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Dynamic input demand functions and resource adjustment for US agriculture: state evidence

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Abstract

The paper presents an econometric model of dynamic agricultural input demand functions that include research based technical change and autoregressive disturbances and fits the model to annual data for a set of state aggregates pooled over 1950-1982. The methodological approach is one of developing a theoretical foundation for a dynamic input demand system and accepting state aggreage behavior as approximated by nonlinear adjustment costs and long-term profit maximization. Although other studies have largely ignored autocorrelation in dynamic input demand systems, the results show shorter adjustment lags with autocorrelation than without. Dynamic input demand own-price elasticities for the six input groups are inelastic, and the demand functions possess significant cross-price and research effects.

1. Introduction

Farmers in the developed countries do not hire their workforce or rent machinery and land afresh each day or week because it is more profitable to have longer term arrangements/contracts. Hiring/training and firing/terminating workers, searching/learning to use and refurbishing/returning machinery, and searching/learning to use and returning land to its original condition are all costs over and above a per-unit time rental rate. These costs insure that farmers' demand for most inputs depend not only on current exogenous factors but also on past use and expectations about future use. These are arguments that agricultural input demand functions, at least for the developed countries, are dynamic, requiring some time for full adjustment to exogenous economic shocks to occur.

Friesen et al. (1992) identify two different approaches to dynamic input demand. First, there are theory-based models where dynamics arise from optimal agent behavior. These models have generally taken an adjustment-cost route (e.g., see Lucas, 1967a; Nichell, 1986; Chambers and Lopez, 1984; Vasavada and Chambers, 1986; Vasavada and Ball, 1988), or resources deterioration with use (e.g., Tegene et al., 1988). Second, data-based dynamic models have been used where dynamics are used to describe the pattern of input use but do not arise from explicitly optimal agent behavior, e.g., see Friesen et al. (1992). Both of these approaches have claimed advantages and disadvantages.

Earlier econometric studies of dynamic agricultural demand functions have pursued methods that could color their results. First, models have been fitted to data containing a high level of aggregation.

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Most have used national aggregate data, but an exception is Tsigas and Hertel (1988). Second, when technical change has been incorporated conceptually, it has been proxied empirically by a time trend. Huffman and Evenson (1989, 1993), however, have shown that during the post-World War II period shifts in US agricultural supply and input demand schedules and multifactor agricultural productivity change were significant. They have also shown that agricultural research stocks are part of the story explaining these changes even after allowing for a trend. Third, dynamic input demand functions have been fitted frequently to annual data, ignoring possible time series problems. Autocorrelation, when it is present, can cause estimated coefficients to be statistically inconsistent (Greene, 1993).

The objective of this paper is to present an econometric model of dynamic agricultural input demand functions that include research-based technical change and autoregressive disturbances, and to fit the model to data for a set of state aggregates for a developed country pooled together. We follow the methodological approaches of developing a theoretical foundation for our dynamic input demand system, and assume that state aggregate behavior is approximated by (nonlinear) adjustment costs and long-term profit maximization. We chose to use data over the post-World War II period for the United States, a major developed country, and the basic data are from Huffman and Evenson (1993), Chap. 7.

2. The model

The models leading to quasi-fixed inputs in agriculture for developed countries are ones built largely upon a hypothesis of significant internal costs associated with resource adjustment. Significant location and geoclimate specificity to farmland characteristics means that commercially available nonhuman durable goods (e.g., equipment and building) must be modified to function efficiently. Breeding stock are heterogenous with respect to genotype and location, which means that large herd adjustment over a short period requires major search costs (or premium/discount on the price). Changing the number of farm workers also requires searching/training or terminating/retraining costs. Thus, rapid adjustment of farm resources may consume valuable resources that might be used to produce crop and livestock outputs. If the marginal cost of rapid resource adjustment is increasing with the size of adjustments, farmers face incentives to spread resource adjustments over several years (Nichell, 1986; Barro and Sala-i-Martin, 1995, p. 119–122).

Consider the following representation of production:

$$y_o = F(\boldsymbol{Y},\boldsymbol{X},\boldsymbol{K},I,Z) \tag{1}$$

where y_o is denoted the first output, $\boldsymbol{Y}$ is a vector of other outputs, $\boldsymbol{X}$ is a vector of variable inputs, $\boldsymbol{K}$ is a vector of quasi-fixed inputs, I is the gross investment in quasi-fixed inputs ($\boldsymbol{K}$), and Z is technology and environmental factors. Now the hypothesis of adjustment cost is summarized as $\frac{\partial F}{\partial \boldsymbol{K}}(\boldsymbol{Y},\boldsymbol{X},\boldsymbol{K},I,Z) > 0$, $\frac{\partial F}{\partial I}(\boldsymbol{Y},\boldsymbol{X},\boldsymbol{K},I,Z) < 0$ where $\frac{\partial F}{\partial I}$ is the marginal adjustment cost associated with changing the quasi-fixed factors. Thus, the adjustment cost model is assumed to have a symmetric representation. The dynamic accounting relationship for quasi-fixed inputs can be summarized as:

$$\dot{\boldsymbol{K}} = I - \delta \boldsymbol{K} \tag{2}$$

where $\dot{\boldsymbol{K}} = \mathrm{d}\boldsymbol{K}/\mathrm{d}t$ and $\delta \geq 0$ is a constant depreciation rate. To be a quasi-fixed input, an input is fixed in the short-run but variable in the long-run.

A general dynamic input demand system can be represented as:

$$\begin{aligned}\dot{\boldsymbol{K}}(t) = \mathbf{M}\boldsymbol{K}(t-1) &+ \boldsymbol{\beta}_1 p(t-1) + \boldsymbol{\beta}_2 w(t) \\ &+ \boldsymbol{\beta}_3 q(t) + \boldsymbol{\beta}_4\left[\gamma \boldsymbol{Z}(t-1) - \dot{Z}(t)\right] \\ &+ \boldsymbol{\beta}_0 + \epsilon(t)\end{aligned} \tag{3}$$

where $\dot{\boldsymbol{K}}(t)$ is an $m \times 1$ vector of (net) investment rates for m (potentially) quasi-fixed input stocks $K(t)$, $\boldsymbol{p}(t)$ is a $k_1 \times 1$ vector of output prices, $\boldsymbol{w}(t)$ is a $k_2 \times 1$ vector of variable input prices, $\boldsymbol{q}(t)$ is a $k_3(=m) \times 1$ vector of rental prices on the quasi-fixed inputs, $\boldsymbol{Z}(t)$ is a $k_4 \times 1$ vector of agricultural research, and $\boldsymbol{\epsilon}(t)$ is an $m \times 1$ vector of random disturbances. $\mathbf{M}$ is a matrix of constant but unknown adjustment coefficients; and $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, $\boldsymbol{\beta}_3$, and $\boldsymbol{\beta}_4$ are matrices of unknown coefficients; and $\boldsymbol{\beta}_0$ is a vector of unknown coefficients. Farmers are implicitly assumed to observe current input prices and lagged output prices when making decisions at the beginning of a production period.

Following Epstein and Denny (1983) and Vasavada and Chambers (1986), the dynamic demand Eq. (3) can be rewritten in the form of the multivariate flexible accelerator (MFA) model:

$$\dot{K}(t) = \mathbf{M}\left[K(t-1) - \bar{K}\right] + \epsilon(t) \tag{4}$$

where

$$\bar{K} = -\mathbf{M}^{-1}\left[\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 p(t-1) + \boldsymbol{\beta}_2 w(t) + \boldsymbol{\beta}_3 q(t) + \boldsymbol{\beta}_4\left(rZ(t-1) - \dot{Z}(t)\right)\right]. \tag{5}$$

$\bar{K}$ denotes the 'long-run' or 'desired' level of the quasi-fixed input stocks, $K(t)$, $\mathbf{M}$ represents the adjustment matrix; and r is the discount rate. The system (4) and (5) permits *slow* or *fast* adjustments in the quasi-fixed inputs. In particular, high adjustment costs will prevent farmers from quickly attaining their long-run or desired level of quasi-fixed inputs. These adjustment costs drive a wedge (or, a disequilibrium) between the short-run (or actual) and long-run (or desired) input use levels. The matrix $\mathbf{M}$ provides information needed to characterize how fast farmers adjust to the long-run equilibrium level. [1]

Early attempts to incorporate adjustment-cost theory into agricultural input demand models used univariate partial-adjustment models. This was a straightforward application of the Nerlovian partial-adjustment model to input demand functions derived from a static model. Much of the early empirical evidence is for the US. Griliches (1960) used this approach for an empirical study of US demand for farm tractors, 1921–1957. [2] He obtained an estimate for the adjustment coefficient of 0.17, and concluded that the results supported the adjustment cost hypothesis. Heady and Tweeten (1963), also made extensive use of the univariate partial-adjustment model in this study of US agricultural resource demand. They applied the model to demand functions for hired labor, family labor, and operating inputs. They concluded that adjustments of labor and operating inputs were rapid (e.g., adjustment coefficients were about 10) but of farm structures were rather slow (e.g., adjustment coefficients were about 4). [3]

The early versions of dynamic input demand owe a debt to Eisner and Strotz (1963) and Lucas (1967a). The unambiguous comparative results obtained by these authors were a consequence of an assumption of separability of the traditional production and investment decisions. [4] The responses to rental price changes in dynamic models, however, need not be symmetric as in static models (see Treadway, 1971 and Mortensen, 1973). In our paper, Eq. (4) is a first-order difference equation, and $\mathbf{M}$, the adjustment matrix, and stability of the dynamic input demand system are closely linked. Stability requires that all the eigenvalues of $\mathbf{M}$ lie within a unit circle.

In this study of a developed country, potentially quasi-fixed inputs under the control of farmers are placed in one of six groups: labor, automobiles and trucks, tractors, equipment, service structures (primarily buildings and fencing), and land. There is a seventh input group, labeled intermediate inputs, which is assumed to be variable. [5] Other studies have aggregated inputs into smaller or similar number of groups. Friesen et al. (1992) aggregate inputs into three groups: capital, labor, and materials; Vasavada and Chambers (1986) into four groups: labor, capital, intermediate materials, and land; and Vasavada and Ball (1988) into seven groups: durable

[1] The discussions of equilibrium throughout this study correspond to the equality between the actual and the desired levels of the quasi-fixed input stocks, and not between the supply and demand of such inputs in the market.

[2] Cromarty (1959) estimated the farm investment demands for tractors, machinery, and trucks for 1923–1954 period. He included lagged stock in his specification for machinery but not for tractors and trucks. Theoretical justification in terms of adjustment cost hypothesis was not provided.

[3] Other studies are worth mentioning. Penson et al. (1981) derived an intertemporal rental price in their empirical study of investment demands for tractors. Lamm (1982) applied several macroeconomic models of investment demand to real farm investment. Another model is based on mathematical programming applied to farm investment and replacement (e.g., Reid and Bradford, 1987).

[4] In any case, the relative prices affect directly the investment demands as this is clear from the presence of p, w, and q directly in the system (3).

[5] The model is one of production and investment decisions, but not of financing decisions. Needed financial resources are assumed to be available, and financial decisions do not affect the terminal value of the firm (Merton, 1982, p. 642–50).

equipment, real estate, family labor, farm produced durables, hired labor, and materials. Vasavada and Chambers (1986) concluded that farm labor was quasi-fixed and Vasavada and Ball (1988) concluded that family labor was fixed. The latter assumed rather than tested that hired labor was variable. To keep the dimension of the estimation problem manageable, we choose to stay with one-farm labor input. For developed countries, most studies of dynamic agricultural input demand have concluded that automobiles and trucks, tractors, equipment, and service structures are quasi-fixed. The test results for fixity of land, however, have been mixed. Lyu and White (1985) and Vasavada and Chambers (1986) concluded that land is quasi-fixed. In contrast, Vasavada and Ball (1988) concluded that land is variable. If the model was applied to a developing country, the input groups would most likely be modified.

2.1. Inter-dependency and fixity in resource adjustments

The model (Eqs. (3) and (4)) permits interdependencies in input adjustments. If interdependency in input adjustments do not exist, a univariate partial-adjustment model is appropriate. In such a model, the adjustment of each quasi-fixed input is independent of the stocks of other quasi-fixed inputs. Therefore, no indirect effect of relative price changes occur. Indirect effects of changes in opportunity costs are channelled only through an input's own lagged stock. In these univariate partial adjustment models, the adjustment matrix **M** is a diagonal matrix. The model collapses into six separate dynamic input demand equations, each depending only on relative prices and one lagged quasi-fixed input. This is basically the model that was applied by Griliches (1960) and Heady and Tweeten (1963).

Alternatively, subgroups of quasi-fixed inputs may possess interdependent adjustments. For instance, the six inputs in our model might be grouped into capital, land, and labor. Then we could examine whether inter-dependencies exist in adjustments among the aggregated input groups. In this case, the adjustment matrix **M** is block-diagonal with each block containing the adjustment coefficients of the inputs belonging to the three groups.

The system of dynamic input demand Eqs. (4) and (5) can also be employed to examine input adjustment rates. Consider first the significance of the adjustment cost hypothesis. In the absence of adjustment costs for inputs, farmers, when facing changes in relative prices, adjust their inputs freely without suffering short-run output losses. In this case, the quantity of inputs will always be equal to (long-run) desired levels so that no short-run 'disequilibrium' exists in input usage. This outcome requires $\dot{\boldsymbol{K}}(t) = 0$ so that $K(t) = \bar{K}$ for all t, and the adjustment matrix **M** is an (negative) identity matrix.

Thus, if the ith input is variable (hence is not quasi-fixed), the following restrictions on the adjustment matrix **M** hold:

$$\boldsymbol{M}_{ii} = -1, \boldsymbol{M}_{ji} = 0, \forall j \neq i \tag{6}$$

The first restriction implies that no disequilibrium exists in variable input usage (i.e., $\dot{\boldsymbol{K}}_i(t) = 0$ and $K_i(t) = \bar{K}_i$ for all t). The second restriction implies that the lagged value of input i does not appear in the demand equation for the other inputs. These restrictions apply only to the ith column of the adjustment matrix **M** and do not require that $M_{jk} = 0$ for all j and $k \neq i$. Variable inputs, by definition, are always in equilibrium use. Input demand, however, can still be affected by the lagged quantity of other quasi-fixed inputs, and interdependency may exist among adjustment rates of quasi-fixed inputs. Therefore, we have testable implications.

Table 1 summarizes the parameter restrictions on the adjustment matrix **M** for several different hypotheses (assuming no autocorrelation of disturbance in the model). Some of the hypotheses (e.g., symmetry) are not listed since they are clear from the context.

2.2. The estimation procedure

The dynamic agricultural input system (3) forms a seemingly unrelated six-equation system, one each for the (potentially) quasi-fixed inputs. [6] Thus, if the vector of disturbances $\boldsymbol{\epsilon}(t)$ is contemporaneously

[6] The discussion in this section focuses primarily on estimating the system with static price expectation. For the autoregressive output price expectation, the estimation procedures are similar.

Table 1
Selected hypotheses of interest and the implied parameter restrictions on the system of agricultural demand equations (when autocorrelation is absent)[a]

Hypotheses	Parameter restrictions on the adjustment matrix **M**
Independent adjustment among all inputs (i.e., univariate partial adjustment model)	$\mathbf{M}_{12} = \mathbf{M}_{13} = \mathbf{M}_{14} = \mathbf{M}_{15} = \mathbf{M}_{16} = \mathbf{M}_{21} = \mathbf{M}_{23} = \mathbf{M}_{24} = \mathbf{M}_{25} = \mathbf{M}_{26} = \mathbf{M}_{31} = \mathbf{M}_{32} = \mathbf{M}_{34} = \mathbf{M}_{35} = \mathbf{M}_{36} = \mathbf{M}_{41} = \mathbf{M}_{42} = \mathbf{M}_{43} = \mathbf{M}_{45} = \mathbf{M}_{46} = \mathbf{M}_{51} = \mathbf{M}_{52} = \mathbf{M}_{53} = \mathbf{M}_{54} = \mathbf{M}_{56} = \mathbf{M}_{61} = \mathbf{M}_{62} = \mathbf{M}_{63} = \mathbf{M}_{64} = \mathbf{M}_{65} = 0$
Independent adjustment among groups	$\mathbf{M}_{15} = \mathbf{M}_{16} = \mathbf{M}_{51} = \mathbf{M}_{61} = \mathbf{M}_{25} = \mathbf{M}_{26} = \mathbf{M}_{52} = \mathbf{M}_{62} = \mathbf{M}_{35} = \mathbf{M}_{36} = \mathbf{M}_{53} = \mathbf{M}_{63} = \mathbf{M}_{45} = \mathbf{M}_{46} = \mathbf{M}_{54} = \mathbf{M}_{64} = \mathbf{M}_{56} = \mathbf{M}_{65} = 0$
All inputs are variable (i.e., the absence of adjustment cost theory)	$\mathbf{M}_{11} = \mathbf{M}_{22} = \mathbf{M}_{33} = \mathbf{M}_{44} = \mathbf{M}_{55} = \mathbf{M}_{66} = -1$, $\mathbf{M}_{12} = \mathbf{M}_{13} = \mathbf{M}_{14} = \mathbf{M}_{15} = \mathbf{M}_{16} = \mathbf{M}_{21} = \mathbf{M}_{23} = \mathbf{M}_{24} = \mathbf{M}_{25} = \mathbf{M}_{26} = \mathbf{M}_{31} = \mathbf{M}_{32} = \mathbf{M}_{34} = \mathbf{M}_{35} = \mathbf{M}_{36} = \mathbf{M}_{41} = \mathbf{M}_{42} = \mathbf{M}_{43} = \mathbf{M}_{45} = \mathbf{M}_{46} = \mathbf{M}_{51} = \mathbf{M}_{52} = \mathbf{M}_{53} = \mathbf{M}_{54} = \mathbf{M}_{56} = \mathbf{M}_{61} = \mathbf{M}_{62} = \mathbf{M}_{63} = \mathbf{M}_{64} = \mathbf{M}_{65} = 0$
Automobile/truck stock is variable	$\mathbf{M}_{11} = -1$, $\mathbf{M}_{21} = \mathbf{M}_{31} = \mathbf{M}_{41} = \mathbf{M}_{51} = \mathbf{M}_{61} = 0$
Tractor stock is variable	$\mathbf{M}_{22} = -1$, $\mathbf{M}_{12} = \mathbf{M}_{32} = \mathbf{M}_{42} = \mathbf{M}_{52} = \mathbf{M}_{62} = 0$
Equipment is variable	$\mathbf{M}_{33} = -1$, $\mathbf{M}_{13} = \mathbf{M}_{23} = \mathbf{M}_{43} = \mathbf{M}_{53} = \mathbf{M}_{63} = 0$
Service structure is variable	$\mathbf{M}_{44} = -1$, $\mathbf{M}_{14} = \mathbf{M}_{24} = \mathbf{M}_{34} = \mathbf{M}_{54} = \mathbf{M}_{64} = 0$
Land is variable	$\mathbf{M}_{55} = -1$, $\mathbf{M}_{51} = \mathbf{M}_{52} = \mathbf{M}_{53} = \mathbf{M}_{54} = \mathbf{M}_{56} = 0$
Labor is variable	$\mathbf{M}_{66} = -1$, $\mathbf{M}_{61} = \mathbf{M}_{62} = \mathbf{M}_{63} = \mathbf{M}_{64} = \mathbf{M}_{65} = 0$

[a] 1 is for automobiles/trucks, 2 is for tractors, 3 is for equipment, 4 is for service structures, 5 is for land, and 6 is for labor.

but not serially correlated, the seemingly unrelated regression (SUR) estimation procedures developed in Zellner (1962) is a good choice for conducting the empirical analysis. When autocorrelations in the errors of Eq. (3) is present, the estimation procedure must be modified. If the disturbances $\epsilon(t)$ follow a vector autoregressive process of first degree:

$$\boldsymbol{\epsilon}(t) = \boldsymbol{\Phi}\epsilon(t-1) + \xi(t) \tag{7}$$

where $\boldsymbol{\Phi}$ is an $\mathbf{M} \times \mathbf{M}$ matrix of coefficients, and $\xi(t)$ is a $\mathbf{M} \times 1$ vector of white noises having a mean 0 and covariance matrix $\boldsymbol{\Sigma}$. With this specification, the system of dynamic input demand Eq. (3) can be transformed into:

$$\begin{aligned}\dot{\boldsymbol{K}}(t) = {} & \boldsymbol{\Phi}\dot{\boldsymbol{K}}(t-1) + \mathbf{M}[K(t-1) - \boldsymbol{\Phi}K(t-2)] \\ & + \boldsymbol{\beta}_1[p(t-1) - \boldsymbol{\Phi}p(t-2)] \\ & + \boldsymbol{\beta}_2[q(t) - \boldsymbol{\Phi}q(t-1)] \\ & + \boldsymbol{\beta}_3[\{r\mathbf{Z}(t-1) - \dot{Z}(t)\} \\ & - \boldsymbol{\Phi}\{r\mathbf{Z}(t-2) - \dot{Z}(t-1)\}] \\ & + \boldsymbol{\beta}_0^* + \xi(t)\end{aligned} \tag{8}$$

where $\boldsymbol{\beta}_0^* = (\mathbf{I}\text{-}\boldsymbol{\Phi})\boldsymbol{\beta}_0$; $\mathbf{I}$ is the identity matrix. Several estimation procedures have been proposed in the literature for such a system.

Since the system (3) with error structure of Eq. (7) is a special case of a general simultaneous equation model having first-order vector autoregressive errors, the full-information maximum-likelihood (FIML) estimation method developed in Sargan (1961) can be applied. The procedure is to transform the system of Eq. (3) into Eq. (8) and then, under the assumption that the random errors $\xi(t)$ are distributed as a multivariate normal, having mean 0 and covariance matrix $\boldsymbol{\Sigma}$, to apply the FIML estimation to the transformed model. The method is one of solving a nonlinear system of equations.

Since the FIML estimation procedure is time-consuming to solve, several approximating methods appear in the literature. They involve extending the two-step SUR procedures suggested in Zellner (1962) to incorporate the autocorrelated errors in the system. Spencer (1979) has adapted the two-step procedures suggested both in Hatanaka (1976) and in Dhrymes and Taylor (1976) for estimating models that include lagged dependent variables. In the first step, a consistent estimate of the parameters in the system is obtained either from an instrumental variable procedure, a nonlinear least squares estimate of each equation, or Hatanaka's single equation estimation technique. The 'preliminary' estimates of the autoregressive matrix ($\boldsymbol{\Phi}$) and cross-covariance matrix of residuals ($\boldsymbol{\Sigma}$) are then calculated. In the second step, the generalized least square procedure is applied to the transformed system using the 'preliminary' estimates of $\boldsymbol{\Sigma}$ and $\boldsymbol{\Phi}$. This stage provides the final estimates of the parameters in the model and 'corrections' to the 'preliminary' estimate of $\boldsymbol{\Phi}$. The resulting estimates are consistent and asymptotically efficient.

An alternative estimation procedure is one for a system that is nonlinear in parameters. Gallant (1975) provides a procedure for estimating nonlinear SUR equations based on the least-square method. Apart from nonlinearity in the system, the procedure is similar to that of a linear system. In particular, the estimated covariance matrix obtained from estimating each equation separately is used to estimate the complete system using Aitken-type estimation method. This procedure will be applied in the empirical analysis in this study.

3. The data

Annual input and price data for US agriculture are available from Huffman and Evenson (1993) for the years 1950–1982. The six New England states are excluded because farm output is small, and frequently intertwined with off-farm jobs. Hence, the observations are 42 state aggregates. The quantities are the Tornquist–Theil indices and the prices are the associated implicit prices (i.e., revenues or expenditures divided by the quantity indices) with a 1977 base period (i.e., 1977 = 100).

Measures of the agricultural inputs needed for this study were derived as follows. The labor input is a derived measure of annual hours of hired labor and operator and family labor. Annual hours of hired labor were derived from expenditures on hired labor and an average hourly wage rate. The annual hours of operator and hired labor were derived from USDA survey estimates of the number of persons working on farms and an estimate of average hours of farm work for these individuals (see Huffman and Evenson, 1994, pp. 355–356). The wage rate for hired farm labor is assumed to be the marginal cost or price of farm labor.

For capital inputs—autos and trucks, tractors, equipment, and service structures—the quantity is derived as follows. The value of the capital stock in these four capital types was derived from unpublishable USDA data (of the late 1980s) of state level estimates of annual depreciation at current replacement cost on a straight-line basis for each capital type (see Huffman and Evenson, 1994, pp. 360–361). [7] The value of capital stock was obtained as annual depreciation divided by the corresponding depreciation rate. The rental price for each of the capital types was derived as the sum of interest and depreciation on the current new price of the durable. A 4% interest, approximating a long-term opportunity cost, was applied to all types of capital for all years.

The land input is derived as cropland-equivalent units from data on cropland used for crops, cropland used for pasture, other cropland, irrigated land, woodland used for pasture, and other pasture. The weights were taken from Hoover (1961).

Intermediate inputs encompass purchased and nonpurchased feed, seed, fertilizers, repairs and operation, and miscellaneous inputs. An aggregate quantity index was computed using actual or imputed expenditures on these inputs and state prices (or opportunity cost) measures where possible and national prices where state prices did not exist.

Farm outputs are aggregated into two groups, crops and livestock, and two expected price indexes are defined. For crops with well-defined growing seasons and meat animals having long gestation and feeding periods, one-year lagged prices are used as a proxy for the expected price. Current-year prices are employed as expected prices for outputs produced continuously throughout the year (e.g., dairy and poultry products), and where the main current production decisions involve harvest and marketing (e.g., tree and vine crops).

[7] The raw material for creating our capital input measures were comparable to Ball (1985). The USDA has recently invested heavily in revising all of input and output measures for US agriculture (Ball et al., 1996).

Table 2
The sample means of quantity indices and implicit prices of inputs and outputs[a]

Inputs/Outputs	Quantity indices (1977 = 100)	Implicit prices
Labor	150.03	3.108
Hired labor	121.24	0.990
Family labor	168.72	2.116
Capital stocks	97.98	14.077
Automobiles and trucks	172.47	0.374
Tractors	86.57	2.936
Equipment	89.74	5.901
Service structures	109.94	4.844
Land	97.41	2.060
Intermediate inputs	82.33	8.780
Feed	97.01	3.315
Seed	94.81	0.378
Fertilizer	65.75	1.180
Repair and operation	84.05	1.728
Miscellaneous inputs	70.76	2.216
Crops	86.26	646.447
Livestock	95.72	1,972.122

[a] Total number of observations is 1386. The prices of capital stocks and land are rental prices. Wage rate for hired labor is assumed as the marginal cost for the family labor.

Research stocks are also from Huffman and Evenson (1993). Public research includes USDA and SAES research. Private research encompass applied research on food and kindred products, textile mill products, agricultural chemicals, drugs and medicine, and farm machinery obtained from reports of the National Science Foundation. All research variables are represented as stocks obtained using trapezoidal weight patterns to aggregate research expenditures over the previous 35 years. After a gestation period of 2 years, the research expenditures are assumed to increase production linearly for 7 years, constant for 6 years, and then declines for 20 years (see Huffman and Evenson, 1993).

Table 2 presents the sample mean values of the quantity indices and implicit prices of the inputs and outputs for this study. Detailed descriptions of data sources and constructions can be found in Huffman and Evenson (1993, 1994).

4. The empirical results

The estimated parameters of the system of dynamic agricultural input demand equations under the

Table 3
Nonlinear SUR estimates of the agricultural demand system under diagonal first-order vector autoregressive errors[a]

	Dependent variables: change of (potentially) quasi-fixed input					
	Autos and trucks	Tractors	Equipment	Service structure	Land	Labor
Lagged input use						
Autos and trucks	−0.369 (15.91)	−0.012 (4.45)	−0.026 (4.37)	0.014 (2.00)	−0.001 (0.59)	0.017 (2.92)
Tractors	0.046 (0.66)	−0.068 (4.85)	0.047 (1.63)	−0.036 (1.05)	0.010 (1.29)	−0.091 (3.12)
Equipment	−0.013 (0.57)	−0.001 (0.11)	−0.096 (9.53)	−0.006 (0.54)	0.005 (2.07)	0.008 (0.77)
Service structure	0.057 (2.06)	0.013 (3.20)	0.025 (3.01)	−0.088 (8.02)	−0.007 (2.28)	−0.012 (1.45)
Land	0.445 (3.98)	0.011 (1.42)	0.042 (2.72)	−0.021 (1.10)	−0.133 (3.61)	−0.022 (1.41)
Labor	0.127 (4.99)	−0.002 (0.61)	−0.002 (0.48)	0.014 (2.14)	−0.006 (2.19)	−0.076 (14.20)
Relative prices of:						
Autos and trucks	−0.550 (9.41)	−0.572 (11.42)	0.189 (1.67)	−0.338 (2.79)	−0.057 (3.13)	−0.042 (0.38)
Tractor	1.610 (6.32)	−0.446 (5.74)	0.158 (0.89)	0.254 (1.38)	−0.130 (4.41)	0.607 (3.45)
Equipment	−2.798 (11.98)	0.713 (8.88)	−0.501 (2.71)	0.267 (1.40)	0.213 (8.18)	−0.690 (3.77)
Service structure	−0.225 (2.15)	0.096 (3.51)	0.064 (1.03)	−0.042 (0.64)	−0.013 (1.10)	0.211 (3.41)
Land	0.008 (0.42)	0.005 (1.32)	−0.004 (0.54)	0.019 (2.02)	−0.002 (1.20)	−0.016 (1.94)
Labor	−0.242 (3.77)	0.019 (1.38)	0.006 (0.21)	−0.040 (1.24)	−0.007 (0.97)	−0.010 (0.36)
Intermediate input	0.050 (0.57)	0.014 (0.53)	−0.057 (0.95)	−0.081 (1.27)	−0.001 (0.03)	0.016 (0.26)
Crops	0.091 (1.65)	0.128 (6.93)	0.104 (2.47)	0.057 (1.30)	−0.006 (0.96)	−0.085 (2.02)
Research variables						
Public	7.435 (5.49)	−0.062 (0.45)	−0.366 (1.26)	0.088 (0.25)	0.042(0.30)	0.549 (1.85)
Private	48.563 (5.77)	−4.453 (5.20)	1.205 (0.67)	−0.885 (0.41)	0.703(0.90)	−2.638 (1.45)
Other variables						
Intercept	−1.564 (0.74)	8.739 (6.21)	5.505 (1.32)	3.924 (1.29)	2.357(9.90)	18.301 (4.86)
$\boldsymbol{\Phi}_{ii}$	0.837 (47.20)	0.026 (0.88)	−0.307 (11.09)	0.148 (4.48)	0.832(18.46)	−0.181 (6.35)
R^2	0.631	0.366	0.197	0.165	0.816	0.282
RMSE	8.177	3.387	9.311	7.492	0.901	8.611

[a]Numbers in parentheses are the absolute sample t-values. The numeraire is the price of livestock. The independent variables are the transformed variables.

assumption that the errors are contemporaneously and AR(1) correlated are reported in Table 3. $\dot{\boldsymbol{K}}(t)$, and the technical change rates, $\dot{Z}(t)$, have been approximated by first-differences in the appropriate terms. Except for the agricultural outputs that are produced continuously, the prices for outputs produced in year t are the prices observed in $t-1$.[8] Current prices are used for inputs. The transformed dynamic agricultural input demand system is fitted using the nonlinear SUR estimation procedure of Gallant (1975).

The model as represented in Eq. (8) is a special case of a more general vector autoregressive specification, and it contains 108 parameters. Starting values for the nonlinear estimation were obtained by first fitting Eq. (3) without autocorrelation using the SUR method, then using the residuals to obtain estimates of the first-order autoregressive [AR(1)] coefficient for each dynamic input demand equation. The final estimates were obtained using SAS-SYSNLIN. The estimation converged globally after a total of 16 interactions.

Each of the estimated autoregressive coefficients for the dynamic agricultural input demand system is significantly different from zero at the 5% significance level, except for the tractor input (see $\boldsymbol{\Phi}_{ii}$ in Table 3). Furthermore, the hypothesis that all six of the autoregressive coefficients are jointly zero is soundly rejected. The sample Gallant-Jorgenson (G-J) statistic is 3130, which is well above the critical chi-squared value of 12.59 with 6 degrees of freedom at the 5% significance level.

[8] Certainly other empirical representations of output prices could be employed.

Table 4
Tests of hypotheses on the agricultural demand equations under diagonal first-order vector autoregressive error structure

Hypotheses	χ^{2a}	Degree of freedom	Conclusion
Absence of auto-correlations	3130.07	6	Reject
Independent in adjustments of all inputs	141.69	30	Reject
Independent in adjustments among groups	92.18	18	Reject
All inputs are variable	394,386.65	42	Reject
Automobile stock is variable	19,465.68	7	Reject
Tractor stock is variable	5296.33	7	Reject
Equipment is variable	4748.17	7	Reject
Service structure is variable	11,645.73	7	Reject
Capital group is variable	49,438.64	28	Reject
Land is variable	239,572.65	7	Reject
Labor is variable	21,966.41	7	Reject

[a]The χ^2 statistics are based on Gallant and Jorgenson (1979). The entries in this column are the differences of the products of the objective function and the number of observations in the full and restricted models.

A statistically significant AR(1) time series process for the error terms means that economic shocks to dynamic input demand die out slowly or persist for many years (see Enders, 1995, Chap. 2). In three of the five dynamic agricultural input demand equations, the autoregressive coefficient $\mathbf{\Phi}_{ii}$ is positive, and two are relatively large—about 0.84 for autos and trucks, and for land. These positive $\mathbf{\Phi}_{ii}$ values imply a correlogram for the residuals that is smooth and gradually declining. Hence, a positive shock in year t to these dynamic input demand equations will have positive effects on input demand for many years in the future. In the remaining two equations—equipment and labor inputs—$\mathbf{\Phi}_{ii}$ is negative, and they imply an osculating in sign correlogram. For example, a large positive shock to dynamic input demand for these inputs in year t (say when a significant addition of equipment is made) will cause alternating negative and positive increments to demand in successive years going into the future. The finding of a statistically significant time series process for the dynamic agricultural input demand system seems to represent an important advance in the modeling of dynamic agricultural input demand systems over previous studies. Furthermore, our results cast doubt on the credibility of several earlier findings.

The empirical results are interesting. Most of the estimated parameters are statistically significant at the 5% level. The R^2's are low due to the first-difference specifications of the system. All the diagonal elements of the adjustment matrix, $\hat{\mathbf{M}}$, have negative signs and are statistically significant. The eigenvalues of this matrix are below unity in absolute value [-0.377, -0.133, -0.65, -0.022, -0.093 and -0.097]. [9] Therefore, the adjustment matrix and the dynamic agricultural input demand equations are stable systems, and all own-price effects are negative and statistically significant. The largest value for estimated contemporaneous correlation of error terms is between the tractor and land inputs, -0.203. If the autocorrelated errors in the demand system are ignored, the estimated adjustment coefficient for autos and trucks, equipment, and land are much different (see below). Hence, model specification seems to matter.

4.1. Interdependency in resource adjustments

Some test results for alternative specifications of the dynamic agricultural input demand equations are reported in Table 4. The testing procedure is based on the strategy developed by Gallant and Jorgenson (1979). For hypothesis testing in the system of equations, the estimate of the covariance matrices between the 'unrestricted' and the 'restricted' models must be held constant. The procedure is first to fit the unrestricted model and then to import the esti-

[9] The eigenvalues when first-order autocorrelated is ignored is [-0.143, -0.052, -0.131, -0.099, -0.068, and -0.027].

mated covariance matrix from the unrestricted model into the restricted model. Gallant and Jorgenson (1979) showed that the change in the least-squares criterion function for the 'unrestricted' and 'restricted' models using this procedure is distributed asymptotic χ^2 with degrees of freedom equal to the number of restrictions under the null hypothesis.

When vector autoregressive errors are part of a dynamic input demand system, the parameter restrictions for specialized resource adjustments are complex. In the transformed dynamic input demand Eq. (8), parameter restrictions on the adjustment matrix $\mathbf{M}$ alone (see Table 1) are not sufficient to imply interdependency of adjustments or input quasi-fixity. Further restrictions on the vector autoregressive coefficient matrix $\mathbf{\Phi}$ are required. For example, the fact that $\mathbf{M}$ is a diagonal matrix does not necessarily imply that the univariate partial-adjustment hypothesis holds. As long as $\mathbf{\Phi}$ is unrestricted, the interdependency in the adjustments of the quasi-fixed inputs is still prevalent either directly from $K(t-2)$ or indirectly from $\dot{K}(t-1)$. The univariate partial-adjustment model, however, holds whenever we cannot reject a joint null hypothesis that both the adjustment matrix $\mathbf{M}$, and the vector autoregressive coefficient $\mathbf{\Phi}$ are diagonals. Appendix A presents an example showing the derivation of the parameter restrictions on the dynamic input demand system for first-order vector autoregressive errors and two inputs.

The reasoning can be extended to test for quasi-fixity of each input. Recall from Eq. (8) that the ith agricultural input is variable and hence is not quasi-fixed if we cannot reject the joint null hypotheses that $\mathbf{M}_{ii}=-1$ and $\mathbf{M}_{ji}=0$ for all $j \neq i$. These parameter restrictions are valid only if the vector auto-regressive matrix is null. If $\mathbf{\Phi}$ is unrestricted, however, the instantaneous adjustment of the ith input cannot hold when $\mathbf{\Phi}_{ii}$ is non-zero. Furthermore, the quantity of the ith input still affects the change in demand for the jth input as long as $\mathbf{\Phi}_{ji}$ is non-zero. Thus, as shown in Appendix A, the ith input is said to be variable and is not quasi-fixed if we cannot reject a joint null hypothesis that, $\mathbf{M}_{ii}=-1$, $\mathbf{M}_{ji}=0$ for all $j \neq i$, and $\mathbf{\Phi}_{ji}=0$ for all j. To be able to conclude that all agricultural inputs are variable, it is necessary for the adjustment matrix $\mathbf{M}$ to be an (negative) identity and the vector-autoregressive coefficient $\mathbf{\Phi}$ be a null matrix.

The null hypothesis of independent adjustments in all six US dynamic agricultural input equations is easily rejected at the 5% significant level. The sample G-J statistic of 141.7 exceeds the critical χ^2 value of 43.8 at the 5% level and 30 degrees of freedom. This means that there are interdependencies in input adjustments among some or all six agricultural inputs. Therefore, a multivariate flexible-accelerator model appears to be a better representation of US state aggregate input adjustment behavior during 1950–1982 than a univariate adjustment representation. This conclusion is consistent with results for US national aggregate behavior reported in Vasavada and Ball, 1988; Vasavada and Chambers, 1986; Epstein and Denny, 1983.

Next, consider independent adjustment among groups of agricultural inputs. For this purpose, the six input groups have been consolidated into the following three groups: capital, land and labor. The capital group includes automobiles/trucks, tractors, equipment and service structure. Now we can reformulate an interesting null hypothesis that a univariate partial-adjustment model is appropriate for this three-group input demand system. This hypothesis, however, is also rejected at 5% significant level. For example, the previous year's usage of land and labor affect farmers' decisions on current farm aggregate capital input. Similarly, the previous year's quantity of capital input also influences farmers' current investment in land and labor. In short, the conclusions show definite interdependencies among resource adjustments in US agriculture. [10]

4.2. The resource adjustments rate

How rapidly does adjustment of agricultural resources occur in a developed country? The answer to this question may be useful for GATT/WTO or NAFTA policy analyses because knowing something about the speed of adjustment can help policy makers predict the time path of economic adjustments.

[10] The next two hypotheses in Table 4 concern the symmetry in resource adjustments either in all inputs or in capital group. Both hypotheses are rejected at 5% significant level.

This method is best suited to analyze how fast farmers adjust agricultural input usage when there is a once-and-for-all change in policy.

For US agriculture, the hypothesis that each of the six agricultural input groups is variable is rejected at the 5% significance level (Table 4). All the sample G-J statistics are well above the critical χ^2 values. Thus, autos and trucks, tractors, equipment, service structures, land and labor in US agriculture during the post-World War II era were quasi-fixed. This implies that US farmers did not quickly adjust inputs to long-run optimal levels after a change in relative prices (or agricultural research) occurred. Instead, the adjustments were, in general, distributed over many years.

Some interesting insights can be gained by examining the absolute values of the adjustment coefficient. They are as follows: autos and trucks, 0.37; tractors, 0.07; equipment, 0.10; service structures, 0.09; land, 0.13; and labor, 0.08. They imply that, for autos and trucks, the adjustment rate was relatively fast. It takes no more than 5 years to close 90% of a disequilibrium caused by a one-time change in relative prices, and our results imply a faster adjustment rate than what Heady and Tweeten (1963) obtained for US machinery, motor vehicles and equipment. Our adjustment coefficient for tractors, however, is significantly smaller than what Griliches (1960) obtained for US tractors. Our results seem to compare favorably with those for multivariate flexible-accelerator models. Vasavada and Chambers (1986) concluded that the adjustment coefficient for capital was 0.12 and Lyu and White (1985) reported an adjustment coefficient for machinery of 0.09.

For the other five agricultural inputs, our results imply that 90% of input usage disequilibrium would be corrected in 10 to 15 years. Our land-adjustment coefficient is larger than the 0.03 estimate of Lyu and White (1985) for (US national) real estate, but low compared to some other US studies. For example, Vasavada and Chambers (1986) reported an estimate of 0.59, and Vasavada and Ball (1988) reported much larger estimated adjustment coefficients (i.e., 0.74) for real estate, which encompassed both farmland and service structures. In addition to treatment for autocorrelation, studies differ in the degree of aggregation (state vs. national) and the definition of land. Our definition of the quantity of land refers to a cropland-equivalent basis, but the other studies use a different measure (see Ball, 1985).

We have rejected the null hypothesis that US farm labor is a variable input. This is for farm labor comprised of an aggregate of family and hired labor. One suspects, however, that the slow adjustment of farm labor is due to the family component. The adjustment coefficient for US farm labor is 0.08, which implies that it takes more than 20 years to close 90% of a disequilibrium caused by an economic shock. This is approximately one-half of a working life. Our estimate is almost the same as 0.07 estimate of Vasavada and Chambers (1986) for US farm labor (an aggregate over family and hired labor), but smaller than Vasavada and Ball (1988) obtained for US family labor. Therefore, evidence is pretty strong for adjustments in US farm labor, especially family labor, as a quasi-fixed, rather than as a variable input.

If we had failed to take account of first-order autocorrelation of the error terms in the dynamic agricultural input demand system, the implied speed of adjustment would have been much different for some of the inputs. The adjustment coefficient for autos and trucks and for land would have been significantly smaller; 0.11 vs. 0.37 for autos and trucks, and 0.07 vs. 0.13 for land. For tractors, service structure and labor, the treatment for autocorrelation does not change significantly the size of the adjustment coefficient; but for equipment, failing to take account of autocorrelation would have resulted in a larger adjustment coefficient, 0.14 vs. 0.10. We conclude that some of the seemingly 'slow' adjustment of quasi-fixed agricultural inputs reported in earlier US studies is most likely due to model misspecification associated with the time series process of the errors in the dynamic input demand system.

Because the observations are for states pooled over time, a concern might arise about differences in parameters across states. A dynamic agricultural input demand system containing state dummy variables was also fitted. In general, the results do not differ very much from the ones excluding state effects. In particular, the univariate partial-adjustment model is rejected, so the results provide evidence for interdependency in optimal input adjustments. The hypotheses that the inputs are variable, either taken as whole, as a group, or individually, are all rejected.

Therefore, the same general conclusions are maintained.

4.3. The rental price effects

Table 3 also reports estimates of responsiveness of input demand to price changes. Recall that all of the short-run own-price effects on agricultural input demand are negative and three of them are significantly different from zero. This is somewhat surprising because the dynamic adjustment-cost theory does not provide any prior sign expectation for these price effects. The short-run own-price elasticity of demand for tractors and equipment are the largest, -0.015 and -0.033, respectively, and the others are smaller in absolute value than -0.01. Thus, although the short-run own-price elasticities are negative, they are, in general, economically small. The cross-price effects are also highly significant. The hypothesis that one input is independent from price effects of other quasi-fixed inputs is easily rejected at 5% significant level. The hypothesis of independent price effects among groups is also rejected.

A closely related issue is whether price effects are symmetric across the dynamic input demand system. The dynamic adjustment–cost theory (Treadway, 1970, 1971; Mortensen, 1973) does not require symmetry. However, Vasavada and Chambers (1986) imposed symmetric rental price effects in their empirical analysis of investment demands for US agriculture. The results from tests reported in Table 3, however, do not support symmetry. The null hypotheses of symmetric (rental) price effects for all inputs and among input groups are rejected at the 5% significant level.

Among short-run cross-price effects on dynamic agricultural input demand, a few additional effects are noteworthy. An increase of the price of tractors, service structures, or land shifts leftward the demand schedule for autos and trucks. An increase of the price of land also shifts leftward the demand for tractors, but an increase of the price of autos and trucks or labor shifts it rightward. An increase in the price of autos and trucks or labor shifts leftward the demand for equipment, but an increase of the price of tractors, service structures, or land shifts it rightward. Finally, an increase of the price of autos and trucks shifts leftward the demand schedule for farm labor.

A change in the relative price of crop to livestock output also affects dynamic input demand functions. An increase of the price of crop (relative to the price of livestock) output shifts rightward the short-run demand schedule for all the quasi-fixed inputs, except for labor and land. These effects seem consistent with livestock production being more labor-intensive overall than crop production, and capital services being more highly substitutable for labor in crop than livestock production.

Thus, the results in Table 4 provide evidence that dynamic agricultural input demand schedules for the US are negatively sloped and affected by changes in (real rental) prices of all inputs. The results are in accord with the theoretical analysis in the general dynamic adjustment–cost theory.

4.4. Research impacts

The results shed new light on the effects of agricultural research on dynamic agricultural input demand in a developed country. They show that an increase in US public and private research cause a significant rightward shift in the short-run US demand schedule for farm automobiles and trucks (see Table 3). Because of seeming labor-saving technical change in US agriculture over the study period (e.g., Huffman and Evenson, 1989; Hayami and Ruttan, 1985), our result that added public agricultural research shifts rightward the demand for labor (significant at 7% level) is surprising. On the other hand, added private agricultural research shifts leftward the demand schedule for tractors and labor (latter significant at 15% level). Public and private agricultural research, however, have no other significant effect on the short-run demand for quasi-fixed US agricultural inputs.

5. Conclusion

This paper has presented new econometric evidence about the demand for inputs in US agriculture viewed from the perspective of a dynamic adjustment–cost model. We considered six potentially quasi-fixed inputs and one group of intermediate inputs. We rejected the hypothesis that inputs of autos and trucks, tractors, equipment, service structures, land, and labor behave as 'variable' inputs.

Instead we accepted the hypothesis that they behave as quasi-fixed inputs, which means that they adjust somewhat sluggishly to an economic shock. We also concluded that a multivariate flexible-accelerator representation of dynamics was superior to six separate univariate flexible-accelerator representations of the dynamic input demand. Therefore, we conclude that the dynamic input demand functions are integrated in complex and economically important ways.

We soundly rejected the hypothesis of no vector first-order autocorrelated errors in the dynamic input demand system. The size of the estimated input adjustment coefficients were shown to differ significantly between a model with and without autocorrelation. When autocorrelation was permitted, the speed of input adjustment was generally increased. Hence, we conclude that part of the explanation for seemingly slow adjustment of dynamic U.S. agricultural input demand to economic shocks reported in other studies (e.g., Vasavada and Ball, 1988; Vasavada and Chambers, 1986) was most likely due to misspecification of the autocorrelation structure for the dynamic input demand system. Other studies have largely ignored the consequence of autocorrelated errors.

Our results imply that dynamic input demand schedules for inputs have negative slopes, although quite own-price inelastic; and to be shifted significantly by cross-price changes, a change in relative price of crop to livestock output, and by a change in the stock of public and private research. Finally, others may wish to test the general applicability of our results to agricultural input demand in other developed countries.

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Appendix A. Parameter restrictions of the investment demand system with vector autoregressive errors

This appendix provides a work-out example for deriving parameter restrictions on the investment demands under a first-order vector autoregressive process for the case of only two quasi-fixed inputs. Generalization to N inputs can be done in a straightforward manner. To begin with, ignoring terms other than stocks of quasi-fixed inputs since they will not affect this analysis, the transformed investment demands (8) can be written in full as follows:

$$\begin{aligned}\dot{K}_1(t) = {} & \boldsymbol{\phi}_{11}\dot{K}_1(t-1) + \boldsymbol{\phi}_{12}\dot{K}_2(t-1) \\ & + \mathbf{M}_{11}K_1(t-1) + \mathbf{M}_{12}K_2(t-1) \\ & - (\boldsymbol{\phi}_{11}\mathbf{M}_{11} + \boldsymbol{\phi}_{12}\mathbf{M}_{21})K_1(t-2) \\ & - (\boldsymbol{\phi}_{11}\mathbf{M}_{12} + \boldsymbol{\phi}_{12}\mathbf{M}_{22})K_2(t-2) \\ & + X_1(t)\psi_1 \end{aligned} \tag{A.1}$$

$$\begin{aligned}\dot{K}_2(t) = {} & \boldsymbol{\phi}_{21}\dot{K}_1(t-1) + \boldsymbol{\phi}_{22}\dot{K}_2(t-1) \\ & + \mathbf{M}_{21}K_1(t-1) + \mathbf{M}_{22}K_2(t-1) \\ & - (\boldsymbol{\phi}_{21}\mathbf{M}_{11} + \boldsymbol{\phi}_{22}\mathbf{M}_{21})K_1(t-2) \\ & - (\boldsymbol{\phi}_{21}\mathbf{M}_{12} + \boldsymbol{\phi}_{22}\mathbf{M}_{22})K_2(t-2) \\ & + X_2(t)\psi_2 \end{aligned} \tag{A.2}$$

where $\boldsymbol{X_1(t)}$ and $\boldsymbol{X_2(t)}$ are vectors of other terms in the system. In the following, some parameter restrictions are derived for testing some hypotheses of interest.

A.1. Univariate partial adjustment hypothesis

This hypothesis exerts that the adjustments of a stock of quasi-fixed input do not depend on the stocks of other inputs. This can be attained if both the adjustment matrix $\mathbf{M}$ and the autoregressive matrix $\boldsymbol{\Phi}$ are restricted to be diagonal. Thus, we need that $\mathbf{M}_{12} = \mathbf{M}_{21} = 0$ and $\boldsymbol{\Phi}_{12} = \boldsymbol{\Phi}_{21} = 0$. This is because, under such restrictions, the system becomes:

$$\begin{aligned}\dot{K}_1(t) = {} & \boldsymbol{\Phi}_{11}\dot{K}_1(t-1) + \mathbf{M}_{11}K_1(t-1) \\ & - \boldsymbol{\Phi}_{11}\mathbf{M}_{11}K_1(t-2) + X_1(t)\Psi_1 \end{aligned} \tag{A.3}$$

$$\begin{aligned}\dot{K}_2(t) = {} & \boldsymbol{\Phi}_{22}\dot{K}_2(t-1) + \mathbf{M}_{22}K_2(t-1) \\ & - \boldsymbol{\Phi}_{22}\mathbf{M}_{22}K_2(t-2) + X_2(t)\Psi_1 \end{aligned} \tag{A.4}$$

As can be seen, the adjustment of each input only depends on its own stock. Notice how this specification differs from those in previous studies. There are still some autoregressive coefficients in the system in this specification.

A.2. All inputs are variable

When all inputs are variable, this means that their adjustments are instantaneous so that their stocks would not affect the adjustment of other inputs. This can be attained simply by restricting $\mathbf{M}$ to be an (negative) identity matrix and $\mathbf{\Phi}$ to be null. Under such restrictions, the system becomes:

$$\dot{\boldsymbol{K}}_1(t) = -K_1(t-1) + \boldsymbol{X}_1(t)\Psi_1 \tag{A.5}$$

$$\dot{\boldsymbol{K}}_2(t) = -K_2(t-1) + \boldsymbol{X}_2(t)\Psi_2 \tag{A.6}$$

By rewriting in the level forms, the system will build down into demands for stocks (as opposed to investments) for inputs as those in the static model specifications.

A.3. Input quasi-fixity tests

To test the quasi-fixity of the inputs, we should be able to show that it is not variable. The ith input is variable if its adjustment is instantaneous so that its stock does not affect the adjustment of other inputs. To test the variability of the ith input, it is necessary and sufficient that $\mathbf{M}_{ii} = -1$ and the ith columns of both $\mathbf{M}$ (except $\mathbf{M}_{ii}$) and $\mathbf{\Phi}$ matrices are deleted. For instance, if we want to show that the first input is variable, impose restrictions that $\mathbf{M}_{11} = -1$ and $\mathbf{M}_{21} = \mathbf{\Phi}_{11} = \mathbf{\Phi}_{21} = 0$. Under such restrictions, the system becomes:

$$\begin{aligned}\dot{\boldsymbol{K}}_1(t) = \mathbf{\Phi}_{12}\dot{\boldsymbol{K}}_2(t-1)& \\ - K_1(t-1) + \mathbf{M}_{12}K_2(t-1)& \\ - (\mathbf{\Phi}_{11}\mathbf{M}_{12} + \mathbf{\Phi}_{12}\mathbf{M}_{22})K_2(t-2)& \\ + \boldsymbol{X}_1(t)\psi_1&\end{aligned} \tag{A.7}$$

$$\begin{aligned}\dot{\boldsymbol{K}}_2(t) = \mathbf{\Phi}_{22}\dot{\boldsymbol{K}}_2(t-1) + \mathbf{M}_{22}K_2(t-1)& \\ - (\mathbf{\Phi}_{21}\mathbf{M}_{12} + \mathbf{\Phi}_{22}\mathbf{M}_{22})K_2(t-2)& \\ + \boldsymbol{X}_2(t)\psi_2&\end{aligned} \tag{A.8}$$

It can be seen that the stock of first input disappears in the second equation. The stock of the second input, however, can affect the first input because it is quasi-fixed input. Notice how the autoregressive coefficient is still kept in general forms.

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