Dynamic Adjustment in U.S. Agriculture under Climate Uncertainty

Sansi Yang
School of Economic Sciences
Washington State University
Pullman, WA 99163
sansi.yang@email.wsu.edu

C. Richard Shumway
School of Economic Sciences
Washington State University
Pullman, WA 99163
shumway@wsu.edu

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Abstract

We construct a stochastic dynamic dual model to investigate the structural adjustment of two aggregate output and three aggregate input categories in U.S. agriculture under climatic change uncertainty. A century of national annual data (1910-2011) is used in the empirical analysis. No constraints on asset fixity are imposed. Results indicate that both output categories as well as all input categories exhibit quasi-fixity in response to market change and stochastic climate change. Crops adjust most rapidly toward equilibrium levels and capital adjusts most slowly.

Key words: adjustment costs, agricultural production, climate change, dynamic duality

JEL classification: Q11, Q54

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Introduction

Uncertainty about future climate change may influence a firm's intertemporal investment decisions, especially in the agricultural production sector where weather has a direct and profound impact on production levels. The adjustment process of outputs and quasi-fixed factors towards their long-run equilibrium levels may be affected by the firm's expectation about future climate change as well as expected price changes.

Adjustment costs of factor demand (e.g. learning cost, expansion planning fees, costs of restructuring the production process or preparing equipment) that arise in response to market shocks have been widely studied and well documented in the literature (e.g., Lucas 1967a; Caballero 1994; Hamermesh and Pfann 1996; Hall 2004; Lambert and Gong 2010). However, the fact that environmental shocks such as climate change may cause adjustment costs has received relatively little attention. For instance, decreases in precipitation raise the demand for water which in turn raises the demand for more efficient irrigation systems. To build new irrigation infrastructure takes time and effort, and therefore induces adjustment costs. Kelly, Kolstad and Mitchell (2005) studied adjustment costs in the context of profit loss in the process when a firm with incomplete knowledge learns about the distribution of climate change over time, but they assumed that all inputs are fully variable, and therefore did not consider the costs related to adjusting input demand. These costs may be non-trivial and can make inputs difficult to change over short time intervals.

Our objective is to determine how adjustment costs affect input and output response both to price shocks and to stochastic climate change within the multi-output, multi-input agricultural production industry. Based on dynamic duality theory (Epstein 1981; Vasavada and Chambers 1986; Howard and Shumway 1988; Agbola and Harrison 2005) and more recently developed stochastic models (Pietola and Myers 2000; Krysiak 2006), we construct a stochastic dynamic dual model to investigate the structural adjustment in U.S. agriculture when climate uncertainty is present.[1] We broaden the dynamic input adjustment model to consider adjustment costs in both inputs and outputs associated with price and climate change. We investigate whether adjustment costs may delay firms' adaptation to climate change as well as price shocks and make their investment decisions deviate from the optimal level predicted by the long-term price and weather conditions. Given the stochastic process of climate change, the deviation from equilibrium can be exacerbated as firms are uncertain whether the observed climate change is a temporary shock or a permanent change.

This study contributes to the literature on dynamic production processes by testing for fixity of both outputs and inputs in the adjustment process to stochastic climate change as well as to market changes. We formulate the dynamic optimization problem for a competitive multi-output firm and allow for adjustment costs in outputs as well as inputs. The literature on adjustment costs focuses on inputs with only a few studies noting that changes in output mix can also be costly (Asche, Kumbhakar, and Tveteras 2008; Asche 2009). Adjustment costs may occur with output changes due to a lack of operator experience with a new output or required infrastructure changes when an output is expanded.

Our initial specification is very general. We impose no constraints on asset fixity.

[1] The problem of price uncertainty is not considered in this paper since, compared to climate uncertainty, there are a wide range of financial instruments to manage price risk.

All netputs (i.e., positively measured if output level and negatively measured if input level) are initially allowed to be quasi-fixed. After applying the envelope theorem to the optimization problem, we derive a complete system of interrelated netput supply equations in the flexible accelerator form (i.e., the rate of change of actual capital stock is proportional to the difference between actual and desired stock level) (Lucas 1967b). Tests both of full variability and strict fixity are performed for each netput. A netput is fully variable if there are no costs associated with its adjustment, and it is strictly fixed if it does not respond to price shocks or climate change. For quasi-fixed netputs, i.e., those that are neither fully variable nor strictly fixed, the rate of adjustment toward equilibrium levels is estimated in response to price and climate changes.

Our results indicate that all five netputs exhibit quasi-fixity. Livestock, crops, and capital adjust 17 percent, 68 percent, and 1 percent, respectively of the way toward their long-run equilibrium in one year. With the estimated adjustment rate for labor and fertilizer lower than -1.0, labor and fertilizer oscillate rather than converge smoothly to equilibrium. Both approach equilibrium at a slightly slower rate than crops.

The remainder of the paper is organized as follows. The next section presents the theoretical framework. In the empirical model section, we discuss the data, model the structure of the climate change process, and specify a functional form for the value function. The empirical results are presented in the following section. The final section concludes.

Theoretical Model

To model the adjustment path of quasi-fixed netputs over time, it is necessary to construct an inter-temporal optimization problem. Consider a competitive, profit-maximizing firm that chooses variable netputs and investment on quasi-fixed netputs to maximize the following infinite horizon problem at time $t = 0$, given her expectations of prices, climate and technology:

(1) $$J(Y, W, Q, v, \omega) = \max_{I} E\left\{\int_0^\infty e^{-rt}\left[\Pi\left(Y, \dot{Y}, W, Q, \omega\right) + v'Y\right]dt\right\}$$

subject to

(1a) $$\dot{Y} = I_t - \delta Y_{t-1},$$

(1b) $$\dot{W} = \mu(W) + \sigma\varepsilon,$$

(1c) $$Y(0) = y_0\,, W(0) = w_0\,, Q(0) = q_0\,,\ v(0) = v_0,\ \omega(0) = \omega_0,$$

where $J(\cdot)$ is the optimal value function which depends on the quasi-fixed netput vector Y with rental prices v, the price vector for variable netputs ω, the strictly fixed netput vector Q, and the climate vector W that consists of temperature and precipitation indices. $\Pi(\cdot)$ is a restricted (short-run) profit function, I_t represents gross investment, r is the real discount rate, and δ is a diagonal matrix of depreciation rates. $\dot{Y}$ and $\dot{W}$ are net change in Y and W respectively. All variables are implicit functions of time t, but the subscript t is omitted to simplify the notation; y_0, w_0, q_0, v_0, and ω_0 are initial levels observed at the base time, t=0, which are known with perfect certainty.

The climate vector W evolves stochastically and exogenously following a Brownian motion with drift which is characterized by the transition equation (1b); $\mu(W)$ denotes a non-random vector of drift parameters; and σ is a vector with $\sigma\sigma' = \Sigma$; ε is an i.i.d. normal vector with $E[\varepsilon] = 0, var(\varepsilon) = dt,\ E\left[\varepsilon_i\varepsilon_j\right] = 0$ for all $i \neq j$. It is assumed that the firm has rational expectations on climate change which implies that predictions of future climate are not systematically wrong. But the firm also realizes that future climate change is a stochastic process, so that uncertainty will be taken into account when making investment decisions (Pietola and Myers 2000).

We incorporate the climate elements into the profit function and model them as exogenous factors that can directly affect production. The optimal choices of the firm, therefore, depend on its expectations about climate as well as market conditions in each period. We include $\dot{Y}$ in the profit function and assume $\Pi_{\dot{Y}} < 0$ to reflect adjustment costs as internal costs in the form of foregone output (Lucas 1967a) or increased input use.

Assuming the production technology satisfies the standard regularity conditions, the stochastic Hamilton-Jacobi-Bellman equation (Stokey 2008, p. 31) takes the form:

(2)
$$\begin{aligned} &rJ(Y, W, Q, v, \omega) \\ &= \max\left[\Pi\big(Y, \dot{Y}, W, Q, \omega\big) + v'Y + J_Y\dot{Y} + J_W\mu(W) + \frac{1}{2}\text{vec}(J_{WW})'\text{vec}(\Sigma)\right], \end{aligned}$$

where J_Y and J_W are gradient vectors, J_{WW} is the hessian matrix with respect to W, and vec is the column stacking operator. The complete duality between the profit function Π and value function J is established by applying the envelope theorem. If production technology satisfies appropriate regularity conditions, then a value function J derived from equation (2) satisfies the regularity conditions and vice versa (Epstein 1981, pp 84-86).

Differentiating equation (2) with respect to prices and rearranging, we obtain the dynamic netput supply of quasi-fixed netputs Y and variable netputs X:

(3)
$$\dot{Y} = J_{Yv}^{-1}\left(rJ_v - Y - J_{Wv}\mu(W) - \frac{1}{2}\nabla_v[\text{vec}(J_{WW})'\text{vec}(\Sigma)]\right),$$

(4)
$$X = rJ_\omega - J_{Y\omega}\dot{Y} - J_{W\omega}\mu(W) - \frac{1}{2}\nabla_\omega[\text{vec}(J_{WW})'\text{vec}(\Sigma)].$$

If the value function has a form such that $J_{Yv} = (r - M)^{-1}$, then equation (3) can be expressed as a multivariate flexible accelerator model with the form:

(5) $$\dot{Y} = M(Y - \bar{Y}),$$

where M is a constant adjustment matrix, and $\bar{Y}(W, \Sigma, Q, v, \omega)$ is the steady state stock level (Epstein and Denny 1983). This form states that the rate of change in each quasi-fixed netput in each period is proportional to the gap between its actual level and desired level (Lucas 1967b).

We impose no constraints on asset fixity so the degree of fixity for each netput can be tested. Equation (4) is a special case of equation (3) in which some netputs in Y are treated as fully variable. Therefore, no loss of generality occurs if we initially allow all netputs to be quasi-fixed. Whether any specific netput takes the form of equation (4) will be determined by empirical test of whether it is fully variable (Asche, Kumbhakar, and Tveteras 2008).

Empirical Model

We model the U.S. agricultural sector as a representative firm using the above theoretical model. One may legitimately question the exogeneity of climate change in this decision model since total agricultural production may influence climate. However, with respect to global climate change, U.S. agriculture is a small production sector and it has a rather low level of greenhouse gas (GHG) emissions compared with other industries in the U.S., e.g., manufacturing and transportation, and with respect to world-wide productive activities. For instance, activities related to agriculture accounted for roughly 7 percent of total U.S. GHG in 2007, while manufacturing and transportation accounted for 30 percent and 28 percent, respectively (U.S. Environmental Protection Agency 2014). With the U.S. contributing 17 percent to world-wide GHG in 2007, U.S. agriculture only accounts for about 1.2 percent of global GHG emissions (World Resources Institute 2014).

Another issue arising with aggregation of the U.S. agricultural production sector is the endogeneity of prices since they are simultaneously determined with quantities as the intersection of supply and demand. We will explicitly consider the problem of price endogeneity in our model by obtaining strong and valid instruments.

Data

The model is estimated using national annual data from 1910 to 2011 for U.S agriculture. We utilize aggregate price and quantity data for two outputs (livestock and crops) and three inputs (capital, labor and fertilizer). National-level climate data include temperature and precipitation indexes. Public and private agricultural research stocks are created using research expenditures and are incorporated to capture technical change.

Aggregate prices and quantities for the two outputs and three inputs are compiled from three data sources. Data for the period 1948-2011 comes from the U.S. Department of Agriculture (USDA 2014). It contains aggregate price and quantity for three outputs (livestock, crops and farm related output) and three input categories (capital, labor and intermediate goods).[2] The intermediate goods are disaggregated into fertilizer and lime, pesticides, energy, purchased services, farm origin, and other intermediate inputs (USDA 2014). Input data for the period prior to 1948 was compiled by Thirtle, Schimmelpfennig, and Townsend (2002). It contains price and quantity indices (1880-1990) for four inputs – agricultural land, machinery and animal capital stock, labor, and fertilizer. Machinery and animal capital stock and land are aggregated for the purpose of this study as capital.

[2] Farm related output includes output of goods and services from certain non-agricultural or secondary activities that are closely related to agricultural production but for which information on output and input use cannot be separately observed (USDA, 2014). The ratio of farm related output revenue to total output revenue ranges from 1.21% to 6.58% during the period 1948-2011.

Aggregate capital price is formed as a Törnqvist index, and quantity is computed as total capital expenditures divided by the capital price index. Stefanou and Kerstens (2008) augmented this dataset to incorporate price and quantity for two outputs, livestock and crops, from 1910 to 1990.[3] The USDA indices for crops, livestock, capital, fertilizer and lime, and labor are spliced to the Thirtle-Schimmelpfennig-Townsend and Stefanou-Kerstens datasets using the symmetric geometric mean formula developed by Hill and Fox (1997). This formula generates consistent spliced series that are invariant to rescaling of the original series, especially when the two index series have different base years.

National-level annual data of average temperature and total precipitation for the period 1910-2011 are from the National Oceanic and Atmospheric Administration (NOAA 2014). NOAA provides monthly precipitation and time bias-corrected monthly average temperature for the U.S.[4] We calculated annual average temperature as the simple average of the monthly data. Annual total precipitation was calculated as the sum of the monthly data.

Since it takes approximately 35 years for public research and 19 years for private research expenditures to have their full effect on agricultural production (Wang et al. 2013), we need research expenditures for many years prior to 1910 to fully utilize the century of price and quantity data. Huffman and Evenson (2008, pp.105-107) compiled total annual real public agricultural research expenditures, 1888-2000, and total annual real private research expenditures, 1956-2000. They also provided decade averages of real private research expenditures for the period beginning with 1888. We interpolated

[3] The full data series and its documentation can be found in Stefanou and Kerstens (2008, Appendices A and B).
[4] The time bias of the means of monthly temperature arises because of different observation schedules for weather stations across the United States. These biases were rectified by Karl, Williams and Young (1986) by adjusting for the varying observation times.

annual private research expenditures from 1888 to 1955 using a piecewise cubic interpolation method, which results in a smooth and continuous spline, and preserves the shape of the data.[5] Public research expenditures were linearly extrapolated back to the year 1876. Huffman (2014) updated public agricultural research funding for the years 2001-2010. Nominal agricultural research funding in private sectors (2001-2010) come from Fuglie et al. (2011). We converted these to constant dollar values using the price index for agricultural research from Jin and Huffman (2013).

Public and private research stocks were created using trapezoidal lagged structures specified in Wang et al. (2013). Based on their specifications, the impacts of public research expenditure are negligible in the first two years, then become positive and increase linearly in the next seven years, reach a maximum and remain constant for the following six years, and then decline linearly to zero at 35 years. The effects of private research on production have a one year lag with zero weight, then rise linearly and peak at year six, stay constant through the next three years, and then decline linearly to zero in year 19.

The Structure of Climate Change

Climate conditions have a direct effect on agricultural production. Changes in temperature and precipitation lead to changes in land and water regimes that subsequently affect agricultural productivity (Kurukulasuriya and Rosenthal 2003). Analysis of our climate data for the U.S. indicates that average temperature has risen by roughly 0.04˚C per decade, and total precipitation has increased by roughly 11.4mm per decade over the period 1910-2011 (see Figure 1).

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[5] We used the piecewise cubic Hermite interpolation technique provided by STATA (command package "pchipolate").

As noted by the Intergovernmental Panel on Climate change (IPCC 2007), observed changes in regional temperature and precipitation are often physically related to each other. Higher surface temperatures most often lead to an increase in evaporation from oceans and land, which often results in increased precipitation. However, their relationship is not always dominated by a positive correlation and is affected by local geographical conditions (IPCC 2007). We use a vector autoregression (VAR) model to let the data directly identify the empirical relationship between temperature and precipitation over our data period. The temperature and precipitation series are standardized to the same orders of magnitude. Augmented Dickey-Fuller (ADF) unit root tests were conducted to examine their stationary properties. The null hypothesis of a unit root was rejected for each series. They were found to be best fitted as a VAR (4) without intercept:

(6) $$W_t = \alpha_1 W_{t-1} + \alpha_2 W_{t-2} + +\alpha_3 W_{t-3} + \alpha_4 W_{t-4} + \sigma_t,$$

from which we derived the discrete form for equation (1b),

(7) $$\Delta W_{\mathrm{t}} = \mu(W) + \sigma_{\mathrm{t}},$$

where Δ is a first difference operator, and α_i and σ_t are (2×2) and (2×1) respectively . The above equation is used to describe the expected climate change process with drift term $\mu(\mathrm{W})$ and error term σ_t.

Functional Form

A modified Generalized Leontief (GL) functional form (Howard and Shumway 1988) is used for the value function. It maintains linear homogeneity in prices and allows uncertainty in climatic conditions to alter investment decisions (Pietola and Myers 2000). It takes the form:[6]

[6] In the non-stochastic dynamic model, if first derivatives of J are linear in prices, then convexity of J in prices is sufficient for convexity of π in prices (Luh and Stefanou 1996). Under climate uncertainty, the

$$
(8) \quad \begin{aligned} J(Y,W,Q,v,\omega) &= v'A^{-1}Y + \omega'BY + [v'\omega']CW + [v'\omega']Dvec(WW') \\ &+ [v^{.5'}\omega^{.5'}]F\begin{bmatrix} v^{.5} \\ \omega^{.5} \end{bmatrix} + [v'\omega']GQ, \end{aligned}
$$

where A^{-1}, B, C, D, F, G are matrices of appropriate dimensions, and F is specified as symmetric so that the symmetry of J in prices is maintained.

Starting from equation (3) with a general form that allows for all netputs to be quasi-fixed, the above value function with the terms involving ω and Q (i.e., prices of variable netputs and quantities of fixed netputs) removed generates the following system of dynamic netput supply equations:

$$
(9) \quad \begin{aligned} \dot{Y} &= (rI - A)Y + AC\big(rW - \mu(W)\big) \\ &+ AD\left(r[\text{vec}(WW')] - \text{vec}_W(WW')\mu(W) - \frac{1}{2}\text{vec}(\Sigma)\right) + rA[\text{diag}(v^{-.5})]Fv^{.5}, \end{aligned}
$$

where I is an identity matrix. Writing the above equation in the multivariate flexible accelerator form results in the adjustment matrix, $M = rI - A$. Incorporating the public and private research stock vector Z to capture technical change, and approximating $\dot{Y}$ discretely as $Y_t - Y_{t-1}$, equation (9) is replaced by:

$$
(10) \quad \begin{aligned} Y_t &= (I + M)Y_{t-1} + AC\big(rW - \mu(W)\big) \\ &+ AD\left(rvec(WW') - vec_W(WW')\mu(W) - \frac{1}{2}vec(\Sigma)\right) + rA[\text{diag}(v^{-.5})]Fv^{.5} \\ &+ HZ, \end{aligned}
$$

which is the estimation equation. In all netput equations, r is the real discount rate (4 percent), which is calculated as the average annual nominal yield on Moody's BAA

sufficient conditions also include J_{WW} linear in prices.

corporate bonds over all maturities (available after 1919) less the rate of inflation.[7] To avoid spurious results, time-series properties of the data are addressed. We conduct unit root and cointegration tests sequentially to investigate whether series are stationary, and, if not, whether there exists a stationary relationship between the nonstationary series in the equation.

The degree of asset fixity for each netput can be estimated and tested directly based on the adjustment matrix M. The ith row of M represents the adjustment process for the ith netput. The diagonal element M_{ii} represents the adjustment rate of netput i to the long-run equilibrium in response to changes in relative prices and climate, given that all other netputs are at their equilibrium levels (Buhr and Kim 1997). The off-diagonal elements capture the dynamic interaction between two netputs (Asche, Kumbhakar, and Tveteras 2008). The condition $M_{ij} = M_{ji} = 0$ for any $i \neq j$ (M is not necessarily symmetric), implies independence of the adjustment path between quasi-fixed netputs i and j. If M_{ii} = -1 and $M_{ij} = 0$ for all $j, j \neq i$, input i can be adjusted instantaneously and independently and should be modeled as a variable netput. If $M_{ii} = 0$ and $M_{ij} = 0$ for all $j, j \neq i$, changes in the quantity of netput i does not respond to changes in prices or climate, implying that adjustment cost is prohibitively high and hence the netput should be modeled as strictly fixed.

Since equations (10) are nonlinear in parameters and netput prices are endogenous, parameters of the value function are estimated using a nonlinear Generalized Method of Moments (GMM) estimator. We address the problem of price endogeneity

[7] The nominal rate for 1919-2011 is from Federal Reserve Economic Data (2014). We use the Consumer Price Index taken from Robert Shiller's webpage (2014) to calculate the inflation rate for 1919-2011. As a robustness check, we used a real discount rate at 5%. We repeated the estimation and found the same results for tests of fixity. The estimated own-adjustment parameters for the quasi-fixed netputs are the same with respect to sign and significance level except for capital, which becomes significant.

using the lagged netput prices and quantities as instruments. Tests show that these instruments are both strong and valid. Diagnostics suggest that there is no autocorrelation of error terms, which justifies the specification of lagged dependent variables as predetermined variables.[8] The test of over-identifying restrictions shows that the null hypothesis of exogeneity of all instruments is not rejected.[9] Based on the results of the fixity test for each netput, a system consisting of equations (3) and (4) will be estimated if variable netputs are found to be present.

Empirical Results

The results of the ADF unit root tests reported in Table 1 show that most series are stationary in levels or first differences. Exceptions include labor quantity and the stock of private research expenditures, which are stationary in second differences, and the stock of public research expenditures, which is stationary in third differences. Because nonstationary series in the system may lead to spurious results unless a linear combination of these series is stationary (Lim and Shumway 1997), we conduct a cointegration test for all nonstationary series in the estimation equation. Higher order nonstationary variables, including labor quantity and the stock of public and private research expenditures, are differenced to be integrated of order one, $I(1)$, before the test. The Engle and Granger (1987) residual-based method is used. Both ADF and Phillips-Perron (PP) unit root tests on the residuals show that equilibrium error is stationary, indicating that a cointegrated relationship exists between the nonstationary series (see Table 2).

[8] For livestock, crops, capital, labor and fertilizer, the p-values of Durbin's *t*-test are 0.1940, 0.4493, 0.1362, 0.2400, and 0.1584, respectively. The null hypothesis of no autocorrelation cannot be rejected for any equation.

[9] Hansen's *J*-test statistic is 25.55 with 60 degrees of freedom. The null hypothesis that the overidentifying restrictions are valid cannot be rejected at the 0.05 level.

Structural Tests

The estimated parameters of the value function allowing for all netputs to be quasi-fixed are reported in Table 3. The initial model explained nearly all of the variation in four netput supply equations but less than a third in the labor equation. The R^2 for livestock, crops, capital, labor, and fertilizer are .997, .98, .99, .25, and .93, respectively. Eight adjustment parameters, including all own-adjustment parameters except capital are statistically significant at the 0.05 level. One third of the price coefficients and more than half of the private research parameters are significant at the 0.10 level. The parameters of the matrix A, $A_{ij}, i, j = 1, 2, 3, 4, 5$, are of particular interest, as tests of the dynamic adjustment of U.S. agriculture are based on the structure of M, where $M = rI - A$.

Table 4 provides a summary of tests on the dynamic adjustment and their empirical results. The hypothesis of independent instantaneous adjustment (*IIA*) for the system, $M = -I$, is rejected. This result confirms the existence of adjustment costs in the dynamic system (Buhr and Kim 1997). A test of independent adjustment of the system is conducted by examining whether the adjustment matrix M is diagonal; the null hypothesis is rejected which implies that the dynamics of adjustment in each netput supply equation are dependent on other netputs in the system (Asche, Kumbhakar, and Tveteras 2008). The hypothesis of strict fixity of the system, $\mathrm{M} = 0$, is also rejected, which confirms that quasi-fixity exists in the system's adjustment process.

We then test each netput to determine whether any of them can be treated as completely variable or strictly fixed. The hypothesis of *IIA* is rejected for each netput, indicating that no netput instantaneously and independently adjusts to changes in market and climate conditions. The hypothesis of strict fixity is rejected for livestock, crops, labor, and fertilizer at the 0.05 level and for capital at the 0.10 level. These results suggest that each netput exhibits quasi-fixity when it responds to price shocks and climate changes. Although not previously documented, this finding is not particularly surprising. For example, livestock production adjusts slowly to market conditions due to relatively long biological lags of production. Instantaneous adjustment of livestock and crops to climate change may be retarded by limited adaptation capacity of plant and animal species. Capital (land, machinery, and service buildings) are typically owned or under long-term lease and, thus, are the least flexible of inputs within a certain production period. Labor includes both self-employed and hired labor and so is partially adjustable over short periods. As a purchased input, the quantity of fertilizer and the timing of its application can be adjusted within a single production period, and yet even this input exhibits some degree of sluggishness in adjustment.

Implications

Since all five netputs are found to be quasi-fixed, the final model is the same as the initial model. From Table 3, the corresponding adjustment rate for each netput can be derived from the estimated parameters, $M_{ii} = r - A_{ii}$, which are -0.1742 for livestock, -0.6810 for crops, -0.0138 for capital, -1.3543 for labor, and -1.3510 for fertilizer. The estimated adjustment rates imply that livestock, crops, and capital adjust 17 percent, 68 percent, and 1.4 percent respectively of the way toward their equilibrium levels in one year. Capital is estimated to move very slowly, to the extent that it takes about 70 years to fully adjust to its optimal value. With estimated adjustment rates lower than -1.0, labor and fertilizer both overshoot by 35 percent in each period, but their oscillations get smaller over time and they gradually converge to equilibrium levels. The relative distances from equilibrium for labor and fertilizer are the same as if they adjusted 65 percent of the way toward equilibrium in each period.

Asche, Kumbhakar, and Tveteras (2008) also found evidence of quasi-fixity in U.S. livestock supply, but they estimated a higher livestock adjustment rate of 47 percent and did not reject the hypothesis of IIA in crop supply. The very sluggish capital adjustment is consistent with the findings of Serra, Stefanou, and Lansink (2010), who estimated an adjustment rate of 2 percent under state-contingent production uncertainty. Labor adjustment rate estimates from other studies for U.S. agriculture range from 7 percent (Vasavada and Chambers 1987) to 52 percent (Asche, Kumbhakar, and Tveteras 2008), all lower than our estimates. The fertilizer adjustment rate cannot be compared to other dynamic dual models since previous literature has imposed the assumption that it is fully variable rather than testing for its degree of fixity. All of the cited literature examined rates of adjustment in response to price shocks, but none considered environmental shocks.

The off-diagonal parameters in the adjustment matrix ($M_{ij} = -A_{ij}$) represent the dynamic interactions between pairs of netputs. They measure how the disequilibrium of one netput affects the adjustment speed of another. Four off-diagonal parameters are statistically significant at the 0.05 level and one at the 0.10 level. The adjustment paths of livestock and crops are significantly interrelated with each other. If livestock and crops are both above or below their own equilibrium, disequilibrium in one output increases the adjustment speed of the other. If they are on opposite sides of equilibrium, e.g., livestock is above but crops are below optimal levels, disequilibrium in one output slows the adjustment speed for the other. The adjustment path of capital is significantly dependent on the disequilibrium in livestock, crops, and fertilizer. If livestock is on the same side or crops or fertilizer are on the opposite side of equilibrium compared with capital, its adjustment speed decreases; if livestock is on the opposite side or crops or fertilizer is on the same side of the equilibrium, its adjustment speed increases.

The submatrices C and D capture the estimated effects of climate change on the discounted present value of profits. All coefficients in these submatrices are statistically insignificant, which implies that, from a long-term view, climate changes do not significantly affect expected profits when the firm has rational expectations about future climate and has the capacity to make adaptations. The submatrix F measures estimated price effects on the value function. One of the price parameters is significant at the 0.05 level and four at the 0.10 level. The estimated effects of public and private agricultural research stocks on netput supplies are provided by the submatrix H. Results show that public research does not have any significant impact on netput supplies but private research has significant effects on livestock, crops and capital. An increase in private research stock leads livestock supply to increase and crop supply and capital demand to decrease.

Price elasticities of output supply and input demand are reported in Table 5.[10] They are reported for both partial adjustment (short run, or one production period) and full adjustment (long run). In the short run, own-price elasticities of labor and fertilizer, and three cross-price elasticities are significant at the 0.05 level and the own-price elasticity of capital is significant at the 0.10 level. Short-run livestock supply increases

[10] Standard errors are provided only for short-run elasticity estimates since it is impracticable to compute standard errors for long-run elasticities. Deriving the long-run elasticities requires inverting the adjustment matrix. Since M is not a diagonal matrix, the long-run elasticities are highly nonlinear which makes it difficult to track standard errors for each component .

significantly when crop price increases implying they are complements. Capital and fertilizer are short-run substitutes for each other.

The short-run own-price demand elasticities for capital and fertilizer are both negative, which is consistent with the static theorem. However, the own-price supply elasticities for livestock and crops are both negative (although insignificant), and the demand elasticity for labor is positive. In the long run, except for fertilizer, all the own-price elasticities have signs consistent with the static theorem. Downward sloping output supplies and upward sloping input demands, even in the long run, are not theoretically inconsistent nor empirically implausible when adjustment costs are present in the dynamic system (Treadway 1970, pp. 341-345). Three of the long-run own-price elasticity values are at least as large in absolute value as the short-run elasticities. Labor and fertilizer respond more strongly to price changes in the short run than in the long run, partially because they overshoot the optimal values in the short run and oscillate as they adjust toward the long-run equilibrium.

In the long run, crop and fertilizer own-price response is elastic and livestock, capital, and labor own-price response is inelastic. Our estimates of own-price supply elasticity are higher than those from Luh and Stefanou (1993) which are negative and inelastic (-0.037 for crops, -0.052 for livestock). Our estimate of the own-price labor demand elasticity is higher than Vasavada and Chambers's (1986) estimate of -0.5066 but close to Luh and Stefanou's (1993) estimate of -0.737. The absolute value of our estimated capital own-price elasticity is higher than the estimate (-0.021) of Serra, Stefanou and Lansink (2010) and the positive value (0.116) of Vasavada and Chambers

(1986). We are unable to compare our fertilizer elasticity since no prior studies were found reported the long-run elasticity for fertilizer estimated by a dynamic model.

Conclusions

Climate conditions can directly affect agricultural production. Firms' expectations of future climate change can influence their investment decisions and the adjustment process of quasi-fixed netputs. A dynamic dual model with climate uncertainty is used in this paper to investigate the adjustment costs associated with two output categories (crops and livestock) and three input categories (capital, labor, and materials) that arise in response to price changes as well as climate change. National annual data for U.S. agriculture for the period 1910-2011 is used for empirical analysis. No constraints on asset fixity are imposed initially, and the degree of fixity for each netput is tested with respect to market and climate shocks.

Hypotheses of independent instantaneous adjustment (*IIA*), independent adjustment, and strict fixity for the system are all rejected, confirming quasi-fixity of the dynamic adjustment process in U.S. agriculture. The null hypothesis of *IIA* and strict fixity is also rejected for each netput; thus, it is concluded that each netput faces some adjustment costs. Livestock, crops, and capital adjust 17 percent, 68 percent, and 1.4 percent respectively of the way toward their optimal levels in one year. Labor and fertilizer both overshoot by 35 percent of the disequilibrium in each period and oscillate instead of converging smoothly toward their equilibrium levels.

Our finding that outputs are quasi-fixed indicates that for the multi-output firm, adjustment costs related to output changes cannot be ignored. Changing the product mix may reduce overall output levels in the short run due to long biological processes, need to develop new skills, or build infrastructure. In addition, disequilibrium in outputs can also influence input adjustment rates. Understanding of such interrelationships and their magnitudes are important in forecasting short-run and long-run impacts of market changes and policy interventions.

Our research also provides an additional perspective for evaluating climate change impacts, which is relevant for the climate change policy debate. We find that climate change effects on agricultural production are not limited to the benefits and costs associated with new equilibria. Producers adapt to climate change, and this adaptation takes time. During the adaptation process, costs of adjustment occur which, if ignored, will result in under-estimation of the full costs of climate change so net benefits (costs) will be over- (under-) estimated. This finding is likely also applicable to other sectors with large and long-lived assets and/or output mixes that are difficult to adjust (e.g., forestry).

The research reported in this paper is also subject to limitations. For example, although the model permits adjustment costs induced by climate shocks as well as market shocks to be estimated, it does not permit decomposition of the two effects. Changes in relative prices and climate occur simultaneously, and the model's dynamic adjustment matrix does not differentiate between the sources of change. Consequently, the estimated adjustment process cannot be decomposed between the responses to price changes and climate change.

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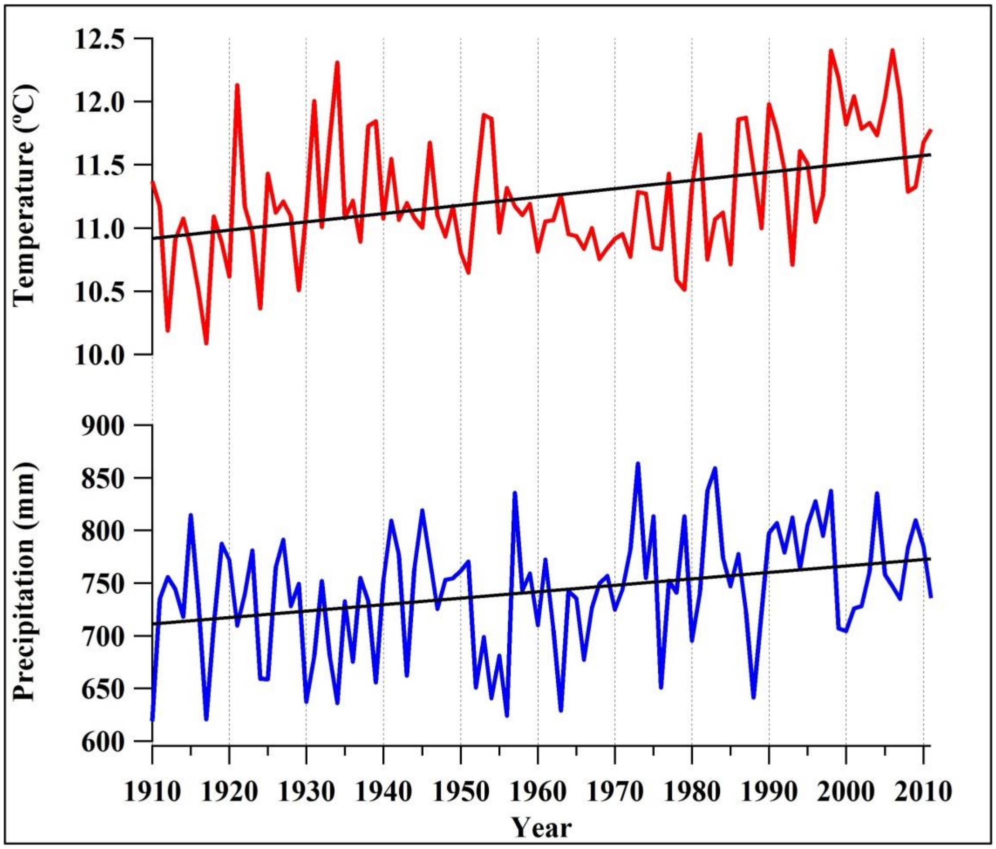

Figure 1: U.S. annual average temperature and total precipitation, 1910-2011

Table 1. Unit Root Test Results[a]

	ADF Statistics			
Series	Levels	1st Differences	2nd Differences	3rd Differences
Y_1	-2.67(1)	-9.39(0)*		
Y_2	-1.82(3)	-8.26(2)*		
Y_3	-1.60(3)	-3.13(2)*		
Y_4	-1.37(7)	-2.21(6)	-5.81(6)*	
Y_5	-1.54(3)	-7.59(3)*		
v_{12}	-3.94(2)*			
v_{13}	-2.66(1)	-10.35(0)*		
v_{14}	-2.42(1)	-10.94(0)*		
v_{15}	-3.06(1)	-9.08(0)*		
v_{21}	-3.93(2)*			
v_{23}	-2.65(1)	-11.31(0)*		
v_{24}	-2.11(3)	-5.46(2)*		
v_{25}	-2.82(1)	-7.67(2)*		
v_{31}	-2.74(1)	-9.41(0)*		
v_{32}	-2.23(1)	-10.93(0)*		
v_{34}	-2.16(3)	-6.76(2)*		
v_{35}	-2.24(3)	-7.85(2)*		
v_{41}	-3.84(2)*			
v_{42}	-2.94(2)	-7.85(2)*		
v_{43}	-2.04(1)	-10.00(0)*		
v_{45}	-1.45(1)	-9.82(0)*		
v_{51}	-3.15(1)	-9.10(0)*		
v_{52}	-2.81(1)	-7.57(2)*		
v_{53}	-3.91(1)*			
v_{54}	-2.87(2)	-6.70(2)*		
L_1	-2.16(7)	-6.28(6)*		
L_2	-6.53(1)*			
L_3	-9.13(0)*			
L_4	-11.96(0)*			
L_5	-10.82(0)*			
Z_1	-2.05(10)	-1.90(9)	-1.47(8)	-4.50(7)*
Z_2	2.04(9)	-2.89(11)	-3.82(10)*	

[a] Optimal lag length is in parentheses. Lag k is chosen such that the residuals behave like a white noise series and lags larger than k are not significant. * denotes that the null hypothesis of a unit root is rejected at the 0.05 significance level, implying that this series is stationary. Codes: Y_i are netput quantities, $v_{ij} = v_i^{-.5} v_j^{.5}$ for $i \neq j$ are price terms, 1 is livestock, 2 is crops, 3 is capital, 4 is labor, 5 is fertilizer, Z_1 is stock of public research expenditures and Z_2 is stock of private research expenditures, $[L_1 L_2]' = rW - \mu(W)$, and $[L_3\ L_4\ \ L_4\, L_5]' = rvec(WW') - vec_W(WW)\mu(W) - \frac{1}{2}vec(\Sigma)$.

Table 2. Cointegration Test Results

Variables included in cointegration tests	ADF		PP	
	Statistics	p-value	Statistics	p-value
Y_1, Y_2, Y_3, $Y_4(1)$[a], Y_5, v_{13}, v_{14}, v_{15}, v_{23}, v_{24}, v_{25}, v_{31}, v_{32}, v_{34}, v_{35}, v_{42}, v_{43}, v_{45}, v_{51}, v_{52}, v_{54}, L_1, $Z_1(2)$, $Z_2(1)$	-5.60(5)[b]	<.0001	-5.17(5)[b]	<.0001

[a] The number of differences to make the data series $I(1)$ is noted in parentheses.
[b] The number in parentheses is the optimal lag for the ADF test and the truncation parameter for the PP test, respectively.

Table 3. Nonlinear GMM Parameter Estimates of the Value Function (Allowing All Netputs to be Quasi-fixed)

Parameter	Estimate	Standard Error	Parameter	Estimate	Standard Error
A_{11}	0.2142**	0.0503	D_{21}	0.0261	0.0830
A_{12}	-0.1351**	0.0413	D_{22}	0.0436	0.0393
A_{13}	0.0097	0.0258	D_{24}	0.0506	0.0583
A_{14}	0.0055	0.0114	D_{31}	-0.0768	0.0738
A_{15}	-0.0082	0.0269	D_{32}	0.0371	0.0415
A_{21}	-0.9654**	0.2653	D_{34}	-0.0071	0.0503
A_{22}	0.7210**	0.2080	D_{41}	-0.0326	0.0308
A_{23}	-0.0691	0.0909	D_{42}	-0.0096	0.0196
A_{24}	-0.0302	0.0342	D_{44}	-0.0250	0.0263
A_{25}	0.0324	0.1106	D_{51}	-0.0558	0.0927
A_{31}	0.1148*	0.0684	D_{52}	-0.0417	0.0549
A_{32}	-0.1361**	0.0653	D_{54}	-0.0509	0.0700
A_{33}	0.0538	0.0335	F_{11}	9.6901	10.6437
A_{34}	-0.0047	0.0164	F_{12}	16.9605*	8.9356
A_{35}	-0.0599**	0.0289	F_{13}	-10.9040	8.2079
A_{41}	-0.0828	0.4767	F_{14}	-1.1051	3.2831
A_{42}	0.0840	0.5335	F_{15}	-13.7809	9.1528
A_{43}	-0.0048	0.1942	F_{22}	13.1544	14.7830
A_{44}	1.3943**	0.1209	F_{23}	-4.0303	12.2258
A_{45}	-0.3983	0.3541	F_{24}	-5.2133	4.8211
A_{51}	0.8131	0.7478	F_{25}	-24.0225*	12.1719
A_{52}	0.8757	0.8307	F_{33}	38.1979*	21.7207
A_{53}	-0.3119	0.4840	F_{34}	-3.1377	7.8211
A_{54}	0.0141	0.0721	F_{35}	-14.9859	17.5163
A_{55}	1.3910**	0.4407	F_{44}	19.0255*	9.7664
C_{11}	0.0498	0.0946	F_{45}	4.4567	7.9131
C_{12}	0.0251	0.0601	F_{55}	60.3078**	20.1854
C_{21}	0.0764	0.1341	H_{11}	-0.0003	0.0015
C_{22}	0.0248	0.0866	H_{12}	0.0002*	0.0001
C_{31}	0.1312	0.1520	H_{21}	0.0052	0.0068
C_{32}	-0.1113	0.0815	H_{22}	-0.0011**	0.0004
C_{41}	0.0156	0.0705	H_{31}	0.0006	0.0031
C_{42}	0.0118	0.0429	H_{32}	0.0003**	0.0001
C_{51}	-0.0479	0.1821	H_{41}	-0.0022	0.0195
C_{52}	-0.0237	0.0970	H_{42}	-0.0017	0.0011
D_{11}	0.0278	0.0582	H_{51}	-0.0294	0.0346
D_{12}	0.0252	0.0276	H_{52}	0.0009	0.0017
D_{14}	0.0341	0.0401			

Note: Level of significance: ** $p<0.05$, * $p<0.1$ Codes: Parameters refer to the parameter matrices in equation (10). For example, A_{ij} is the ijth entry of matrix A, $i = 1, 2, 3, 4, 5$, 1 is livestock, 2 is crops, 3 is capital, 4 is labor, and 5 is fertilizer.

Table 4. Hypothesis Test Results for the Adjustment Process

Hypothesis Tested	Wald Test	*df*	*p*-value
Independent and instantaneous adjustment (*IIA*)	40828.00	25	0.0000
Independent adjustment	141.96	20	0.0000
Strict fixity	400.74	25	0.0000
IIA for			
Livestock	490.47	5	0.0000
Crops	46.60	5	0.0000
Capital	1480.20	5	0.0000
Labor	11.71	5	0.0389
Fertilizer	27.81	5	0.0000
Strict fixity for			
Livestock	21.29	5	0.0007
Crops	21.16	5	0.0008
Capital	9.79	5	0.0814
Labor	139.16	5	0.0000
Fertilizer	13.42	5	0.0197

Table 5. Short- and Long-Run Output Supply and Input Demand Elasticities for U.S. Agriculture

	Elasticity with Respect to the Price of				
Quantity	Livestock	Crops	Capital	Labor	Fertilizer
<u>Short-Run:</u>					
Livestock	-0.0285 (0.0406)	0.0735** (0.0367)	-0.0405 (0.0349)	0.0092 (0.0197)	-0.0131 (0.0291)
Crops	0.2244 (0.2197)	-0.3226 (0.1962)	0.1697 (0.1543)	-0.0616 (0.1147)	-0.0138 (0.1463)
Capital	0.0240 (0.017)	-0.0355 (0.0214)	-0.0373* (0.0221)	-0.0005 (0.00924)	0.0470** (0.0232)
Labor	0.4229 (0.5225)	-0.0350 (1.0449)	-0.0842 (5.9495)	0.7652** (0.3622)	-1.1687 (1.5462)
Fertilizer	-0.0658 (0.2457)	0.3693 (0.502)	1.3954** (0.5417)	-0.0605 (0.2381)	-1.5165** (0.6762)
<u>Long-Run:</u>					
Livestock	0.7264	0.9169	-1.3612	0.0063	-0.2498
Crops	0.8869	2.1393	-2.4483	0.0621	-0.5904
Capital	-0.0052	-0.6570	-0.8003	0.1844	1.3881
Labor	-1.1770	-1.2455	3.2248	-0.7026	-0.0357
Fertilizer	1.0423	1.3390	-3.6840	0.1566	1.1547

Note: Elasticities are evaluated at the means of the variables. Standard errors are in parentheses.
Level of significance: ** $p < 0.05$, * $p < 0.1$