthly temperature and rainfall for four representative months during the year: January, April, July, and October.

the climate change scenario is exactly realized.[24] The climate thus evolves according to

$$\omega_{i,t} = \overline{\beta}_{i0} + \overline{\beta}_{i1}t \quad i = 1\ldots 8, \tag{24}$$

and weather evolves according to:

$$W_{it} = \overline{\beta}_{i0} + \overline{\beta}_{i1}t + \varepsilon_{it}, \quad \varepsilon_{i,t} \sim N(0, 1/\rho_i). \tag{25}$$

Here $1/\rho_i$ is the variance of the actual weather around the true mean, known to both farmers and the analyst.

It is appropriate that the model of climate change used by the farmer be a "rational expectations" model; i.e., the model of climate change in the mind of farmers should be the same as the model used by the analyst. For this reason, we let the farmer assume the climate follows the process in Eqn. (24), with $\overline{\beta}_0 = \beta_0$ known (estimated on historic weather observations – actual data) but $\overline{\beta}_1$ unknown. Assume the farmer believes $\overline{\beta}_{i1}$ is distributed normally with mean b_{it} and precision p_{it}. Then priors are updated into posteriors using Eqn. (14):

$$b_{i,t+1} = \frac{b_{it}p_{it} + \rho\left(W_{it} - \overline{\beta}_{i0}\right)t}{p_{it} + \rho t^2} \tag{26a}$$

$$p_{i,t+1} = p_{it} + \rho_i t^2. \tag{26b}$$

Eqns. (25), (26), (12), (16) and the initial conditions determine how expected profits per acre evolve over time. Let $\phi = 0.05$, then the estimated Equilibrium Response and adjustment costs are:

$$\widehat{NL}_{ER} = E\sum_t \left(\frac{1}{1+\phi}\right)^t \left(\widehat{\Pi}^P(\beta'Z_t, \rho, W_t) - \widehat{\Pi}^P(\overline{\beta}'Z_t, \rho, W_t)\right) \tag{27}$$

$$\widehat{NL}_{ADJ} = E\sum_t \left(\frac{1}{1+\phi}\right)^t \left(\widehat{\Pi}^P(\overline{\beta}'Z_t, \rho, W_t) - \widehat{\Pi}^P(b'_t Z_t, \left(\frac{1}{\rho} + \frac{t^2}{p_t}\right)^{-1}, W_t)\right) \tag{28}$$

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[24]Sohngen and Mendelsohn [46] assume a linear change over 70 and 150 years in their study of US Timber, whereas Schneider et al. [43] assume the climate increases in three discrete jumps over 60 years. Yohe et al. [53, 1996] assume a quadratic sea level rise over 110 years.

Since we have estimated a quadratic profit function, it is straightforward (but very tedious) to calculate the expectations and derive an analytic expression for the adaptation and adjustment costs.

Following Kelly and Kolstad [18], we suppose the farmer consults the scientific literature to get an idea of how the climate might change in the future. We suppose farmers consult the IPCC Third Assessment Report [49] and begins with priors equal to the IPCC estimate of a range of temperature changes equal to 2.52°F to 10.44°F and a range of rainfall increases of 5% to 20%. We therefore let initial beliefs b_0 be such that the mean of the range given in the IPCC will be reached after 100 years. We determine p_0 so that the high and low values correspond to 95% confidence intervals when the prior distribution is normal. The actual climate change that will occur in the next 100 years is of course unknown. We therefore assume the actual climate, $\overline{\beta}_1$, is drawn from the distribution which represents the best scientific estimate: $\overline{\beta}_1 \sim N(b_0, 1/p_0)$.[25]

5.2   Equilibrium Response and Adjustment Costs

At this point, it is useful to summarize the three major assumptions we have made in our measurement of adjustment costs. First, we have assumed a very simple learning process. Uncertainty is only over the 8 trend parameters at which temperature and rainfall increase. According to Eqn. (26b) uncertainty regarding the trend parameters declines monotonically in this model of learning. However, uncertainty over the climate change, $\overline{\beta}_1 t$, is non monotonic since as t increases small amounts of uncertainty over $\overline{\beta}_1$ are magnified. Initially t rises more quickly that the degree of certainty regarding the trend parameter, causing uncertainty over the magnitude of climate

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[25]Many other scenarios of climate change are possible; in fact, there is no "correct" scenario about the future. For example, we have also examined the climate change scenario of Mendelsohn et al. [24], assuming farmers have a prior generated from historical weather observations. Behavior is similar to the case in the text, though somewhat more pronounced. This results in an initial rapid increase in uncertainty over the climate with an associated drop in profits. Profits recover within a few decades as the farmer becomes convinced that the climate has changed. The net present value of adjustment costs are higher, about 7.6% of annual profits per acre. Other scenarios also result in adjustment costs greater than the 1.4% derived here.

change to rise. After a short period, the second effect begins to dominate and uncertainty over the degree of climate change falls to zero. Figure III depicts the time path of the variance of July temperature weather under uncertainty.

Since uncertainty over the magnitude of climate change $\overline{\beta}_1 t$ affects profits in the same way as an actual increase in the variability of weather (Eqn. 11), the effect of uncertainty on agricultural profits can be expected to be similarly non-monotonic. Of course an increase in variability can be expected to decrease profits (for example, farmers may take costly defensive actions such as planting more robust crops) even if, unknown to the farmer, the climate is initially changing very little.

Second, with high probability b_0 is close to $\overline{\beta}_1$, but with smaller probability $\overline{\beta}_1$ takes on a value not close to b_0, leading to adjustment costs caused by under or over-estimating temperature and rainfall. Initially t is small enough in Eqn. (25) so that the predicted weather is not far off. However, over time t rises quickly relative to the speed at which $b_t \to \overline{\beta}_1$, so weather predictions become less accurate, causing adjustment costs to rise. Eventually, $b_t \to \overline{\beta}_1$ at a faster rate than t rises, since convergence is at an exponential rate, so weather predictions becomes more accurate, causing adjustment costs to fall.

Finally, according to Eqn. (15), the rate of learning is sensitive to the natural variability of weather $(1/\rho)$. The hypothesized change in climate relative to the underlying variability of the weather is much greater for temperature than for rainfall. The farmer almost immediately attributes what is eventually a more than 3 standard deviation increase in temperature to climate change whereas after 100 years the increase in rainfall is still less than one standard deviation, which appears to be normal variation. Hence the adjustment costs are present even after 100 years due to incomplete learning about rainfall.

Figure IV shows how profit per acre responds to the hypothesized climate change. The hor-

izontal dotted line corresponds to value without the climate change (in the context of Figure 1, this would correspond to a horizontal line at V_0). The broken line is the profits per acre for the median county when the changing climate is perfectly observed (corresponding, in Figure 1, to a horizontal line at V_1 to the right of t_0). The solid line shows the profits per acre under incomplete information about the climate shock (corresponding to $V(t)$ in Figure 1).

For the median county, profits per acre increase as the climate warms and becomes wetter – which is expected since the estimated elasticities of temperature and rainfall each sum to a positive number. Climate change is unambiguously good for agriculture for this median county, the equilibrium response is actually a benefit with a net present value (discount rate of 5%) of $3.07 per acre, which is a benefit of approximately 3.7% of annual profits per acre. Mendelsohn et al. [24] look at the long run effect of the same climate change scenario and estimate that the scenario results in a change in annual land rents (analogous to our profits per acre) between a loss of 5.7% and a gain of 1.2%. The upper limit of this range is slightly lower our point estimate of 2.3% (when we impose the same climate change scenario, although we focus only on the Midwest).

Adjustment costs are something that has not been estimated by others. Total adjustment cost is $1.38 per acre. Thus the net benefit associated with the change is $1.69 per acre. The adjustment cost is not enormous – about 1.4% of the annual profits per acre. However, there are 175 million acres in our sample. This translates to an aggregate adjustment cost of $0.24 billion.

6   Conclusions

The goals of this paper have been to develop a theoretical and empirical structure to conceptualize, examine, and compute adjustment costs from incomplete information about a change in the distribution of technology shocks. This is an extension of the well-known work involving adjustment costs from price shocks due to physical rigidities in inputs. In contrast to the factor-fixity

basis for price-induced adjustment costs, we have focused on the incomplete information about a shift in the distribution of technology shocks as the basis for adjustment costs.

The work presented here is motivated by the problem of better understanding the monetized impacts of climate change. In particular, we are not only concerned with the standard measure of impacts, the long-run equilibrium impact, but also the impact along a transition path as climate changes – the adjustment costs from climate change. It is argued here is that firms will not instantly observe a change in climate since climate is merely the representation of the distribution of weather shocks. Although the shocks are observable, the distribution is only indirectly observable. If agents are unaware of the extent of a change in the distribution, costs will be incurred (relative to perfect information) while they are becoming perfectly informed about the change. Our hypothesis is that this can be a significant source of costs associated with climate change.

Our results show that adjustment costs from incomplete information regarding shifts in the distribution of stochastic shocks is in fact a well-defined concept. Furthermore, those costs can be computed by first characterizing the profit function and then simulating the shift in the distribution. We have estimated profit relationships involving both weather and the distribution of weather (climate) for agriculture in the middle United States. A first result concerns the equilibrium response from climate change (not adjustment costs). Our results show an increase in returns to land on the order of 3.7%, a result somewhat higher than that reported by Mendelsohn et al. [24]. This is not a cost but rather a benefit from climate change. We then use our estimated production relation to compute the adjustment costs, as defined above. We find those one-time costs on the order of $0.24 billion dollars, approximately 1.4% of annual land rents, though well under 1% of the asset value of the land. However, note that we ignore general equilibrium effects such as effects on technological change, substitutes, complements, and prices (possible worldwide) for

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agricultural output, and that we do not account for possible carbon fertilization effects caused by a change in agricultural activity. Carbon Fertilization effects can be especially large, improving yields by as much as 30% [34].

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7 Figures and Tables

Table I: Summary statistics on variables used.

VARIABLE	MEAN	MEDIAN	STD. ERROR	MINIMUM	MAXIMUM
input price index	-90.65	-93.55	13.97	-118.90	-51.34
meat price index	85.77	86.50	12.09	56.00	105.00
grain price index	108.73	107.00	16.02	75.00	149.00
oil crop price index	110.59	110.00	12.50	89.00	131.00
poultry price index	98.59	97.50	10.14	81.00	120.00
January temp/precip covar	0.04	-0.09	0.54	-1.93	4.77
January precip std. err	0.69	0.60	0.45	0.047	2.69
January precip mean (inches)	0.66	0.51	0.60	-0.58	3.50
January temp std. err	3.09	2.92	1.01	1.56	12.65
January temp mean (°F)	23.12	23.45	5.27	10.84	35.45
April temp/precip covar	-0.17	-0.09	0.48	-7.99	3.27
April precip std. err	1.33	1.31	0.33	0.58	3.66
April precip mean (inches)	2.58	2.73	0.84	-0.44	4.29
April temp std. err	1.79	1.73	0.59	0.87	9.53
April temp mean (°F)	51.89	51.90	3.35	44.20	59.24
July temp/precip covar	-0.83	-0.78	0.633	-4.79	8.16
July precip std. err	1.67	1.63	0.46	0.69	4.03
July precip mean (inches)	3.21	3.41	0.61	-0.71	4.47
July temp std. err	1.34	1.28	0.45	0.72	6.79
July temp mean (°F)	76.21	76.31	2.30	70.83	84.42
October temp/precip covar	-0.25	-0.33	0.48	-1.64	7.06
October precip std. err	1.39	1.42	0.38	0.38	3.48
October precip mean (inches)	1.95	2.11	0.79	-0.53	3.67
October temp std. err	1.90	1.82	0.59	0.99	8.55
October temp mean (°F)	54.27	54.26	2.88	47.24	60.59
January precip z-score	0.11	-0.14	0.99	-3.12	6.13
January temp z-score	0.03	0.04	1.35	-4.34	3.57
April precip z-score	0.03	-0.14	1.18	-3.95	6.58
April temp z-score	-0.69	-0.81	1.24	-4.15	4.67
July precip z-score	0.15	-0.11	1.31	-3.12	6.42
July temp z-score	-0.23	-0.25	1.03	-4.45	3.83
October precip z-score	0.01	-0.21	1.02	-3.41	5.72
October temp z-score	-0.45	-0.44	0.78	-7.37	7.91
Clay (0/1; 1=low granularity)	0.20	0	0.40	0	1
Flooding (frac land prone fld)	0.19	0.13	0.19	0	1
Irrigation (frac land irrig)	0.11	0	0.22	0	1
K-factor (soil permeability)	0.31	0.32	0.06	0	0.45
Salinity (frac land treated)	0.01	0	0.02	0	0.21
Sand (0/1; 1=high granularity)	0.03	0	0.16	0	1
Slope (avg ft to water basin)	2.34	1.98	1.37	0	8.78
Wetland (frac land wetland)	0.02	0	0.04	0	0.26
Available Ag land (1000 acres)	12.64	12.68	0.52	9.75	15.23
Per capita income (log)	9.64	9.58	1.19	6.05	15.50
Population (log)	9.40	9.46	0.41	7.88	10.75
Net Revenue per acre ($)	29.23	20.98	37.42	-99.00	407.57

NB: All price indices use 1990-1992=100. Some rainfall data are erroneously negative in primary data set; we have not changed the primary data in order to preserve normality of the error structure. Sample size: 10,752; statistics cover 512 counties, 21 years (1976-97). Z-score on weather variables equals value less the county mean over time all divided by county standard error.

Table II: Estimated Effects of Price, Climate, Weather, and Exogenous Variables on *ex post* Profits and Error Structure. **: significant at 99% level.

| Price Index	Marginal Effect	Std. Error	Elasticity
Inputs	−1.16**	0.19	−3.73**
Meat	0.28**	0.06	0.86**
Grain	−0.15**	0.07	−0.58**
Oil	1.17**	0.07	4.54**
Dairy	2.58**	0.06	8.80**
Poultry	0.46**	0.07	1.60**
Climate			
January temp/precip covariance	0.30**	0.06	3e−4**
January precipitation std. dev.	2.63**	0.24	0.06**
January precipitation mean	−2.65**	0.29	−0.06**
January temperature std. dev.	0.82**	0.04	0.09**
January temperature mean	−0.38**	0.01	−0.30**
April temp/precip covariance	1.58**	0.04	−0.01**
April precipitation std. dev.	7.56**	0.13	0.35**
April precipitation mean	−5.04**	0.08	−0.45**
April temperature std. dev.	−0.08	0.06	−0.01
April temperature mean	0.71**	0.06	1.28**
July temp/precip covariance	−0.58**	0.04	0.02**
July precipitation std. dev.	−5.36**	0.06	−0.31**
July precipitation mean	3.55**	0.05	0.40**
July temperature std. dev.	−5.01**	0.10	−0.23**
July temperature mean	−0.38**	0.06	−1.01**
October temp/precip covariance	1.36**	0.04	−0.01**
October precipitation std. dev.	−0.40**	0.11	−0.019**
October precipitation mean	2.53**	0.14	0.17**
October temperature std. dev.	−0.26**	0.09	−0.02**
October temperature mean	0.43**	0.06	0.81**
Weather			
January precipitation	−0.375**	0.016	−0.0009**
January temperature	−0.387**	0.009	−0.0004**
April precipitation	−0.007	0.006	0.0000
April temperature	3.876**	0.010	−0.0940**
July precipitation	0.495**	0.012	0.0036**
July temperature	−2.520**	0.015	0.0229**
October precipitation	0.044**	0.016	0.0001**
October temperature	−0.646**	0.018	0.0104**
Exogenous Variables			
Soil – clay	0.38**	0.02	3e−3**
Soil – flooding	−0.91**	0.07	−0.01**
Soil – irrigation	−0.01	0.11	0.00
Soil – k-factor	−3.38**	0.19	−0.04**
Soil – salinity	0.26**	0.83	2e−3**
Soil – sand	1.59**	0.07	1e−3**
Soil – slope	0.43**	0.01	0.04**
Soil – wetlands	21.07**	0.41	0.01**
Land area	−2.27**	0.06	−1.00**
Demographics – per capita inc.	−0.49**	0.01	−0.17**
Demographics – population	0.75**	0.09	0.25**
Time	2.29**	0.01	0.96**
Error Structure Parameter	**Marginal Effect**	**t-statistic**	
Temporal autocorrelation	0.59**	988.50	
Spatial autocorrelation	0.89**	146.40	
Non-county specific std. dev.	0.28	< 0.01	
Effect of county size on std. dev.	0.56	< 0.01	
Effect of total variance on std. dev.	1.30	< 0.01	
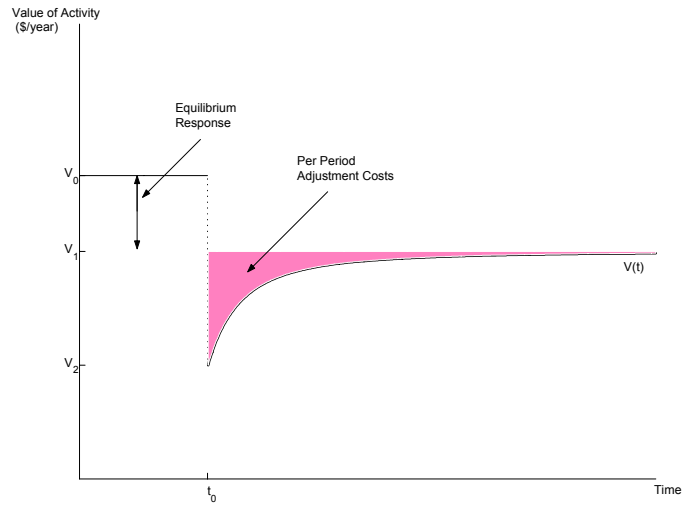
Figure I: Adjustment costs for an activity from instantaneous technology (eg, climate) shock
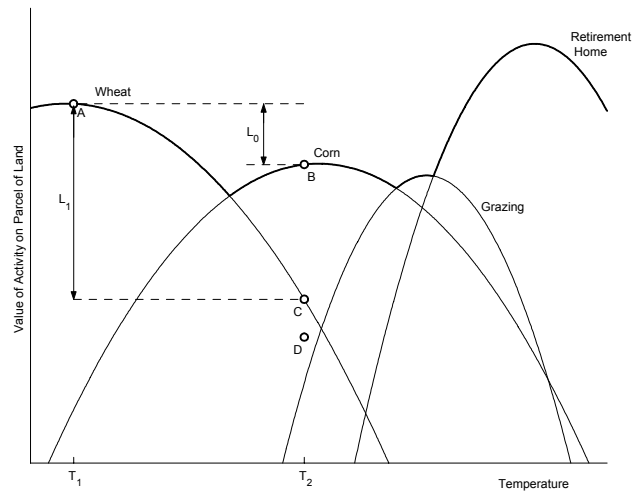

Figure II: Value of land as a function of climate.

NB: Adapted from Mendelsohn et al, 1994.

L_o: Loss from observed and known temperature increase from T_1 to T_2.

L_1: Loss from unobserved temperature. increase; agent believes temperature is T_1, whereas in actuality it is T_2.
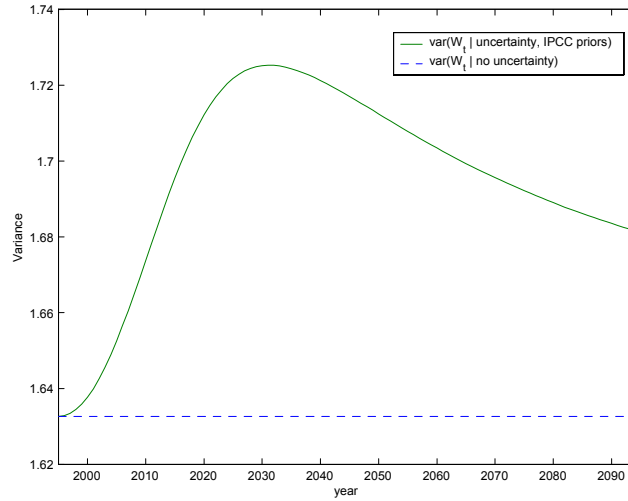
Figure III: Perceived variance of July weather when climate change is uncertain. NB: given uncertainty, $\text{var}(W_t) = 1/\rho + t^2/p_t$, whereas under certainty $\text{var}(W_t) = 1/\rho$.
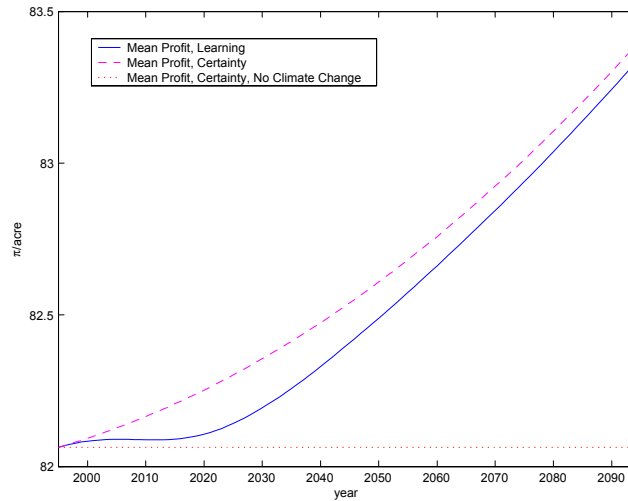

Figure IV: Profits per acre given priors determined from the Third IPCC Assessment and average climate change equal to the mean value given in the Third IPCC Assessment.