School of Economic Sciences

Working Paper Series
WP 2015-17

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Boying Liu
C. Richard Shumway

September 24, 2015

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Sansi Yang and C. Richard Shumway

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 stochastic climatic change. More than a century of national annual data (1910-2011) is used in the empirical analysis. No constraints on asset fixity are imposed. Results indicate that, with rational expectations, both output categories as well as all input categories exhibit quasi-fixity in response to market change and stochastic climate change. Crops adjust twice as fast as livestock. Fertilizer adjusts most rapidly toward equilibrium levels, and capital adjusts most slowly. Failing to anticipate climate change dramatically slows the estimated rate of adjustment for two netputs and modestly speeds the rate for two others, thus likely increasing overall adjustment costs. Failing to account for uncertainty in anticipated climate change has little impact on adjustment rates.

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

JEL classification: Q11, Q54

The authors are Ph.D. Graduate Research Assistant and Regents Professor, respectively, in the School of Economic Sciences, Washington State University. We wish to express appreciation to Hayley Chouinard, Gregmar Galinato, Daegoon Lee, Darlington Sabasi, Tristan Skolrud, and the anonymous *Journal* reviewers for helpful comments on earlier drafts of this paper and to Wallace Huffman for providing data for this research. This project was supported by the Washington Agricultural Research Center and by the USDA National Institute of Food and Agriculture, Hatch grant WPN000275.

Dynamic Adjustment in U.S. Agriculture under Climate Change

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.

The dynamic adjustment of input demands that arises in response to market shocks has 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). The existence of adjustment costs (e.g. learning costs, expansion planning fees, costs of restructuring the production process or preparing equipment) may delay firms' response to market shocks. However, the fact that environmental shocks such as climate change may affect the adjustment costs and therefore affect the adjustment process of inputs and outputs has received relatively little attention.

For instance, with a gradual increase in precipitation, a wheat farmer may want to shift some of her cropland to corn. Learning costs may become a source of adjustment costs if she has no experience producing corn. Farmers in areas that experience a decrease in precipitation may increase the demand for irrigation water which in turn increases the demand for more efficient irrigation systems. To build new irrigation infrastructure, search fees and the value of time required to prepare the investment may become part of the adjustment costs. Kelly, Kolstad and Mitchell (2005) studied adjustment costs in the context of profit loss 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 and outputs slow to change over short time intervals.

Our objective is to examine 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, we test whether the adjustment toward equilibrium is slowed when firms are uncertain if 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).

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

[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.

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, capital, and fertilizer, respectively, adjust 20 percent, 49 percent, 5 percent, and 88 percent of the way toward their long-run equilibrium in one year. With the estimated adjustment rate for labor lower than -1.0, it oscillates rather than converges smoothly toward equilibrium. Its distance from equilibrium is the same as if it adjusted 59 percent of the way towards its optimal level. Failing to anticipate climate change dramatically slows the estimated rate of adjustment for two netputs and modestly speeds the rate for two others, thus likely increasing overall adjustment costs. Failing to account for uncertainty in anticipated climate change has little impact on adjustment rates.

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 and robustness checks 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 investment in quasi-fixed netputs to maximize the following infinite horizon problem at time $t = 0$, given her expectations of prices, climate and technology:

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

subject to

(1a) $$\dot{Y} = I - \delta \mathrm{Y},$$

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

(1c) $$Y(0) = y_0\,, W(0) = w_0\,, Q(0) = q_0\,, Z(0) = z_0,\ v(0) = v_0,\ \omega(0) = \omega_0,$$

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, technology Z, and the weather vector W that consists of temperature and precipitation indices. $\Pi(\cdot)$ is a restricted (short-run) profit function, I 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, and $\dot{W}$ is climate change. All variables are implicit functions of time t, but the subscript t is omitted to simplify the notation; y_0, w_0, q_0, z_0, v_0, and ω_0 are initial levels observed at the base time, t=0, and are known with perfect certainty.

The climate change vector $\dot{W}$ 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 $\sigma\sigma' = \Sigma$ that captures the variance of climate change; ε is an i.i.d. normal vector with $E[\varepsilon] = 0, var(\varepsilon) = dt,\ E[\varepsilon_i\varepsilon_j] = 0$ 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 change elements (equation 1b) 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 change as well as market conditions in each period. We also include $\dot{Y}$ (equation 1a) in the profit function and assume $\Pi_{\dot{Y}} \leq 0$ 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:

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

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

(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 $J_{Yv} = (rU - M)^{-1}$ where U is an identity matrix, 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 $\bar{Y}(W, \Sigma, Q, Z, v, \omega)$ 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. A firm-level adjustment cost model is frequently used to model the aggregate behavior of firms in an industry or economy due to the lack of firm-level data and the relative simplicity of the aggregate model. Further, in their nonparametric tests, Williams and Shumway (1998) found that the empirical evidence did not refute the joint hypothesis that U.S. agricultural producers behave collectively as though they are a price-taking, profit-maximizing firm. Blackorby and Schworm (1982) shows that a necessary and sufficient condition for consistent aggregation across firms is that the value function be linear in the aggregate capital stock, i.e., $J_{YY} = 0$, a property that will be maintained in our empirical model.

Modeling U.S. agriculture as though it were a single agent, we use national average temperature and total precipitation as weather variables to describe the aggregate climate change path. The use of national-level weather variables renders a tractable theoretical model and makes the empirical estimation possible, but the substantial variation of climate conditions across the U.S. is not addressed in this aggregate model. Since production can shift between regions, it is likely that U.S. agricultural production will be less sensitive to changes in climate conditions than will individual firms and even states and regions (Lazo et al. 2011).

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 changes in technology.

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 prices and quantities 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 agricultural land are aggregated for the purpose of this study as capital. 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

[2] In this dataset for the period 1948-2011, net distorting payments (deficiency, diversion, loan deficiency, market gains, certificate gains, milk income loss payments) are added to market prices of individual commodity output prices and distorting taxes (dairy assessment) are subtracted. 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 1.2 percent to 6.6 percent during the 1948-2011 period.

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 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

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

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

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).[6]

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

[6] They have changed more dramatically, and not always in the same direction, in some states and regions.

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 stationarity 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:

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

where $\varepsilon_t \sim N(0,1)$. This equation implies that the producer uses the most recent four years of observations in forming expectations of weather variables. From equation (6), we derived the discrete form for equation (1b),

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

where Δ is a first difference operator, and μ and σ_t are (2×1) vectors. The above equation is used to describe the producer's rational expectation of the climate change process with drift term $\mu(\mathrm{W})$ and covariance matrix $\Sigma = E(\sigma_t \sigma_t{}')$ that captures the volatility of climate change.[7]

Functional Form

A modified Generalized Leontief (GL) functional form (Howard and Shumway 1988; Luh and Stefanou 1991) is used for the value function. A functional form that allows for consistent aggregation, maintains linear homogeneity in prices, and allows uncertainty in climatic conditions to alter investment decisions (Pietola and Myers 2000) takes the form:[8]

[7] Though the mean temperature and precipitation both increase, our analysis reveals no clear trend in the variance of temperature or precipitation over time.

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

$$J(Y,W,Q,Z,v,\omega) = v'A^{-1}Y + \omega'BY + [v'\omega']CW + [v'\omega']Dvec(WW')$$

(8)

$$+ \left[v^{.5'}\omega^{.5'}\right]F\begin{bmatrix} v^{.5} \\ \omega^{.5} \end{bmatrix} + [v'\omega']GQ + [v'\omega']HZ,$$

where A^{-1}, B, C, D, F, G, H 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) $$\dot{Y} = (rU - A)Y + AC\big(rW - \mu(W)\big)$$

$$+ AD\left(r[\text{vec}(WW')] - \text{vec}_W(WW')\mu(W) - \frac{1}{2}\text{vec}(\Sigma)\right) + rA[\text{diag}(v^{-.5})]Fv^{.5}$$

$$+ rAHZ,$$

where U is an identity matrix. Writing the above equations in the multivariate flexible accelerator form results in the adjustment matrix, $M = rU - A$.

Net distorting payments of government programs since 1948 are included in the output price series. These account for a large portion of federal policy distorting impacts in the agricultural markets. In addition, three dummy variables $d = (d_1, d_2, d_3)$ are created and appended to the five netput supply equations to account for the impacts to national agricultural markets of two world wars, 1914-1918 and 1939-1945, and the 1983 Payment-In-Kind (PIK) program.[9] Approximating $\dot{Y}$ discretely as $Y_t - Y_{t-1}$ and representing rAH as $\widehat{H}$, equation (9) is replaced by:

[9] We use the dates that Europe was engaged in the world wars. Although the U.S. entered the wars later, it was involved in supplying allies considerably earlier. The Payment-In-Kind (PIK) program was implemented by the U.S.

$$(10) \quad Y_t = (U + M)Y_{t-1} + AC\big(rW - \mu(W)\big)$$
$$+ AD\left(rvec(WW') - vec_W(WW')\mu(W) - \frac{1}{2}vec(\Sigma)\right) + rA[\mathrm{diag}(v^{-.5})]Fv^{.5}$$
$$+ \hat{H}Z + Rd,$$

which is the system of estimation equations.

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 corporate bonds over all maturities (available after 1919) less the rate of inflation.[10]

To avoid spurious results, time-series properties of the data are addressed. We conduct unit root and cointegration tests sequentially to investigate whether each series is 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 $M = rU - A$. 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 $j, j \neq i$,

Department of Agriculture in 1983, under which farmers were paid with commodities to reduce crop production in order to lower government-held commodity supplies.

[10] 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 percent. 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.

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 equation (10) is nonlinear in parameters and netput prices are endogenous, parameters of the value function are estimated using a nonlinear iterative three-stage least squares (IT3SLS) estimator. We address the problem of price endogeneity 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.[11] The test of over-identifying restrictions shows that the null hypothesis of exogeneity of all instruments is not rejected.[12] Based on the results of the fixity test for each netput, a system of equations will be estimated. It will consist of equation (10) for quasi-fixed netputs and the corresponding equation for variable netputs derived from equation (4) 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, we conduct a cointegration test for all nonstationary series in the estimation equation. Higher order

[11] For livestock, crops, capital, labor and fertilizer, the p-values of Durbin's *t*-test are 0.19, 0.45, 0.14, 0.24, and 0.15, respectively. The null hypothesis of no autocorrelation cannot be rejected for any equation.

[12] 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.

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).

Structural Tests

The estimated parameters of the value function allowing for all netputs to be quasi-fixed are reported in Table 3. The total number of observations used is 98 after fitting equation (7). The initial model explained nearly all of the variation in four netput supply equations but less than a fifth in the labor equation. The R^2 for livestock, crops, capital, labor, and fertilizer are .997, .98, .99, .14, and .97, respectively, with 80 degrees of freedom in each equation and 400 for the system of equations. Eleven adjustment parameters, including all own-adjustment parameters are statistically significant at the 0.05 level. Another is significant at the 0.10 level. Sixty percent of the price coefficients are also significant, all at the 0.05 level. Two private research parameters and one dummy variable parameter are significant at the 0.10 level. Two dummy variable parameters are significant at the 0.05 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 $M = rU - A$.

Table 4 provides a summary of test results about the dynamic adjustment. The hypothesis of independent instantaneous adjustment for the system, $M = -U$, 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 independent instantaneous adjustment 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 only 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 -0.2026 for livestock, -0.4865 for crops, -0.0513 for capital, -1.4126 for labor, and -0.8782 for fertilizer. The estimated adjustment rates imply that livestock, crops, capital, and fertilizer adjust 20 percent, 49 percent, 5 percent, and 88 percent, respectively, of the way toward their equilibrium levels in one year. Crops adjust more than twice as fast as livestock, which is not surprising since the production cycle is so much longer for most livestock. Capital is estimated to move relatively slowly, to the extent that it takes about 20 years to fully adjust to its optimal value.

With an estimated adjustment rate lower than -1.0, labor overshoots by 41 percent in each period, but its oscillations get smaller over time and it gradually converges to its equilibrium level. The relative distance from equilibrium for labor is the same as if it adjusted 59 percent of the way toward equilibrium in each period. This is a more rapid rate of adjustment than any other netput except fertilizer. Overshooting of an input relative to its long-run equilibrium level is not unusual. If output levels were held constant, at least one input would have to overshoot its long-run equilibrium if other inputs only partially adjust toward their equilibria. Because outputs also adjust only partially toward equilibrium in one period, labor's overshooting its long-run value may indicate its buffer role in the adjustment process since capital is more difficult and costly to adjust.

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 independent instantaneous adjustment in crop supply. The sluggish capital adjustment is actually a little higher than the findings of Serra, Stefanou, and Lansink (2010), who estimated an adjustment rate of only 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.

All diagonal parameters in the adjustment matrix ($M_{ii} = r - A_{ii}$) are statistically significant at the 0.05 level. 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. Six 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. Similarly, the adjustments of capital and fertilizer are also significantly dependent on each other in the same fashion. Disequilibrium in labor significantly affects the adjustment of crops and disequilibrium in crops significantly affects the adjustment of fertilizer at the 0.05 level. Disequilibrium in capital significantly affects the adjustment of labor at the 0.10 level. Except for the impact of disequilibrium in crops on adjustment of fertilizer, all qualitative impacts are the same: if one disequilibrium is on the same side of equilibrium compared with the impacted netput, the latter's adjustment speed increases; if on opposite sides of the equilibrium, its adjustment speed decreases.

The submatrices C and D capture the estimated equilibrium effects of temperature and precipitation 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. Nine of the 15 price parameters are significant at the 0.05 level. A comparison of submatrices C, D and F illustrates an important outcome: the estimated impacts of weather conditions on long-run national-level profits from agricultural production are relatively trivial compared to market effects. This finding is consistent with that of Quiggin and Horowitz (2003), who found that the equilibrium effects of climate change tend to cancel out at the aggregate level since the adverse effect of warming in one area can be offset by benefits in another area where the temperature is initially below the optimum for production.

The estimated effects of public and private agricultural research stocks on netput supplies are provided by the submatrix $\widehat{H}$. Results show that public research does not have any significant impact on netput supplies but private research has significant effects on outputs at the 0.10 level. An increase in private research stock leads livestock supply to increase and crop supply to decrease.

The submatrix R represents the estimated impact of two world wars and the PIK program on netput supplies. During World War II, livestock supply increased significantly, reflecting the government's mobilization efforts to meet increased food demand. As expected, the intervention of the PIK program significantly reduced both crop (at the 0.05 level) and livestock (at the 0.10 level) supplies.

Price elasticities of output supply and input demand are reported in Table 5.[13] They are reported for both partial adjustment (short run, or one production period) and full adjustment

[13] 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

(long run). In the short run, four own-price elasticities and five cross-price elasticities are significant at the 0.05 level. Another own-price elasticity and two more cross-price elasticities are significant at the 0.10 level. Short-run supply of livestock and crops increase as the price of the other output increases, implying they are economic complements in the short run. An increase in livestock price leads to a significant increase in capital demand and a decrease in fertilizer demand. A possible explanation for the negative relationship between short-run fertilizer demand and the price of livestock is that our data on fertilizer only accounts for the use of chemicals. It does not incorporate animal manure, which is a substitute for chemical fertilizer and nearly proportional to the livestock inventory. Capital and fertilizer are significant short-run substitutes for each other. Labor demand decreases significantly with an increase in fertilizer price.

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, and the demand elasticity for labor is positive. In the long run, except for capital and 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).

In the long run, own-price response is inelastic for both outputs and all inputs. Our estimates of the own-price output supply elasticities are higher than those from Luh and Stefanou (1993) which are negative and inelastic (-0.05 for livestock, -0.04 for crops). Our estimated

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not a diagonal matrix, the long-run elasticities are highly nonlinear which makes it difficult to track standard errors for each component.

capital own-price elasticity is higher in absolute value than the estimates (-0.021 and 0.116) of Serra, Stefanou and Lansink (2010) and Vasavada and Chambers (1986), respectively. Our estimate of the own-price labor demand elasticity is lower in absolute value than both Vasavada and Chamber's (1986) estimate of -0.51 and Luh and Stefanou's (1993) estimate of -0.74. We are unable to compare our fertilizer elasticity since no prior studies were found that reported the long-run elasticity for fertilizer estimated by a dynamic model.

Robustness Checks

To explore whether the dynamic adjustment process is sensitive to the firm's expectation of climate change, we replace the stochastic rational expectation with two different assumptions: naïve (or static) expectation and rational expectation without uncertainty. The former assumes that the firm uses the current observation as the prediction for all future periods, and therefore does not adapt to climate change. The latter retains the firm's rational expectation but assumes the future path of weather variables is known with complete certainty. To implement these options, equation (1b) is replaced by $\dot{W} = 0$ for static expectations and $\dot{W} = \mu(W)$ for rational expectations with certainty. The remainder of the model specification remains the same.

Under naïve expectations of climate change, the hypothesis of fixity cannot be rejected for livestock. All other netputs still exhibit quasi-fixity. Re-estimating the model with livestock treated as a fixed netput, naïve expectations demonstrate mixed effects on the estimated adjustment rates, and correspondingly on adjustment costs. The adjustment speed for crops does not change much with naïve expectations, but capital adjusts much more slowly (0.5 percent compared to 5 percent) and fertilizer becomes more variable with the adjustment rate increasing from 88 percent to 97 percent. Labor still overshoots but converges toward equilibrium level more rapidly (73 percent compared to 59 percent). Although two adjust more rapidly, the relative increase in their adjustment rates (1/10 to 1/4 faster) are small in comparison to the much slower adjustment rate for capital (9/10 slower) and the lack of adjustment for livestock. Consequently, the qualitative evidence supports the hypothesis that overall adjustment costs are greater when producers fail to anticipate climate change.

Without uncertainty involved, results of the structural tests are the same as under rational expectations with uncertainty. Hypotheses of full variability and strict fixity are rejected both for the system and for each netput at the 0.10 level. Estimated adjustment rates do not change much for any netput with respect to either significance level or magnitude. The largest difference was a single-digit change at the second decimal place. With rational expectations, the adjustment process is insensitive to the uncertainty of climate change.

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 fertilizer) 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, 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 independent instantaneous adjustment and strict fixity is also rejected for each netput; thus, it is concluded that each netput faces some adjustment costs. With rational expectations of climate change, livestock, crops, capital and fertilizer adjust 20 percent, 49 percent, 5 percent, and 88 percent respectively of the way toward their optimal levels in one year. Labor overshoots by 41 percent of the disequilibrium in each period and oscillates instead of converging smoothly toward its equilibrium level.

Results of our robustness check show that producers' adaptation to climate change has mixed effects on adjustment costs. Failing to account for climate change generally increases overall adjustment costs. However, failing to account for the uncertainty in climate change has little effect on the adjustment process as long as firms' expectations of future climate change are not systematically biased.

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 and other output 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. The impacts of changing weather conditions on equilibrium national-level profit are relatively trivial compared with market effects. However, during the adjustment process, firms' recognition of and adaptation to climate change can have an important impact on individual netput adjustment rates and overall adjustment costs. Consequently, the analysis of climate change effects on agricultural production should not be limited to the benefits and costs associated with new equilibria. Producers adapt to climate change, and this adaptation takes time, thus warranting benefit-cost analysis of the dynamic adaptation process as well as the new equilibrium.

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 not necessarily independently, 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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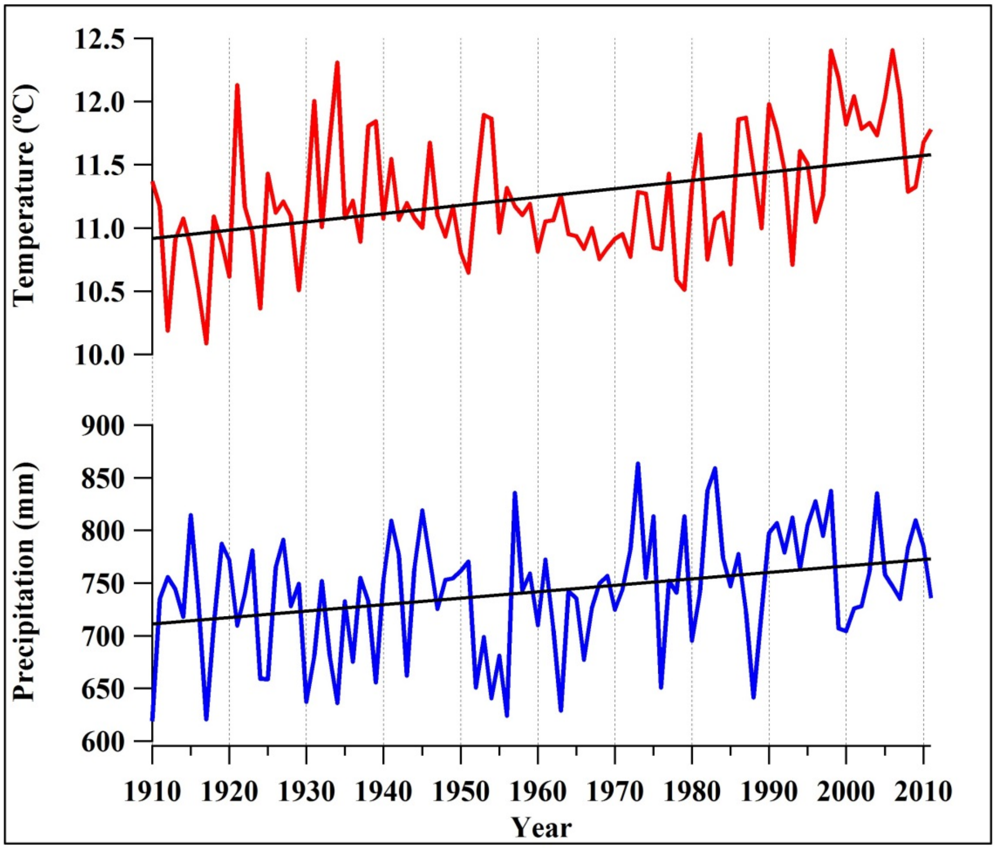

Figure 1: U.S. annual average temperature and total precipitation, 1910-2011

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

	ADF		PP	
Variables included in cointegration tests	Statistics	p-value [a]	Statistics	p-value [a]
Y_1, Y_2, Y_3, Y_4(1)[b], 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)[c]	<.0001	-5.17(5)[c]	<.0001

[a] Probability of support for the null hypothesis of a unit root.

[b] The number of differences to make the data series $I(1)$ is noted in parentheses.

[c] The number in parentheses is the optimal lag for the ADF test and the truncation parameter for the PP test, respectively.

Table 3. Nonlinear IT3SLS Parameter Estimates of the Value Function (Allowing All Netputs to be Quasi-fixed)

Parameter	Estimate	Standard Error	Parameter	Estimate	Standard Error	Parameter	Estimate	Standard Error
A_{11}	0.2426**	0.0412	C_{32}	-0.0197	0.1044	F_{34}	5.3839	3.6699
A_{12}	-0.1957**	0.0369	C_{41}	0.1391	0.1234	F_{35}	7.3449	5.9128
A_{13}	0.0126	0.0228	C_{42}	0.0097	0.0627	F_{44}	31.6901**	13.9654
A_{14}	-0.0006	0.0107	C_{51}	0.2657	0.2987	F_{45}	1.2860	2.4872
A_{15}	-0.0088	0.0202	C_{52}	0.0246	0.1545	F_{55}	84.0966**	26.5383
A_{21}	-0.5271**	0.1130	D_{11}	0.0694	0.1053	$\widehat{H}_{11}$	-0.0004	0.0019
A_{22}	0.5265**	0.0979	D_{12}	0.0116	0.0560	$\widehat{H}_{12}$	0.0002*	0.0001
A_{23}	0.0479	0.0616	D_{14}	0.0736	0.0853	$\widehat{H}_{21}$	0.0015	0.0051
A_{24}	-0.0667**	0.0296	D_{21}	0.0722	0.1260	$\widehat{H}_{22}$	-0.0006*	0.0003
A_{25}	0.0558	0.0557	D_{22}	0.0138	0.0671	$\widehat{H}_{31}$	-0.0013	0.0022
A_{31}	0.0094	0.0455	D_{24}	0.0892	0.1017	$\widehat{H}_{32}$	0.0001	0.0001
A_{32}	-0.0123	0.0408	D_{31}	-0.0558	0.0848	$\widehat{H}_{41}$	0.0161	0.0179
A_{33}	0.0913**	0.0258	D_{32}	0.0109	0.0449	$\widehat{H}_{42}$	-0.0014	0.0013
A_{34}	-0.0001	0.0130	D_{34}	-0.0319	0.0693	$\widehat{H}_{51}$	-0.0032	0.0110
A_{35}	-0.0566**	0.0240	D_{41}	-0.0491	0.0515	$\widehat{H}_{52}$	-0.0004	0.0007
A_{41}	0.0273	0.4030	D_{42}	0.0046	0.0270	R_{11}	-0.0008	0.0076
A_{42}	-0.0442	0.3550	D_{44}	-0.0264	0.0410	R_{12}	0.0146**	0.0061
A_{43}	-0.4424*	0.2648	D_{51}	-0.0917	0.1248	R_{13}	-0.0318*	0.0162
A_{44}	1.4526**	0.1051	D_{52}	-0.0076	0.0666	R_{21}	0.0145	0.0210
A_{45}	-0.2595	0.1978	D_{54}	-0.0695	0.1013	R_{22}	0.0125	0.0168
A_{51}	0.1184	0.2222	F_{11}	-8.1850	18.1894	R_{23}	-0.1660**	0.0448
A_{52}	0.4788**	0.2133	F_{12}	29.0257**	5.2534	R_{31}	-0.0076	0.0091
A_{53}	-0.4743**	0.1333	F_{13}	-22.5105**	5.2233	R_{32}	-0.0096	0.0073
A_{54}	-0.0280	0.0607	F_{14}	-5.7615**	2.8134	R_{33}	0.0102	0.0196
A_{55}	0.9182**	0.1155	F_{15}	-22.5583**	6.0062	R_{41}	0.0429	0.0921
C_{11}	-0.2054	0.2522	F_{22}	-11.0113	21.6916	R_{42}	-0.0653	0.0612
C_{12}	-0.0218	0.1299	F_{23}	-20.9335**	5.7436	R_{43}	0.0633	0.1569
C_{21}	-0.2409	0.3012	F_{24}	-4.5660	3.4264	R_{51}	0.0377	0.0438
C_{22}	-0.0242	0.1555	F_{25}	-29.1008**	7.1391	R_{52}	0.0131	0.0345
C_{31}	0.1817	0.2040	F_{33}	52.0595**	19.8808	R_{53}	0.1364	0.0914

Note: Level of significance: * p<0.1, ** p<0.05. The number of observations is 98. The system of equations has 400 degrees of freedom. Codes: Parameters refer to the parameter matrices in equation (10). For example, A_{ij} is the ijth entry of matrix A, $i, j = 1, 2, 3, 4, 5$, 1 is livestock, 2 is crops, 3 is capital, 4 is labor, and 5 is fertilizer; i has the same meaning for all matrices; in matrix C, $j = 1,2$, 1 is temperature and 2 is precipitation; in D, $j = 1,2,4$, 1 is temperature variance, 2 is covariance of temperature and precipitation, and 4 is precipitation variance; in $\widehat{H}$, $j = 1,2$, 1 is public research stock and 2 is private research stock; in R, $j = 1,2,3$, 1 is World War I, 2 is World War II, and 3 is the Payment-in-Kind (PIK) program.

Table 4. Hypothesis Test Results for the Adjustment Process

Hypotheses Tested	Wald Test	*df*	*p*-value
Independent and instantaneous adjustment	24196.00	25	0.0000
Independent adjustment	179.58	20	0.0000
Strict fixity	417.55	25	0.0000
Independent and instantaneous adjustment for:			
Livestock	1178.50	5	0.0000
Crops	258.35	5	0.0000
Capital	4427.30	5	0.0000
Labor	24.93	5	0.0000
Fertilizer	113.96	5	0.0000
Strict fixity for:			
Livestock	34.50	5	0.0000
Crops	36.61	5	0.0000
Capital	9.28	5	0.0984
Labor	188.98	5	0.0000
Fertilizer	60.24	5	0.0000

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
Short-Run:					
Livestock	-0.0515* (0.028)	0.1124** (0.0262)	-0.0359 (0.026)	-0.0115 (0.0163)	-0.0135 (0.0217)
Crops	0.1497** (0.0746)	-0.2917** (0.0753)	0.1088 (0.0798)	0.0147 (0.0473)	0.0174 (0.0657)
Capital	0.0200** (0.00953)	0.0049 (0.0137)	-0.0568** (0.0188)	-0.0063 (0.00615)	0.0382** (0.0149)
Labor	0.4340 (0.4281)	0.8989 (0.6005)	-0.7167 (0.8205)	0.6506** (0.2948)	-1.2569* (0.6463)
Fertilizer	-0.1463* (0.0814)	0.1734 (0.1277)	0.6999** (0.1499)	0.1024 (0.0851)	-0.8233** (0.1358)
Long-Run:					
Livestock	0.5470	0.3015	-0.6549	-0.0575	-0.1311
Crops	0.3969	0.8887	-0.9995	-0.1285	-0.1515
Capital	-0.1439	0.1792	0.4969	0.0051	-0.5466
Labor	-0.3180	-1.0471	0.4151	-0.3534	1.3139
Fertilizer	0.3943	0.5268	-1.1612	-0.1999	0.4299

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