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ESTIMATING SOURCES OF FLUCTUATIONS IN THE AUSTRALIAN WOOL MARKET: AN APPLICATION OF VAR METHODS

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Vector autoregression (VAR) methods are used to analyse the contribution of supply, demand and policy shocks to unpredictable fluctuations in the market for Australian wool. VAR procedures are compared with conventional structural econometric models as methods for decomposing sources of instability. While each has advantages and disadvantages, VAR procedures might be viewed as preferable when the underlying market structure is complex and uncertain, as it is in the case of wool. Based on the results obtained, demand shocks are the dominant source of uncertainty in the wool market in the absence of Australian Wool Corporation intervention, but intervention has blunted their effects, reducing market uncertainty and increasing the average level of prices and revenues.

Economists have long been concerned with the causes of fluctuations in agricultural commodity markets. Most attention has focused on price fluctuations, but interest could centre on other variables including quantity, revenue, consumer surplus and producer surplus. Interest in market fluctuations arises from a desire to understand the way commodity markets work and evolve over time, and from the need to evaluate commodity stabilisation policies and proposals (e.g. Hinchy and Fisher 1988). The economic effects of commodity market fluctuations, and the success of policies designed to counteract them, depend critically on the underlying source of market disturbances (Turnovsky 1978; Newbery and Stiglitz 1981).

The three main types of disturbances which cause fluctuations in commodity markets may be classified as supply shifts, demand shifts and changes in government policies. The aims in this paper are to outline a method of estimating the contribution of each type of disturbance and to apply the method to the Australian wool market. Wool is an interesting case because the Australian Wool Corporation (AWC) operates a buffer-stock scheme designed to stabilise prices. Some attention has been given to analysing the 'hidden' revenue losses and gains that accrue to producers as a result of AWC stock operations (e.g. Campbell, Gardiner and Haszler 1980; Richardson 1982; Haszler and Curran 1982). These analyses typically assume that demand shifts are the dominant cause of market fluctuations. However, little research

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has focused directly on quantifying the relative contribution of supply and demand disturbances.

Another issue that has arisen is how the long-run demand for wool has shifted, if at all, as a result of the scheme. Demand may have expanded because the scheme causes wool prices to be more stable relative to the price of synthetics, or demand may have contracted because the quantity of wool available for purchase by private buyers is destabilised as a result of the scheme. These two influences also may have cancelled each other leaving no effect on long-run demand. As pointed out by Watson (1980), what has actually occurred '. . . is an empirical question about which it is extremely difficult to collect evidence that can be tested in a satisfactory way.' The analysis of wool market fluctuations reported here provides some evidence on this issue.

Numerous methods have been developed for estimating the sources of fluctuations in economic variables (Offutt and Blandford 1983). Early research used a formula for decomposing the variance of random identities (e.g. Borhnstedt and Goldberger 1969; Houck 1973; and Hazell 1984). While useful for some purposes, these variance decompositions are generally incapable of separating fluctuations into supply and demand effects. In response, Piggott (1978) demonstrated how a structural simultaneous equations model (SEM) could be used to decompose revenue fluctuations into supply and demand components; see also Myers and Runge (1985).

The procedure for estimating sources of commodity market fluctuations used in this paper is based on the vector autoregression (VAR) methods pioneered by Sims (1980) and extended by Bernanke (1986) and Sims (1986). A VAR representing the wool market is assumed to be driven by three types of structural disturbances – an aggregate supply shock, an aggregate demand shock, and an aggregate policy shock representing shifts in AWC stockholding behaviour.[1] The contribution of each type of shock to market price, quantity and revenue fluctuations is then estimated. Orden and Fackler (1989) have employed similar VAR methods to study the effects of macroeconomic policies on agriculture.

In the next section the VAR methods employed herein are compared with a conventional structural SEM approach. A simple VAR model of the Australian wool industry is then identified and estimated. Impulse response functions from the VAR illustrate the dynamic response of key wool market variables to typical supply, demand, and policy shocks. Decompositions of forecast error variances define the contribution of each type of shock to unpredictable fluctuations in wool market variables. Finally, alternative paths for supply, demand and policy shocks are simulated in order to evaluate the effects of stockholding on key wool market variables.

Alternative Modeling Techniques

Some kind of economic structure must be imposed on the data to estimate the relative contribution of supply, demand and policy shifts to commodity market fluctuations. Currently, VARs and SEMs con-

[1] The term 'shock' refers to a structural shift in supply, demand or policy which cannot be predicted *ex ante*.

stitute the two main alternatives for imposing structural identification restrictions. The two models can be viewed as alternative representations of the same underlying economic structure, the main difference being in the type (and number) of identification restrictions which are imposed. Each approach has advantages and disadvantages for estimating sources of commodity market fluctuations.

Conventional simultaneous equations models

The structural form of a linear SEM may be written:

(1) $By_t = \Gamma x_t + \varepsilon_t$

where y_t is a $(n \times 1)$ vector of endogenous variables; x_t is a $(k \times 1)$ vector of exogenous, lagged exogenous and lagged endogenous variables; ε_t is a $(n \times 1)$ vector of zero mean, serially uncorrelated structural disturbance terms; and Γ and B are structural parameter matrices of order $(n \times k)$ and $(n \times n)$, respectively. For convenience, all variables are defined to be seasonally adjusted and expressed as deviations from their respective means. In a commodity market model, the n equations in (1) might represent supply and demand for relevant commodities as well as equations explaining government intervention in the market.

Conventional SEMs typically are over identified by imposing zero restrictions on the parameter matrices Γ and B. Remaining parameters are then estimated using a simultaneous equations estimator (e.g. Judge *et al.* 1985). Sources of commodity market fluctuations are estimated by using (1), an estimate of the covariance matrix of x_t, and econometric estimates of Γ and B, to decompose the variance of key elements of y_t into components due to elements of the covariance matrix of x_t. This provides an estimate of the direct contribution of fluctuations in x_t (supply and demand shifters) to fluctuations in y_t (prices, quantities and revenues); see Piggott (1978).

The main advantage of the approach is that, not only can fluctuations in endogenous variables be decomposed into aggregate supply, demand and policy components, but a disaggregated analysis of the contribution of each individual supply, demand or policy shift variable (i.e. each element of x_t) also can be undertaken. This provides a rich set of information on the sources of economic fluctuations in commodity markets.

Nevertheless, the conventional SEM approach has disadvantages. A potential problem with any SEM is that the restrictions used to identify the model may not be valid. SEMs are most useful when substantial certainty exists regarding the true economic structure generating data. In this case, the identification restrictions on the Γ and B matrices are presumably appropriate and the resulting estimates are reliable. But when the true economic structure is highly uncertain, many of these restrictions may be inappropriate. This problem is exacerbated by the common practice of failing to formally test over-identifying restrictions in SEMs.

The problem of finding valid identification restrictions is particularly acute in a model of the Australian wool market because the market is so complex. The demand for Australian wool is derived from many countries; Australian wool competes with wool from other countries as well as with other fibres; and numerous quality classifications exist. Price expectations are important determinants of supply and demand, and uncertainty exists over ways to model the expectation formation process. A recent SEM of wool supply, demand and AWC stockholding behaviour consisted of six blocks (one for each of six grades of wool). Each block had 4 endogenous variables and between 18 and 30 predetermined variables (Connolly 1989). Variance decompositions in such a model would clearly be complex and results are likely to be sensitive to specification error.

Another disadvantage of the SEM approach is that variance decompositions focus on the *unconditional* variance of y_t. This causes two problems. First, fluctuations that are predictable *ex ante* are treated identically to random disturbances that are unpredictable. If market uncertainty is of primary concern, then it is better to concentrate on estimating sources of fluctuations that cannot be predicted based on available information (i.e. to concentrate on decomposing the *conditional* variance of y_t). Second, use of the unconditional joint distribution of x_t means that the elements of x_t will almost certainly be highly correlated, and no satisfactory economic interpretation for the contribution of the covariances among x_t to the variance of y_t has yet been developed. In the Connolly (1989) SEM, there are between 18 and 30 predetermined variables in x_t, generating between 153 and 435 covariance terms for each of 6 blocks of equations. These covariance terms would dominate the variance decomposition results and render interpretation of the relative contribution of different supply and demand shifters extremely hazardous.

Vector autoregression methods

A VAR model explaining the same endogenous variables vector as in equation (1) is:

$$(2) \quad By_t = \sum_{i=1}^{m} B_i y_{t-i} + Au_t$$

where u_t is a $(n \times 1)$ vector of zero mean, serially uncorrelated disturbance terms with an identity covariance matrix; A and B are $(n \times n)$ parameter matrices representing contemporaneous interrelationships among y_t and u_t; and the B_i are $(n \times n)$ parameter matrices defining dynamic interactions among y_t.

Equation (2) differs from (1) in that there are no exogenous variables and the endogenous variables have a flexible lag structure. However, under very mild assumptions on the stochastic properties of x_t, the conventional SEM represented by (1) always has a VAR representation for its y_t vector. Thus, no loss of generality occurs by focusing on this form of the model.[2]

Premultiplication of (2) by the inverse of B yields the reduced form:

$$(3) \quad y_t = \sum_{i=1}^{m} C_i y_{t-i} + v_t$$

where $C_i = B^{-1}B_i$ for $i = 1, 2, \ldots, m$; and $v_t = B^{-1}Au_t$. The covariance matrix of the reduced form disturbances, v_t, is:

[2] While there is no loss of generality, there is clearly loss of information because the model is based on a smaller set of variables.

(4) $\Omega = B^{-1}AA'B^{-1\prime}$

and this equation plays a key role in identification and estimation of VARs.

A distinguishing feature of VAR models is that the reduced form – equation (3) above – is unrestricted, and a set of just-identifying restrictions is imposed on the contemporaneous interactions among variables (the A and B matrices). Bernanke (1986) and Fackler (1988) show that a necessary (order) condition for identification in this case is that the number of free parameters in A and B be less than or equal to the number of unique elements in Ω.[3] Intuitively, VAR identification involves a set of restrictions which ensure that the elements of the A and B matrices can be solved in terms of the unique elements of Ω using equation (4).

The fact that the reduced form is unrestricted permits a simplified two-step estimation procedure. The first step is to estimate the reduced form (3) by ordinary least squares. The second step is to note that, under a normality assumption, the log-likelihood for a set of T observations on y_t can be expressed, up to a constant term, as:

$$(5) \quad \Lambda = -0{\cdot}5T\log|B^{-1}AA'B^{-1\prime}| - 0{\cdot}5\sum_{t=1}^{T} v_t'B'A^{-1\prime}A^{-1}Bv_t.$$

A concentrated log-likelihood is formed by substituting the reduced-form residuals from the first step for v_t in equation (5). The concentrated log-likelihood is then a function only of the reduced-form residuals and the parameters in A and B. Estimates of the A and B matrices are obtained by maximising the concentrated log-likelihood subject to identification restrictions; see Fackler (1988).[4]

The interpretation of the disturbance terms, u_t, is crucial for analysing sources of market fluctuations. Bernanke (1986) suggests thinking of u_t as a vector of structural economic shocks that do not have common causes and are therefore uncorrelated. They represent fundamental economic forces which are orthogonal and which buffet y_t and cause it to shift over time. In this paper, the aim is to impose restrictions sufficient to identify the elements of u_t as an aggregate supply shock, an aggregate demand shock and an aggregate policy shock. While the elements of u_t are uncorrelated, this does not imply that the elements of y_t are uncorrelated unless A and B are diagonal.

The effects of structural shocks on the endogenous variables can be investigated by impulse response analysis. A moving average representation for the VAR is obtained by solving the difference equation (3) to obtain:

$$(6) \quad y_t = \sum_{i=0}^{\infty} D_i u_{t-i} + f(t)$$

[3] A rank condition must also be satisfied but no general results have yet been derived to characterise it. In practice, identifiability is established by examining the rank of the information matrix numerically (Fackler 1988).

[4] In the just-identified case, this two-step procedure is equivalent to applying full information maximum likelihood (FIML) to the original system. However, maximisation of the concentrated likelihood is more straightforward because of the smaller number of parameters involved. Estimation results in this paper were carried out on a microcomputer using a GAUSS routine for nonlinear optimisation.

where $D_0 = B^{-1}A$; $f(t)$ is function of t that is identically zero if y_t is covariance stationary; and the matrices D_i $(i = 1, 2, \ldots)$ can be computed from the recursion:

$$(7) \quad D_i = \sum_{j=1}^{\min(i,m)} C_j D_{i-j}.$$

Equations (6) and (7) trace out the dynamic response of y_t to a typical structural shock in one or more of the elements of u_t.

Another way of using a VAR to analyse commodity market fluctuations is forecast error variance decomposition. From (3), v_t is a vector of errors from the one-step linear projection of y_t on past values of itself. Furthermore, from (4), the covariance matrix of v_t depends only on the parameters in A and B. Thus, estimates of A and B can be used to decompose the variance of the prediction errors for each element of y_t into components due to the variance of each structural shock in u_t. This provides direct evidence on the proportion of unpredictable fluctuations in y_t that can be attributed to different structural shocks (e.g. supply versus demand shocks).

A final way in which the VAR can be employed to explore commodity market fluctuations is through simulation. For example, a no-storage regime could be simulated by choosing a vector of policy shocks that equates supply and demand in every period. Comparing the simulated path of y_t to the historical path would then provide information on the effects of stockpiling over the sample period.

These VAR techniques overcome some of the disadvantages of conventional SEMs. First, VAR models are relatively simple to specify and estimate. Only a minimal set of just-identifying restrictions is employed and no restrictions are placed on the parameters of the reduced form. The rationale is that, given the uncertainty surrounding the underlying economic structure of the market, the unrestricted reduced form provides flexibility which allows the model to be consistent with a wide range of alternative economic structures. Second, the structural shocks, u_t, in the VAR are uncorrelated by construction. Thus, there are no covariance terms in the forecast error variance decomposition and the sum of the proportional contributions of each shock to the variance of y_t is always one. This simplifies considerably the task of interpreting the results of variance decompositions.

Third, the VAR approach focuses attention on fluctuations that are unpredictable *ex ante*. Using the conditional probability distribution of market variables, VAR methods can separate unpredictable market fluctuations into effects caused by supply, demand and policy shocks.

VAR models do have some potential problems. One is the size of the model and the dimension of lag lengths. The virtue of simplicity is lost if the VAR model contains many variables with long lags. But small VAR models are highly aggregated in that the influence of large numbers of 'exogenous' variables must be captured in a small number of structural shocks. Thus, an implicit assumption of our VAR procedure is that it is feasible to capture aggregate supply, demand and policy effects in a relatively simple model. A related issue is the type of identification restrictions used. A common practice in VAR models has been to assume that A is diagonal and B lower triangular, which is equivalent to assuming that the model is recursive. Although different recursive orderings of the equations can be considered, a recursive structure probably is incapable of identifying structural disturbances as aggregate supply, demand and policy shocks.

These problems are not necessarily serious for estimating sources of wool market fluctuations. The systematic variation in wool prices, quantities and revenues should be captured adequately by the lag structure and it is not essential to have large numbers of 'exogenous' variables in order to identify the model. Furthermore, there is no need to impose a recursive ordering on the VAR. Simple restrictions on contemporaneous interactions among variables in a wool market VAR can lead to a just-identified, but non-recursive, system in which disturbances can be interpreted as aggregate supply, demand and policy shocks.

A Quarterly VAR Model of the Wool Market

A simple model which provides a reasonable representation of the wool market consists of four variables – quantity supplied by private traders, quantity demanded by commercial buyers, the net change in AWC stocks, and price. Such an aggregate representation ignores the fact that wool is a heterogeneous commodity and Richardson (1981) and Connolly (1989) are critical of models which do not make allowance for this. However, data availability is a limiting factor and our model is concerned with aggregate effects.

Quantity supplied is defined as the total quantity of wool sold at auction during the quarter. This slightly underestimates actual supply because some wool is sold through private treaties. But auction sales also overestimate the supply from growers, brokers and dealers because they include a modest quantity sold by the AWC. Because these amounts are relatively small and tend to offset one another, the total quantity sold at auction should be a reasonable measure of market supply. Quantity demanded is defined as quantity supplied minus the net change in AWC stocks. The AWC purchases wool only at auctions, but sells mainly outside the auction system. Thus, the amount acquired by commercial consumers is obtained by subtracting the quantity purchased by the AWC from total auction sales and then adding in the quantity sold by the AWC outside the auction system. This is equivalent to subtracting the net change in AWC stocks from the total quantity sold at auction. The price variable is a quantity weighted average of nominal auction prices over the quarter. Data definitions and sources are provided in Table 1.

The sample period runs from 1971:II through 1988:II. The Australian Wool Commission first began buffer-stock operations in November 1970 and the AWC, formed by the amalgamation of the Australian Wool Commission and the Australian Wool Board in January 1973, has continued stockholding activities through to the present. Thus, the sample period spans the era of intervention in the market.

The first step is to estimate the reduced form defined by (3). The net change in AWC stocks was excluded from the VAR because it is identically equal to the difference between supply and demand. This leaves three variables – quantity supplied, quantity demanded, and price. Data were converted to natural logarithms and seasonal dummy

TABLE 1

Variable Definitions, Mean Values and Sources[a]

Variable	Definition	Mean	Source
s_t	Logarithm of total quantity of wool sold at auction during quarter t (tonnes).	11·82	Quantities of wool sold at auction were obtained from National Council of Wool Selling Brokers of Australia (1988) and previous issues; and Australian Bureau of Agricultural and Resource Economics (pers. comm.).
d_t	Logarithm of total quantity of wool purchased by private traders during quarter t (tonnes).	11·81	Net changes in AWC stocks were obtained from the Australian Bureau of Agricultural and Resource Economics (pers. comm.); and the Australian Wool Corporation (pers. comm.). Quantities purchased by private traders were then computed as the quantities sold at auction minus the net change in AWC stocks.
p_t	Logarithm of quantity weighted average of auction prices during quarter t ($/tonne).	7·77	Auction prices were obtained from the National Council of Wool Selling Brokers of Australia (1988) and previous issues.

[a]A data set is available from Myers on request.

variables were included in the model.[5] The lag length for the three-variable system was chosen on the grounds of statistical tests reported in Table 2. First, the Schwartz criterion (see Judge *et al.* 1984, p. 687) was calculated for lag lengths zero through ten, although only results up to lag four are shown in the table. The criterion was minimised for a lag length of one. Second, the one-lag model was overfitted and Sims (1980) modified likelihood ratio approach was used to test the significance of the extra parameters. Using a 0·05

TABLE 2

VAR Lag Length Selection Results

Lag length	Schwartz criterion	$\chi^2(9)$[a]	Significance level
0	−8·49		
1	−12·23	224·38	0·000
2	−11·87	22·49	0·007
3	−11·52	17·78	0·038
4	−11·21	11·96	0·215

[a]Likelihood ratio test of the hypothesis that the lag length is one less than that indicated.

[5] Preliminary investigation of the univariate time-series representations of the three variables was undertaken. Each of the variables exhibited strong seasonality and the unit-root tests of Dickey and Fuller (1981) and Phillips (1987) revealed the quantity variables to be stationary and price to be difference stationary. Despite this, the VAR was estimated in price levels rather than differences. This may entail a small loss in efficiency but Sims, Stock and Watson (1988) provide support for the practice of building VARs in levels, even when the system contains some unit roots.

significance level, the one-lag model is rejected against the alternative of a two-lag model; the two-lag model is rejected against three lags; but the three-lag model could not be rejected against the alternative of four lags (Table 2). Although this suggests a three-lag specification, the final choice was to estimate the model with four lags because the consequences of excluding relevant variables are more serious than those of including irrelevant ones. Furthermore, it was judged desirable to have at least one full year of lags in the model.

Summary statistics from estimating the four-lag VAR are provided in Table 3. Adjusted R^2 statistics indicate that half or more of the variation in dependent variables is explained by the model. Furthermore, Q tests on the residuals from each equation cannot reject the hypothesis of serially uncorrelated errors, even at the 0·10 significance level.

TABLE 3

Model Evaluation Results

Dependent variable	$\bar{R}^2$	$Q(10)^a$	*Significance level*
s_t	0·63	15·40	0·118
d_t	0·51	10·44	0·403
p_t	0·97	13·01	0·223

[a] Q test for tenth-order autocorrelation in the residuals.

The next step is to choose a set of just-identifying restrictions for the model. To begin, a standard recursive structure was imposed (i.e. A was restricted to be diagonal and B lower triangular). Different recursive orderings were tried, but the results gave little confidence that the structural shocks identified could be convincingly interpreted as aggregate supply, demand, and policy shocks. For example, all of the recursive models implied that a positive 'supply' shock leads immediately to a price increase, which could only occur if demand is upward sloping.

A convincing non-recursive identification requires use of *a priori* information about the structure of the wool market. Wool production generally depends on decisions taken in the past, and so the short-run supply of wool is often assumed to be price inelastic. But even in the short run (e.g. within a quarter) growers and brokers have discretion regarding when inventories are released to the market. Thus, price and supply may be simultaneously determined.

Wool demand originates mainly in the industrial centres of the USA, Europe and Japan and is derived from the demand for woollen products. Wool processors typically hold stocks so that they can take advantage of emerging market opportunities without disrupting their processing operations. Hence, the short-run demand for Australian wool may be quite price responsive in a quarterly model.

The AWC operates a buffer-stock scheme for wool that has two components – a minimum reserve price designed to underwrite the market, and a flexible reserve price designed to iron out short-term price fluctuations. The AWC decides whether to accumulate or release stocks based on long-term goals and on current price and quantity trends in the market. In its stabilising role, the AWC attempts to counteract short-term aberrations in the market which might disadvantage individual sellers and erode confidence in the market (Fisher 1983).

These considerations lead to the following identification scheme. Define the endogenous variables vector $y_t = (s_t, d_t, p_t)$ where s_t is quantity supplied, d_t is quantity demanded, and p_t is price; and the vector of structural shocks $u_t = (u_{st}, u_{dt}, u_{at})$ where u_{st} is an aggregate supply shock, u_{dt} is an aggregate demand shock, and u_{at} is an aggregate policy shock. Then restrict the A and B matrices such that

$$A = \begin{bmatrix} \alpha_s & 0 & 0 \\ 0 & \alpha_d & 0 \\ \alpha_{as} & \alpha_{ad} & \alpha_a \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} 1 & 0 & -\beta_s \\ 0 & 1 & -\beta_d \\ 1 & -1 & 0 \end{bmatrix}.$$

Thus, contemporaneous interactions among variables are defined by:

(8a) $s_t = \beta_s p_t + \alpha_s u_{st}$

(8b) $d_t = \beta_d p_t + \alpha_d u_{dt}$

(8c) $s_t - d_t. = \alpha_{as} u_{st} + \alpha_{ad} u_{dt} + \alpha_a u_{at}.$

For this identification, (8a) explains quantity supplied as a function of current price and aggregate supply shocks. The parameters β_s and α_s are a short-run supply elasticity and the standard deviation of the supply shock, respectively. Equation (8b) explains quantity demanded as a function of current price and aggregate demand shocks. Analogous to the supply equation, β_d and α_d are a short-run demand elasticity and the standard deviation of demand shock, respectively. Equation (8c) explains the difference between quantity supplied and quantity demanded (i.e. net changes in AWC stocks) as a function of aggregate supply shocks, aggregate demand shocks, and aggregate policy shocks.[6] The rationale is that, given the stabilisation objectives of the AWC, stocks will be increased (decreased) in response to a positive (negative) supply shock, $\alpha_{as} > 0$, and decreased (increased) in response to a positive (negative) demand shock, $\alpha_{ad} < 0$. Aggregate policy shocks have standard deviation α_a and cause random disturbances to AWC inventories.

This model does not satisfy the order condition for identification because it contains seven unknown parameters in A and B and the (3×3) covariance matrix of the VAR contains only six unique parameters. To resolve this problem one parameter, the demand elasticity, was specified *a priori* and then the six remaining structural parameters were estimated using the two-step maximum likelihood approach. The model was estimated for a range of alternative demand elasticities to determine the sensitivity of results to this *a priori* assumption.

Empirical results are shown in Table 4 with demand elasticity assumptions ranging from $-0{\cdot}5$ to $-5{\cdot}0$. In each case the coefficients are of expected sign – supply response to price increases is positive and

[6] More precisely, the dependent variable is really a ratio of quantity supplied to quantity demanded because the variables are in logarithms. Thus, the AWC stockholding equation implies that stocks are adjusted so as to maintain a desired ratio between supply and demand.

TABLE 4

Maximum Likelihood Estimates of Contemporaneous Wool Model Parameters

Parameter	Assumed demand elasticity (β_d):					
	−0·5	−1·0	−2·0	−3·0	−4·0	−5·0
β_s	4·611	3·849	2·983	2·504	2·201	1·991
	(3·980)[a]	(4·467)	(4·933)	(5·014)	(4·931)	(4·789)
$\hat{\alpha}_s$	0·289	0·253	0·216	0·199	0·190	0·184
	(4·545)	(5·555)	(7·202)	(8·360)	(9·148)	(9·685)
$\hat{\alpha}_d$	0·246	0·263	0·303	0·350	0·402	0·455
	(11·393)	(11·395)	(11·397)	(11·399)	(11·399)	(11·400)
$\hat{\alpha}_a$	0·098	0·100	0·104	0·108	0·111	0·114
	(10·952)	(11·089)	(11·256)	(11·329)	(11·362)	(11·378)
$\hat{\alpha}_{as}$	0·032	0·029	0·025	0·021	0·017	0·016
	(2·187)	(2·022)	(1·696)	(1·426)	(1·215)	(1·053)
$\hat{\alpha}_{ad}$	−0·087	−0·086	−0·083	−0·079	−0·075	−0·071
	(−5·853)	(−5·770)	(−5·477)	(−5·014)	(−4·836)	(−4·572)
Log likelihood	−151·965	−151·965	−151·965	−151·965	−151·965	−151·965

[a]Values in parentheses are asymptotic *t*-ratios.

AWC stocks increase with positive supply shocks and decrease with positive demand shocks. Furthermore, with the exception of α_{as} (the coefficient on supply shocks in the stockholding equation), the estimated coefficients have large *t*-ratios. The low *t*-ratio on α_{as} suggests that AWC stocks may not be sensitive to supply shocks.

There is no way to discriminate among the models on statistical grounds because each is just identified and has the same likelihood value. However, the model with the demand elasticity set at −3·0 is judged to give the most plausible results and, accordingly, this model was chosen for further analysis. The (estimated) elasticity of supply declines as the (assumed) elasticity of demand increases and models with demand less elastic than −3·0 generate supply elasticity estimates that are more elastic than demand. This seems unlikely on *a priori* grounds and so these models were disregarded. Of the remaining models, the demand elasticity of −3·0 gave the highest *t*-ratio on the supply elasticity coefficient, and the other parameters are not very sensitive to the choice of *a priori* demand elasticity, at least in absolute terms.

The supply and demand elasticity estimates (2·5, −3·0) may seem too elastic when compared with previous econometric studies of the wool market (e.g. Campbell, Gardiner and Haszler 1980). But, because of the flexible lag structure in the VAR, the elasticities in this paper measure responses to *transitory* price changes that cannot be predicted *ex ante*. Short-run supply and demand responses to transitory price shocks are logically more elastic than to price changes that are perceived to be permanent, especially when inventories constitute a large part of the quantity response. For example, if a positive price fluctuation is perceived to be temporary, then short-run supply to the market from inventories will expand rapidly to take advantage of the favourable price move before it dissipates. But if the price change is perceived as permanent, then there is no great advantage in speeding supply to market. Similarly, if a wool buyer believes that a positive price fluctuation is temporary, then current purchases of inventories will be delayed until the price returns to normal levels. But if the change is perceived as permanent, no advantage exists in delaying inventory purchases.

An Analysis of Wool Market Fluctuations

Impulse response analysis and forecast error variance decomposition are used to analyse the effects of typical supply, demand and policy shocks on the wool market, and to estimate the relative contribution of each type of shock to market fluctuations. Then equilibrium prices and revenues are simulated over the sample period assuming no wool stockpiling occurred. Comparing simulated outcomes and historical outcomes (with AWC stockpiling) indicates the effects of storage on the market equilibrium. However, it does not isolate the impact of the AWC because private stockpiling activity would presumably increase in the absence of the AWC, and this effect is not accounted for in the model.

Impulse response analysis

The dynamic effects of each structural disturbance are traced out using impulse response functions from the VAR. For example, the dynamic effects of a current shock to, say, demand, are calculated assuming that current supply and policy shocks, and all future shocks of all types, are zero. Effects on quantity supplied, quantity demanded and price can be obtained directly because these variables are in the VAR. Effects on market revenue, defined as quantity supplied times price, can also be obtained because the model is specified in logarithms and the logarithm of revenue is the sum of the logarithms of quantity supplied and price.

The dynamic responses of market variables to a one standard deviation shock in supply, demand and policy are graphed in Figures 1 and 2. The vertical axis measures the response of the logarithm of quantity, price or revenue and the horizontal axis represents the number of quarters ahead the response is being measured. Confidence intervals are not placed around the impulse responses because we are mainly interested in whether the estimated responses lead to logical qualitative conclusions concerning the effects of aggregate supply, demand and policy shocks.

A positive supply shock leads initially to increases in quantity supplied and quantity demanded, but demand increases less than supply, indicating an accumulation of AWC stocks (Figure 1). In subsequent quarters, supply and demand responses oscillate, reflecting the seasonal nature of the supply and demand for wool. Then, after approximately three years, the effect of the supply shock on quantities dies out. This reflects the fact that the quantity variables are stationary so that structural shocks have only temporary effects on quantities traded.

A positive demand shock has almost the same effect as a positive supply shock on the path of quantities traded. There is an initial increase followed by seasonal oscillation and an eventual dampening.

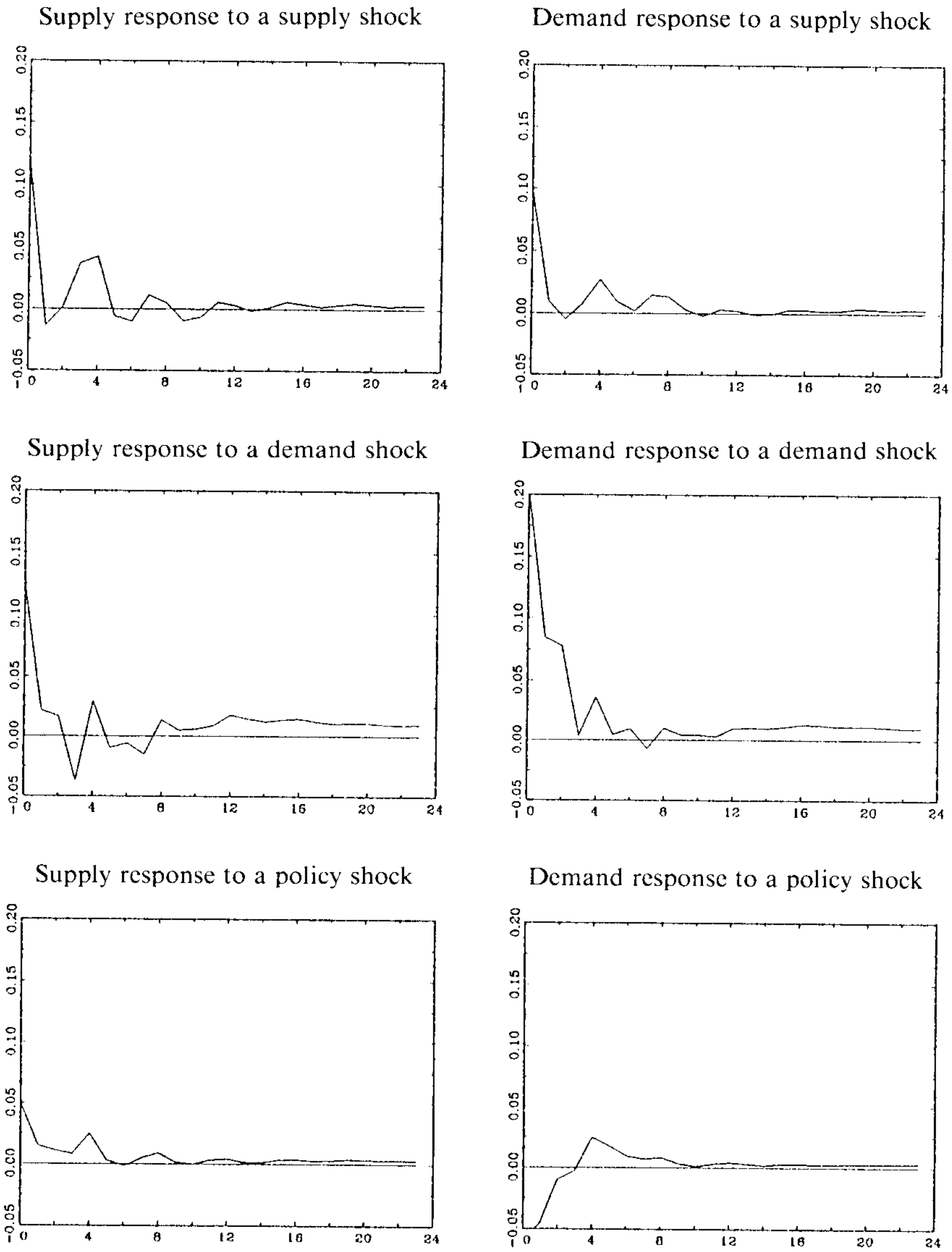


FIGURE 1—Impulse responses for quantities supplied and demanded.

One important difference in the case of demand shocks is that quantity demanded initially increases more than quantity supplied, indicating that the AWC is releasing stocks rather than accumulating them.

Policy shocks have the expected effects on quantities traded. A positive policy shock means that the AWC is storing more wool, which initially leads to an increase in quantity supplied and a reduction in quantity demanded. These effects then die out after some seasonal oscillation. Thus, policy shocks have no long-run effect on quantities traded.

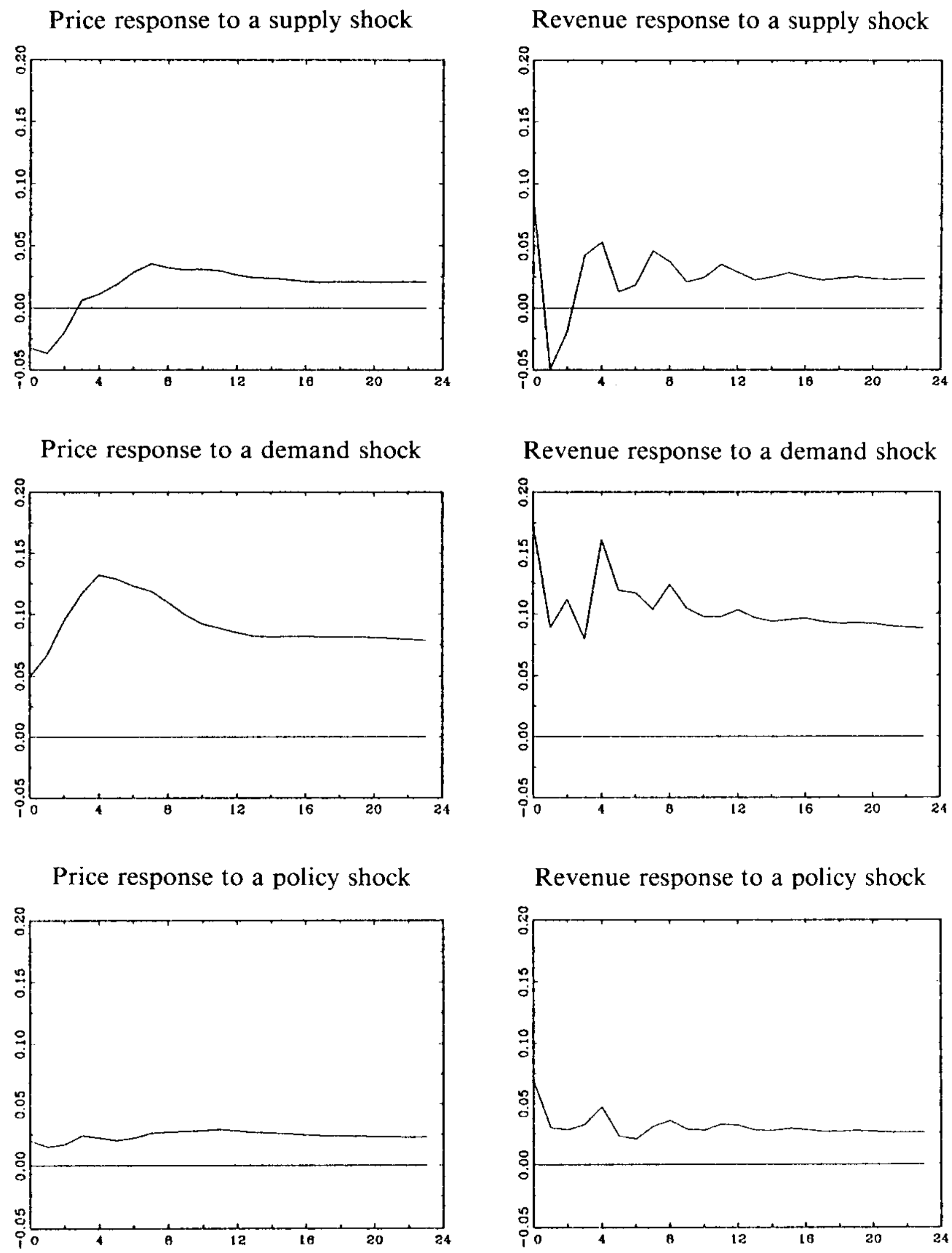


FIGURE 2—Impulse responses for price and revenue.

A positive supply shock initially depresses the price level but, after four quarters, the effect turns positive (Figure 2). In the long run, the effect of the supply shock does not die out and has a permanent positive effect on the price level. The initial effect of a supply shock on revenue is positive because the decline in price is more than offset by an increase in quantity supplied. However, revenue declines sharply in the next quarter as the price level remains lower, but quantity supplied dips downward. Thereafter, revenue oscillates and then converges on its higher long-run equilibrium level.

The positive long-run effect of supply shocks on price and revenue reflects the time-series properties of these variables. The price and revenue variables are both non-stationary. In other words, there is a positive trend built into the dynamics of the VAR for price and revenue, and this long-run trend eventually dominates the response of *any* shock to the system. Thus, the long-run effects of structural shocks on price and revenue might be viewed as a reflection of a permanent inflationary trend which is built into the dynamics of the VAR.[7]

A positive demand shock leads initially to sharp increases in prices and revenues before these variables oscillate and then decline to their long-run equilibrium rates of increase. As expected, a positive policy shock has almost the same qualitative effect on prices and revenues as a demand shock because AWC stock purchases are effectively a substitute for private consumption demand.

In general, the short-run impulse responses are consistent with economic logic concerning the wool market. Positive supply shocks cause prices to fall and quantities traded to rise; demand shocks cause prices to rise and quantities traded to rise; and policy shocks cause prices to rise, quantity supplied to increase, and quantity demanded to decrease. In the long run, impulse responses are governed mainly by the long-run time-series properties of the relevant series. The quantity variables are stationary and so shocks have only temporary effects, but prices and revenues are non-stationary and so shocks have permanent effects.

Forecast error variance decomposition

The variance of forecast errors can be decomposed into components due to the variance of each structural shock. The proportion of the k-step-ahead forecast error variance attributed to, say, supply shocks is a measure of the relative contribution of supply shocks to fluctuations over the next k quarters. The sum of the proportions attributed to each structural shock is always one because the covariances among shocks are zero.

Forecast error variance decompositions for forecast horizons ranging between 1 and 36 quarters are provided in Table 5. The top half of the table shows decompositions for forecasts of quantity supplied and quantity demanded, while the bottom half shows decompositions for forecasts of price and revenue. The contributions of supply shocks, demand shocks and policy shocks are given as percentages of the total forecast error variance over the indicated forecast horizon.

Demand shocks are the dominant source of fluctuations in the wool market. With the exception of quantity supplied, demand shocks account for well over 50 per cent of the total forecast error variance for all variables over all forecast horizons (Table 5). Price and revenue fluctuations are especially influenced by demand shocks, with around 90 per cent of price variance and 80 per cent of revenue variance coming from demand shocks at intermediate forecast horizons. Furthermore, the relative contribution of demand shocks generally

[7] Prices could have been specified in real rather than nominal terms and this may eliminate the nonstationarity in the price series. However, the focus here is on nominal price and revenue effects and the impact of inflation is embodied in the aggregate supply, demand and policy shocks.

TABLE 5

Forecast Error Variance Decompositions Under the Historical AWC Policy Regime

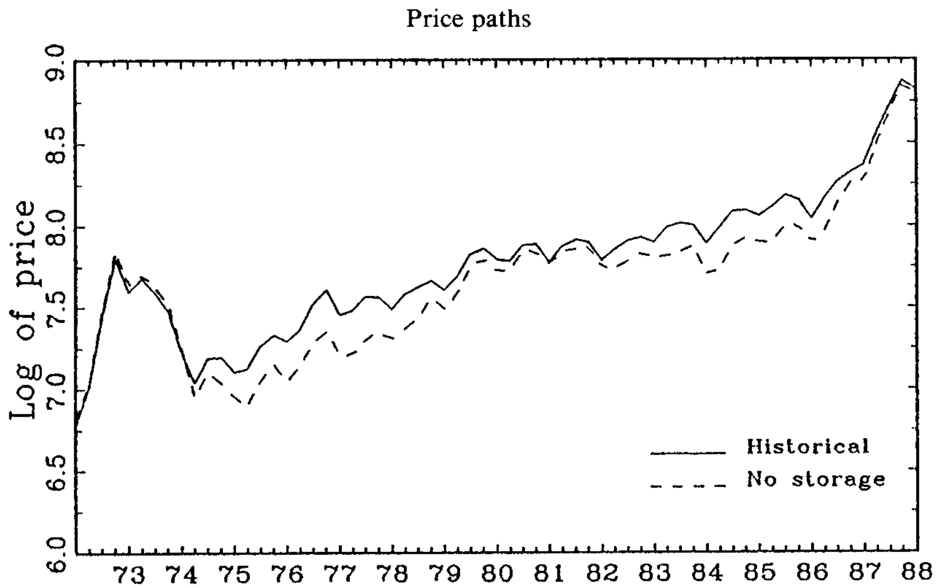
Steps ahead	Supply shocks	Demand shocks	Policy shocks	Supply shocks	Demand shocks	Policy shocks
	Percent of forecast error variance due to:					
	Quantity supplied			Quantity demanded		
1	43·9	48·4	7·7	17·5	76·1	6·5
2	43·3	48·5	8·1	15·1	76·2	8·7
3	42·8	48·8	8·4	13·8	78·2	8·1
4	43·2	48·8	7·9	13·8	78·1	8·1
5	44·2	47·0	8·9	14·3	77·1	8·6
6	44·1	47·0	8·8	14·4	76·6	9·0
7	44·2	47·0	8·8	14·4	76·6	9·1
8	44·1	47·1	8·8	14·6	76·3	9·1
9	43·9	47·2	8·9	14·8	76·1	9·1
10	44·0	47·1	8·9	14·8	76·1	9·1
11	44·0	47·1	8·9	14·8	76·1	9·1
12	43·9	47·2	8·9	14·8	76·1	9·2
24	42·0	49·3	8·7	14·6	76·4	9·1
36	41·0	50·3	8·7	14·4	76·5	9·1
	Price			Revenue		
1	27·0	63·0	10·0	17·4	71·3	11·3
2	24·2	69·7	6·1	18·5	70·9	10·6
3	14·3	81·2	4·5	15·3	75·1	9·6
4	8·4	87·2	4·4	15·9	74·3	9·8
5	5·7	90·5	3·8	13·9	77·0	9·0
6	4·8	91·8	3·4	12·4	79·3	8·4
7	4·8	91·8	3·3	11·3	80·9	7·8
8	5·3	91·2	3·5	11·7	80·6	7·7
9	5·6	90·7	3·7	11·3	81·1	7·6
10	5·8	90·3	3·9	10·8	81·7	7·6
11	6·1	89·7	4·2	10·5	82·0	7·5
12	6·3	89·2	4·5	10·5	81·9	7·6
24	6·3	88·0	5·8	8·8	83·7	7·5
36	6·2	87·7	6·1	8·2	84·3	7·5

increases with the forecast horizon, suggesting that demand becomes an even more important source of uncertainty for long-range forecasting.

Simulation results

The next step is to simulate a no-storage regime over the sample period. This is done by taking the series of structural policy shocks, u_{at}, estimated from the VAR and constructing a new series of policy shocks, u^*_{at}, so that supply equals demand in each period (the net addition to AWC stocks is zero). The model is then simulated using the original supply and demand shock series, u_{st} and u_{dt}, and the newly constructed series of policy shocks, u^*_{at}. This gives the price, quantity and revenue paths that would have occurred had supply and demand shocks been exactly the same over the sample period, but assuming no wool stockpiling occurred.

The price and revenue paths generated by this no-storage regime are compared with historical price and revenue paths in Figure 3. Wool



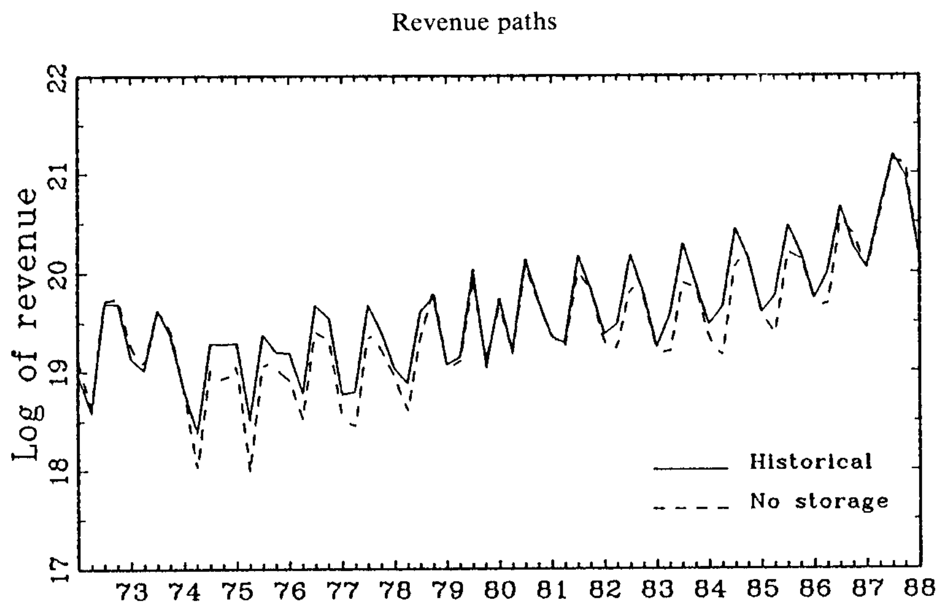


FIGURE 3—Historical outcomes compared to a simulated no storage regime.

storage increased prices and revenues during much of the sample period. In fact, over the entire sample period prices were 1·5 per cent higher on average with stockpiling than without, and revenue was 0·7 per cent higher. Furthermore, using an interest rate of 10 per cent, compounded quarterly, the net present value of the revenue stream in 1988 was 0·4 per cent higher with storage than without. These are not large differences, but they are clearly consistent with the view that stockpiling has shifted the long-run demand for wool outward, thus increasing prices and revenues.[8]

These effects cannot be attributed totally to AWC activities because private storage may increase in the absence of the AWC. Furthermore, these are gross effects and take no account of the cost of operating the buffer stock.[9] Nevertheless, the results do suggest that there are gross benefits to the industry from AWC stockpiling.

Forecast error variance decompositions were applied to the simulated model in which there is no storage (Table 6). All of the market fluctuations are now caused either by supply shocks or demand shocks. The results show that demand shocks are even more dominant as a source of wool market fluctuations than they were with AWC stockpiling. This suggests that wool storage has blunted demand shocks so that they have become a less important source of market fluctuations than they would have been without storage.

TABLE 6

Forecast Error Variance Decompositions Under a Simulated No-Storage Regime

	Percentage of forecast error due to:					
Steps ahead	Supply shocks	Demand shocks	Supply shocks	Demand shocks	Supply shocks	Demand shocks
	Quantity		Price		Revenue	
1	31·6	68·4	24·3	75·7	9·5	90·5
2	28·1	71·9	22·1	77·9	11·9	88·1
3	27·1	72·9	14·2	85·8	10·2	89·8
4	27·7	72·3	8·2	91·8	10·4	89·6
5	29·7	70·3	5·6	94·4	9·4	90·6
6	29·7	70·3	4·7	95·3	8·2	91·8
7	30·1	69·9	4·7	95·3	7·5	92·5
8	30·0	70·0	5·1	94·9	7·8	92·2
9	29·9	70·1	5·5	94·5	8·0	92·0
10	29·7	70·3	5·6	94·4	7·7	92·3
11	29·6	70·4	5·6	94·4	7·4	92·6
12	29·6	70·4	5·5	94·5	7·2	92·8
24	28·2	71·8	4·5	95·5	5·7	94·3
36	27·3	72·7	4·2	95·8	5·1	94·9

Another way to evaluate the effects of wool stockpiling is to compare the variance of price and revenue forecast errors with and without storage. The standard deviation of these forecast errors are graphed in Figure 4 for forecast horizons of 1 through 36 quarters. The standard deviations of price and revenue forecast errors are always smaller with storage than without, although the difference is small over short forecast horizons. The results support the hypothesis that stockpiling has reduced price and revenue uncertainty.

[8] If the AWC had been continually accumulating stocks over the sample period then this conclusion would not be warranted because the higher prices and revenues might be simply a reflection of AWC stock accumulations rather than a shift in long-run demand. However, AWC stocks at the beginning of the simulation period were actually higher than at the end so that the price and revenue increases seem due to the stabilisation attributes of storage causing a shift in demand.

[9] AWC operations are financed with a 5 per cent levy on producer sales.

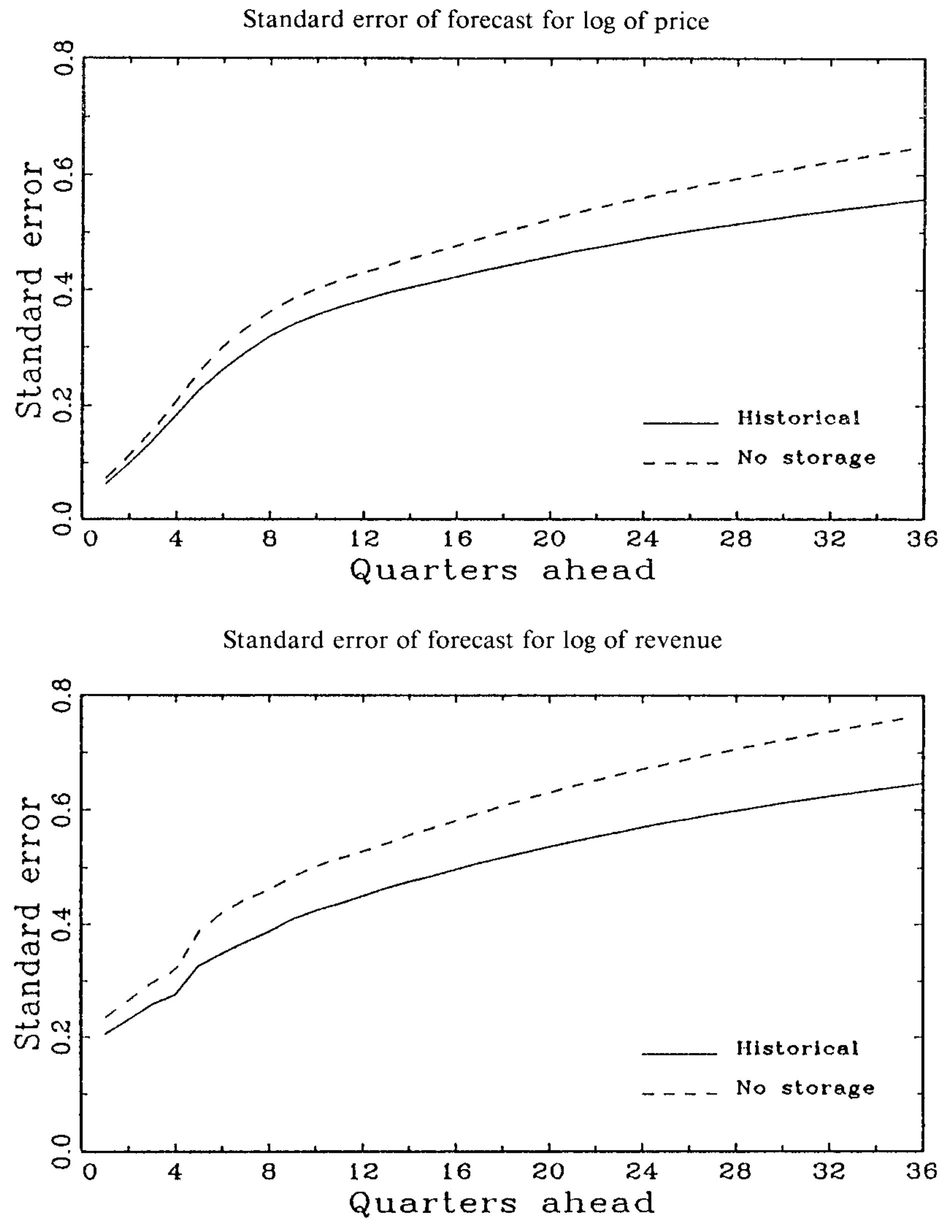


FIGURE 4—Historical forecast standard errors compared to a no storage regime.

Conclusions

In this paper, a VAR is combined with minimal identification restrictions to provide an analysis of economic fluctuations in the Australian wool market. A particular advantage of the approach is that it focuses on market uncertainty by isolating fluctuations that are predictable *ex ante* from those that are not. Impulse response analysis and forecast error variance decomposition should prove useful in a variety of applications to commodity markets whenever it is possible to identify supply, demand and policy shocks by imposing restrictions on contemporaneous interactions among variables in the system. Although the choice of identification restrictions involves much judgment, the logical results of our analysis of the wool market imply that the VAR approach to policy analysis can be useful.

The results of this study indicate that demand shocks are the dominant source of wool market fluctuations, with or without historical AWC stockpiling activities. Storage appears to have blunted the effects of demand shocks, thereby reducing their relative contribution to market fluctuations, reducing market uncertainty and increasing the average level of prices and revenues. If demand shocks are the major source of wool market fluctuations, then wool users might be major beneficiaries of the price-stabilising activities of the AWC. This deduction, however, is highly tentative because many conditioning factors are involved (see, for example, Turnovsky 1978). The results are also consistent with rightward shifts in demand (as a result of more stable prices) outweighing leftward shifts in demand (resulting from less stable quantities of wool being available to the private trade).

A limitation of the study is that no account is taken of the extent to which the stockpiling activities of the AWC displace private storage, and so the effects of storage cannot be totally attributed to the buffer stock operated by the AWC. Furthermore, no account is taken of the costs of operating the buffer stock so that a formal economic welfare analysis of the costs and benefits of AWC activities cannot be undertaken. Nevertheless, the study does indicate that the stockpiling activities of the AWC have been successful in reducing market uncertainty and increasing demand for wool, though the effects are small.

References

Bernanke, B. S. (1986), 'Alternative explanations of the money-income correlation', *Carnegie-Rochester Conference Series on Public Policy* 25, 49–100.

Borhnstedt, G. W. and Goldberger, A. S. (1969), 'On the exact covariance of products of random variables', *Journal of the American Statistical Association* 64(328), 1439–42.

Campbell, R., Gardiner, B. and Haszler, H. (1980), 'On the hidden revenue effects of wool price stabilisation in Australia: initial results', *Australian Journal of Agricultural Economics* 24(1), 1–15.

Connolly, G. (1989), *An Econometric Model of the Australian Wool Market by Grade with Applications to Policy Analysis*, Agricultural Economics Bulletin No. 37, University of New England, Armidale.

Dickey, D. A. and Fuller, W. A. (1981), 'Likelihood ratio statistics for autoregressive time series with a unit root', *Econometrica* 49(5), 1057–72.

Fackler, P. L. (1988), 'Vector autoregressive techniques for structural analysis', *Revista de Analisis Economico* 3(2), 119–34.

Fisher, B. S. (1983), 'Rational expectations in the Australian wool industry', *Australian Journal of Agricultural Economics* 27(3), 212–20.

Haszler, H. and Curran, B. (1982), 'On the hidden revenue effects of wool stabilisation in Australia: initial results – a reply', *Australian Journal of Agricultural Economics* 26(1), 66–71.

Hazell, P. B. R. (1984), 'Sources of increased instability in Indian and US cereal production', *American Journal of Agricultural Economics* 66(3), 302–11.

Hinchy, M. and Fisher, B. S. (1988), 'Benefits from price stabilisation to producers and processors: the Australian buffer stock scheme for wool', *American Journal of Agricultural Economics* 70(3), 604–15.

Houck, J. P. (1973), 'Some aspects of income stabilisation for primary producers', *Australian Journal of Agricultural Economics* 17(3), 200–15.

Judge, G. G. *et al.* (1985), *The Theory and Practice of Econometrics*, 2nd edn, Wiley, New York.

Myers, R. J. and Runge, C. F. (1985), 'The relative contribution of supply and demand to instability in the U.S. corn market', *North Central Journal of Agricultural Economics* 7(1), 70–8.

National Council of Wool Selling Brokers of Australia (1988), *Wool Review 1987–88* (and previous issues), Ramsay Ware Printing, North Melbourne.

Newbery, D. M. G. and Stiglitz, J. E. (1981), *The Theory of Commodity Price Stabilisation*, Oxford University Press, London.

Offutt, S. E. and Blandford, D. (1983), *A Review of Empirical Techniques for the Analysis of Commodity Instability*, Agricultural Economics Research 83-7, Cornell University.

Orden, D. and Fackler, P. L. (1989), 'Identifying Monetary Impacts on Agricultural Prices in VAR Models', *American Journal of Agricultural Economics* 71(2), 495–502.

Phillips, P. C. B. (1987), 'Time series regression with a unit root', *Econometrica* 55(2), 277–301.

Piggott, R. R. (1978), 'Decomposing the variance of gross revenue into supply and demand components', *Australian Journal of Agricultural Economics* 22(3), 145–57.

Richardson, R. A. (1981), 'Premiums and discounts in the wool market', *Rural Marketing and Policy* 11(2), 16–22.

—— (1982), 'On the hidden revenue effects of wool price stabilisation in Australia: initial results – a comment', *Australian Journal of Agricultural Economics* 26(1), 63–5.

Sims, C. A. (1986), 'Are forecasting models usable for policy analysis?', *Federal Reserve Bank of Minneapolis Quarterly Review* Winter, 2–16.

—— (1980), 'Macroeconomics and reality', *Econometrica* 48(1), 1–48.

—— Stock, J. and Watson, M. (1988), *Inference in Linear Time Series Models with Some Unit Roots*, Working Paper, Department of Economics, University of Minnesota.

Turnovsky, S. J. (1978), 'The distribution of welfare gains from price stabilisation: a survey of some theoretical issues', in F. G. Adams and S. A. Klein (eds), *Stabilising World Commodity Markets*, Lexington, New York, pp. 119–48.

Watson, A. S. (1980), 'Wool in 1980', *Australian Journal of Agricultural Economics* 24(2), 79–83.