Working Papers in
AGRICULTURAL ECONOMICS

November **89-10**

Estimating Sources of Fluctuations in the Australian Wool Market:

An Application of VAR Methods

by

Robert J. Myers

R.R. Piggott

William G. Tomek

Department of Agricultural Economics
New York State College of Agriculture and Life Sciences
A Statutory College of the State University
Cornell University, Ithaca, New York, 14853-7801

Revised October 1989

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

Robert J. Myers, R. R. Piggott and William G. Tomek*

Abstract: Economists have considered a variety of methods for estimating the sources of fluctuations in economic variables. Interest in the sources of variability is driven, in part, by the need to evaluate stabilisation policies. This paper estimates the demand, supply and policy sources of variability in the Australian wool market by using vector autoregression (VAR) methods. The possible advantages and disadvantages of a VAR model relative to a structural econometric model are explored. Then, a three-equation VAR model is fitted treating quantity supplied by private traders, quantity demanded by commercial buyers and price as the endogenous variables. Stockholding policies of the Australian Wool Corporation (AWC) are measured by the difference between quantity supplied and quantity demanded. In estimating the model, restrictions associated with recursive specifications were considered, but gave illogical results. In a quarterly model with the acquisition and release of stocks, prices and quantities are presumably simultaneously determined. Thus, assuming simultaneity, identification is based partly on *a priori* knowledge about one of the parameters. The empirical results paint a relatively favourable picture of the buffer-stock scheme of the AWC. In the absence of the scheme, demand shocks are the dominant source of variability, but stockholding did blunt the effects of these shocks. The AWC's policy also appears to have increased the average level of price and revenue. Given the plausibility of the results, we conclude that VAR methods are a potentially useful way to estimate market uncertainty associated with aggregate demand, supply and policy shocks.

---

*Assistant Professor, Department of Agricultural Economics, Michigan State University; Senior Lecturer, Department of Agricultural Economics and Business Management, University of New England; and Professor, Department of Agricultural Economics, Cornell University; respectively. Initial work on this paper was done while Myers and Tomek were visiting the University of New England. Tomek gratefully acknowledges support as a Visiting Fellow. The authors thank Paul Fackler, Jim Oehmke and David Orden for helpful comments on an earlier version of this paper.

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

Economists have long been concerned with the causes of fluctuations in agricultural commodity markets. Most attention has focused on the causes of price fluctuations. In principle, however, interest could centre on any one (or more) of several market variables including price, quantity, revenue, consumer surplus and producer surplus. In part, this concern about market fluctuations arises from a desire to understand the way commodity markets work and evolve over time. But interest in the sources of market fluctuations is also driven by the need to evaluate commodity stabilisation policies and proposals (e.g. Hinchy and Fisher 1988). It is now well understood that 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).

From an economic perspective, three main types of disturbances cause fluctuations in commodity markets—supply shifts, demand shifts and changes in government policies. The aims in this paper are to outline a method of analysing 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 price fluctuations. However, little research has focused directly on quantifying the relative contribution of supply and demand disturbances to price fluctuations.

Another issue that has arisen is how the long-run demand for wool has shifted, if at all, as a result of the scheme. It could be argued that demand has shifted rightward because the scheme results in more stable prices for wool relative to the price of synthetics. On the other hand, demand may have shifted leftward because the quantity of wool available for purchase by private buyers is destabilised as a result of the scheme. There is also the possibility that these two influences have cancelled each other. 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 these issues.

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 (Burt and Finley 1968; Borhnstedt and Goldberger 1969). For example, Houck (1973) decomposed the variance of gross revenues in the Australian beef, wheat and wool industries into components due to price variance, output variance and the covariance between price and output. More recently, Hazell (1984) used the same method to decompose the variance of Indian and U.S. cereal output into components due to area variance, yield variance and the covariance between area and yield.

While useful for some purposes, variance decompositions of random identities are generally incapable of separating market 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. Piggott's method was adapted by Myers and Runge (1985) to identify the relative contribution of supply and demand to fluctuations in the U.S. corn market.

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). As discussed in the next section, VAR models have some advantages over structural models for analysing sources of market fluctuations. 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] Restrictions just sufficient to identify each type of disturbance are imposed on the contemporaneous interactions between variables in the VAR, leaving the reduced form of the system unrestricted. Given this identification, the contribution of each type of structural shock to market price, quantity and revenue fluctuations is estimated. Furthermore, the dynamic responses of market variables to typical shocks in each structural disturbance are traced out and alternative paths for supply, demand and policy shocks are simulated historically.

In the next section the VAR methods employed herein are compared with the conventional structural SEM approach employed by Piggott (1978). A simple model of the Australian wool industry is then identified and estimated within a VAR framework. Impulse response functions from the VAR illustrate the dynamic response of key wool market variables to typical shocks in each type of structural disturbance. Decompositions of forecast error variances define the contribution of aggregate supply, demand and policy shocks 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 AWC stockholding policies on the path of wool market variables.

Alternative Modeling Techniques

In order to estimate the relative contribution of supply, demand and policy shifts to commodity market fluctuations, some degree of economic structure must be imposed on the data. Currently, VARs and conventional SEMs constitute the two main alternatives for imposing structural identification restrictions. As discussed below, there are many similarities between these approaches and they can essentially be viewed as alternative representations of the same basic economic structure. The main difference between them lies 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

A conventional SEM determines the values of a set of endogenous variables in terms of a set of exogenous and lagged endogenous variables. The structural form of a linear SEM is usually written:

$$(1) \quad By_t = \Gamma x_t + \epsilon_t$$

where y_t is a (nx1) vector of endogenous variables; x_t is a (kx1) vector of exogenous and lagged endogenous variables; ϵ_t is a (nx1) vector of zero mean, serially uncorrelated structural disturbance terms; and Γ and B are structural parameter matrices of order (nxk) and (nxn), respectively. For convenience, all variables are defined to be seasonally adjusted and expressed as deviations from their respective means.[2] 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 a large number of zero restrictions on the parameter matrices Γ and B. Remaining parameters are then estimated using a simultaneous equations estimator. These identification and estimation methods are well known and are not discussed further here (see Judge *et. al.* 1985).

The customary approach to estimating sources of commodity market fluctuations with a SEM is to use (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 (commodity prices, quantities and revenues). This approach to estimating sources of commodity market fluctuations is explained in Piggott (1978).[3]

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 the data. In this case, the identification restrictions on the Γ and B matrices are presumably true and the resulting estimates are reliable. But when the true economic structure is highly uncertain, imposing these restrictions may introduce bias if they are inconsistent with the actual economic structure generating the data. This problem is exacerbated by the common practice of failing to formally test over-identifying restrictions when estimating 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 considerable controversy exists over ways to model the expectation formation process. This is especially important given the storability of wool whether it be on the sheep's back, in store awaiting sale, or in inventories held by processors. 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 endogeneous 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 very sensitive to misspecification of structural relationships.

Another disadvantage of the conventional SEM approach is that variance decompositions focus on the *unconditional* variance of Y_t. This causes two problems. First, it means that 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 more appropriate to concentrate on estimating sources of fluctuations that cannot be predicted based on currently available information (i.e. to concentrate on decomposing the *conditional* variance of y_t). Second, use of the unconditional joint distributions of x_t means that the elements of x_t will almost certainly be highly correlated. The problem here is that no satisfactory economic interpretation for the contribution of the covariances between elements of x_t to the variance of y_t has yet been developed. In the Connolly (1989) wool market 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

An alternative model explaining the same endogenous variables vector specified in equation (1) is:

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

where u_t is a (nx1) vector of zero mean, serially uncorrelated disturbance terms with an identity covariance matrix; A and B are (nxn) parameter matrices representing contemporaneous interrelationships between y_t and u_t; and the B_i are (nxn) parameter matrices defining dynamic interactions among y_t.

Equation (2) is called a VAR representation of y_t and differs from (1) in that there are no exogenous variables and the endogenous variables have a flexible lag structure. However, it is shown in the appendix that, under very mild assumptions on the stochastic properties of x_t, the conventional SEM represented by (1) always has a VAR representation for it's y_t vector. Thus, there is no loss of generality from focusing on this form of the model.[4]

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:

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

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

A distinguishing feature of structural analyses of VAR models is that the reduced form—equation (3) above—is unrestricted, and the model is identified by imposing a set of just-identifying restrictions on the contemporaneous interactions between variables in the system (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.[5] Intuitively, one can think of VAR identification as 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 leads to a simplified two-step estimation procedure using maximum likelihood. The first step is to estimate the reduced form (3) and ordinary least squares applied to each equation is an appropriate estimator. The second step is to note that the log-likelihood for a set of T observations on y_t can be expressed, up to a constant term, as:

$$(5) \quad \Lambda = -0.5\ T \log\left|B^{-1}AA'B^{-1'}\right| - 0.5 \sum_{t=1}^{T} v_t' B' A^{-1'} A^{-1} B v_t .$$

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.[6] More details of this estimation procedure are provided in Fackler (1988).

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 than applying FIML to the complete system because of the smaller number of parameters involved.

Having estimated a commodity market VAR, the next step would be to analyse sources of market fluctuations. The interpretation of the disturbance terms, u_t, is crucial for this purpose. 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. As long as the A matrix is not diagonal, then more than one structural disturbance will enter each equation and the elements of y_t will be correlated.

One means of investigating how structural shocks influence the endogenous variables is called impulse response analysis. A moving average representation for the VAR is obtained by solving the difference equation (3) to obtain:

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

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 $(i=1,2,...)$ 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. Results provide information on the importance of different kinds of structural shocks (e.g. supply versus demand shocks) in causing fluctuations in the path of y_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-ahead 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, all of the structural demand shocks could be set to zero and the model simulated over a sample period. Comparing the simulated path of y_t to the actual path would then provide information on how important demand shocks have been over the sample period and what effect they have had on the time path of y_t.

These VAR techniques overcome the disadvantages of conventional SEMs referred to earlier. 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 VAR provides flexibility which allows the model to be consistent with a wide range of alternative economic structures. This is particularly important for modeling the Australian wool market because, as discussed above, considerable uncertainty exists about the specific form of a conventional SEM.

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 decomposition analyses.

Third, in contrast to Piggott's (1978) use of conventional SEMs, 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 supply, demand and policy components.

VAR models do have some potential problems. One relates to 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 because there would be a degrees of freedom problem. But small VAR models are highly aggregated in the sense that the influence of large numbers of 'exogenous' variables must be captured in a small number of structural shocks. An implicit assumption of the VAR procedure used here 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 VAR representation is recursive. Even though different recursive orderings of the equations are possible, it would seem unlikely that a simple recursive structure is capable of identifying structural disturbances as aggregate supply, demand and policy shocks.

Nevertheless, these problems are not necessarily serious from the viewpoint of 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. It will be shown next that simple restrictions on contemporaneous interactions between 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

The simplest model which provides a reasonable representation of the wool market consists of three endogenous variables—quantity supplied by private traders, quantity demanded by commercial buyers, and price. The difference between quantities supplied and demanded represents the net change in AWC stocks. Such an aggregate representation ignores the fact that wool is a heterogeneous commodity and some authors (e.g. Richardson 1981, Connolly 1989) are critical of modeling work which does not make allowance for this. However, data availability is a limiting factor in this regard and most analyses of the wool market have treated wool as a homogeneous commodity.

Quantity supplied is defined as the total quantity of wool sold at auction during the quarter. Actual supply is underestimated by a small amount because wool is sold outside the auction system through private treaties. But auction sales also overestimate the supply from growers, brokers and dealers as these sales 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 with private treaties. 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. All data definitions and sources are provided in Table 1.

Data are sampled quarterly and the sample period runs from 1971:2 through 1988:2. 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 in data analysis is estimation of the reduced form defined in (3). Data on the three endogenous variables were converted to natural logarithms and seasonal dummy variables were included in the model to account for seasonal means in the data.[7] 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. Lutkepohl (1982) provides Monte Carlo evidence supporting the use of the Schwartz criterion for determining lag lengths in VARs. The criterion was minimized for a lag length of one. Second, the one-lag model was overfitted and Sim's (1980) modified likelihood ratio approach was used to test the significance of the extra parameters (Table 2). Using a 0.05 significance level, the one-lag model is rejected against the alternative of a two-lag model, and the two-lag model is rejected against three lags. However, the three-lag model could not be rejected against the alternative of four lags. Although this suggests a three-lag specification, the final choice was to estimate the model with four lags. This is because the consequences of excluding relevant variables are much more serious than those of including irrelevant ones, and it was judged desirable to have at least one full year of lags included in the model.

Summary statistics from estimating the four-lag VAR are provided in Table 3. Adjusted R^2 results indicate a substantial proportion of the variation in dependent variables is explained by the model. Furthermore, a portmanteau test using residuals for each equation cannot reject the hypothesis of serially uncorrelated errors, even at the 0.10 significance level.

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). Note that this leaves a total of six parameters to be estimated from A and B and there are exactly six unique parameters in the covariance matrix of the reduced form. Thus, the order condition for a just-identified model is satisfied. Different recursive orderings were tried but, not surprisingly, 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.

The objective in imposing identification restrictions is to enable a structural interpretation of the three VAR equations as an aggregate supply equation, an aggregate demand equation, and an equation explaining AWC stockholding policies. Thus, a convincing non-recursive identification requires extensive 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 very 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 woolen 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. At each period, the AWC decides whether to accumulate or release stocks based on the long-term goals of the scheme, 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 to be $y_t = (s_t, d_t, p_t)$ where s_t is quantity supplied; d_t is quantity demanded; and p_t is price. Furthermore, define the vector of structural shocks to be $u_t = (u_{st}, u_{dt}, u_{at})$ where u_{st} is an aggregate supply shock; u_{dt} is an aggregate demand shock; and u_{at} is an aggregate policy shock representing changes in AWC stockholding policies. Now restrict the A and B matrices such that

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

Ignoring lagged variables and concentrating on contemporaeous interactions among variables in the system, these restrictions imply a VAR representation

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

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

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

Under 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 disturbance, 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 disturbances, 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.[8] 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.

Clearly, this model does not satisfy the order condition for indentification because it contains seven unknown parameters in A and B and the (3x3) 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 explained above. The model was estimated for a range of alternative demand elasticities in order to determine the sensitivity of results to this *a priori* assumption. This method of achieving identification makes intensive use of *a priori* information, and there are many alternative identification schemes that might be used. Nevertheless, the identification outlined here is broadly consistent with the main characteristics of the wool market and, as discussed next, leads to a sensible interpretation for the structural shocks in the VAR.

Empirical results are shown in Table 4 with demand elasticity assumptions ranging from -0.5 to -5.0. In each case the coefficients are of expected sign—supply response to price increases is positive and 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_{cs} suggests that AWC stocks may not be sensitive to supply shocks. All of the models have exactly the same likelihood value since the model is just identified.

There is no way to discriminate among the models on statistical grounds. Each is just identified and they differ only in terms of the assumed value of the demand elasticity. 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 representation, the elasticities in this paper measure responses to current price changes assuming that expectations of future prices are held constant. Thus, they 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

The VAR model is used to analyse economic fluctuations in wool prices, quantities traded and revenue using the three methods outlined above—impulse response analysis, forecast error variance decomposition and simulation. These methods 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.

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 model. Effects on market revenue, defined as quantity supplied times price, can also be obtained easily 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 in the figures measures (conditional) standard deviations of the variable whose response is being investigated, and the horizontal axis represents the number of quarters ahead the response is being measured. For example, when interpreting the price response to a demand shock a value of two at quarter four would indicate that a one standard deviation positive demand shock today would lead to a two standard deviation increase in price during the fourth quarter from now.

Responses of the two quantity variables are graphed in Figure 1. 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. 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 traded essentially 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. However, 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 a period of seasonal oscillation. Thus, a policy shock has no long-run effect on quantities traded.

Responses of price and revenue are illustrated in Figure 2. A positive supply shock initially depresses the price level but, after four quarters, the effect turns positive. In the long run, the effect of the supply shock does not die out and continues to have a 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 both have unit roots (stochastic trends) and are therefore nonstationary. In other words, there is a positive trend built into the dynamics of the VAR representation 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.

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. This is 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 way the wool market operates. 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. Thus, quantity responses are minimal over long time horizons. On the other hand, prices and revenues are nonstationary and so shocks have permanent effects and long-run responses reflect an inflationary trend in prices and revenues.

Forecast Error Variance Decomposition

Impulse responses identify the dynamic effects of each structural shock, but they are not very helpful in determining the relative importance of different shocks as a source of wool market fluctuations. However, the relative contribution of each structural shock can be estimated directly using forecast error variance decomposition. The errors from a k-step-ahead forecast of prices, revenues and quantities depend on realisations of the structural supply, demand and policy shocks over the next k quarters. Thus, as discussed above, the variance of the forecast error can be decomposed into components due to the variance of each structural shock. The proportion of the 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.

Based on the results in Table 5 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 percent of the total forecast error variance for all variables over all forecast horizons. Price and revenue fluctuations are especially influenced by demand shocks, with around 90 percent of price variance and 80 percent of revenue variance coming from demand shocks at intermediate forecast horizons. Furthermore, the relative contribution of demand shocks generally increases with the forecast horizon, suggesting that demand becomes an even more important source of uncertainty for long-range forecasting.

Simulation Results

Having analysed impulse responses and variance decompositions for the model, the next step is to simulate a no-intervention policy by the AWC 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}, in such a way that the net addition to AWC stocks in each period over the sample 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 AWC buffer-stock scheme had been in operation.

The price and revenue paths generated by this no-intervention policy are illustrated in Figure 3 which also includes the actual historical price and revenue paths to allow a comparison. It is clear that AWC intervention increased prices and revenues during much of the sample period. In fact, over the entire sample period prices were 1.5 percent higher on average with AWC stockholding than without, and revenue was 0.7 percent higher. Furthermore, using an interest rate of 10 percent, compounded quarterly, the net present value of the revenue stream in 1988 was 0.4 percent higher with AWC intervention than without. These are not large differences, but they are clearly consistent with the view that AWC stockholding has shifted the long-run demand for wool outward, thus increasing prices and revenues.[9] The results are also consistent with hidden revenue gains from the buffer-stock scheme exceeding hidden revenue losses.

Impulse response analysis and forecast error variance decompositions were applied to the simulated model in which there is no buffer stock. The impulse responses to supply and demand shocks in this case followed the same basic pattern as the responses shown in Figures 1 and 2, but the variance decompositions assuming no buffer stock are quite different and have interesting implications. Decompositions for the model with no buffer stock are shown in Table 6, where 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 stockholding. This suggests that the buffer-stock scheme has blunted demand shocks so that they have become a less important source of market fluctuations than they would have been under no intervention.

Another interesting way to evaluate AWC stockholding policies is to compare the variance of price and revenue forecast errors with and without the buffer-stock scheme. The standard deviation of these forecast errors are graphed in Figure 4 for forecast horizons of 1 through 36 quarters. At every forecast horizon, the standard deviations of price and revenue forecast errors are smaller with AWC stockholding than without. Although the difference is small over short forecast horizons, the results support the hypothesis that the buffer-stock scheme has reduced price and revenue uncertainty by making these variables more predictable.

Two main conclusions emerge from these results. First, AWC stockholding policies have reduced price and revenue uncertainty over the sample period by dampening the effects of demand shocks on market fluctuations. Second, AWC stockholding policies have also increased average price and revenue levels.

That is, the dynamic interactions embodied in the VAR model imply that the AWC policy, as implemented in the sample period, also led to higher average prices and revenues.

To complete the analysis, a second simulation was run imposing the restriction that all of the historical demand shocks over the sample period are zero. This can be done by simply constructing a series of zero demand shocks and running the model with the original supply and policy shocks, and the newly 'constructed' zero demand shocks. This gives the price, quantity and revenue paths that would have occurred had supply and policy shocks been the same over the sample period, but there had been no demand shocks.[10]

Simulated price and revenue paths in the absence of demand shocks are given in Figure 5, along with the actual paths for purposes of comparison. The simulated paths suggest that neutralising demand shocks eliminates much of the unpredictable variation in prices and revenues. Remaining fluctuations are comprised almost entirely of seasonal variation and a trend. This supports the evidence presented earlier which pointed to demand shocks as the dominant source of economic fluctuations in the wool market. It is also interesting to note that price and revenue levels are generally much higher in the absence of demand shocks. This again suggests that mitigating demand shocks leads to an outward demand shift and higher average prices and revenues.

Conclusions

In this paper a fairly simple dynamic model, in the form of 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 between variables in the system. Although the choice of identification restrictions involves much judgment, the seemingly logical results of our analysis of the wool market imply that the VAR approach to policy analysis is useful.

The results of this study paint a favourable picture of the wool buffer-stock scheme operated by the AWC. In the absence of the scheme, demand shocks are the dominant source of market fluctuations. But AWC stockholding policies 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 in the absence of AWC intervention, 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). Too, the results are consistent with an excess of hidden gains over hidden losses and 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).

Nevertheless, it is important to recognise that a formal economic welfare analysis of the costs and benefits of the buffer-stock has not been undertaken. Rather, this study has estimated sources of wool market fluctuations and some effects of the buffer stock on the path of key wool market variables. Results suggest that AWC stockholding policies have been successful in reducing market uncertainty and increasing the demand for wool, though the effects are quite small in some cases.

APPENDIX

A VAR Representation for Conventional SEMs

This appendix shows the relationship between VARs and conventional SEMs that share the same endogenous variables vector. The conventional SEM is represented by equation (1) of the text. Defining $z_t = \Gamma x_t + \epsilon_t$ then (1) can be written:

$$\text{(A1)} \quad By_t = z_t.$$

Note z_t is a (nx1) vector of aggregate shift variables and structural error terms and therefore it represents a composite of all of the disturbances to the market equilibrium.

Assume that z_t is a joint covariance stationary stochastic process with autoregressive representation:

$$\text{(A2)} \quad z_t = \sum_{i=1}^{m} A_i z_{t-i} + Au_t$$

where u_t is a vector of zero mean, serially uncorrelated disturbance terms with an identity covariance matrix; A is a (nxn) matrix of parameters defining contemporaneous interactions between z_t and u_t; and A_i are (nxn) parameter matrices for i = 1,2,...,m (see Judge *et.al*. Chapter 16). Repeated substitution of (A1) into (A2) gives

$$\text{(A3)} \quad By_t = \sum_{i=1}^{m} B_i y_{t-i} + Au_t$$

where $B_i = A_i B$ for i=1,2,...,m.

Equation (A3) is the VAR representation given in the text. Thus, it is evident that conventional SEMs always have a VAR representation, provided that the aggregate shift variables z_t can be expressed as an autoregression. That economic variables, such as z_t, can be represented satisfactorily by a finite-order VAR has a long history stemming from Sims (1980).

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.

Burt, O. R. and Finley, R. M. (1968), 'Statistical analysis of identities in random variables', *American Journal of Agricultural Economics* 50(3), 734-44.

Campbell, R. Gardiner, B. and Haszler, H. (1980), 'On the hiddden 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 U.S. 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 ed., Wiley, New York.

Lutkepohl, H. (1982), *Comparison of Criteria for Estimating the Order of a Vector Autoregressive Process*, Working Paper No. 8207, Fachbereich Wirtschaft-swissenschaften, Universitat Osnabruck.

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.

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.

ENDNOTES

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

2. This assumption is for expository purposes only so that seasonal terms and a constant can be excluded from the model. Exactly the same results found below can be obtained in a model where deterministic components have not been extracted, though some of the derivations are somewhat more complicated in this case.

3. In his article, Piggott also explains how elements of x_t can be combined into aggregate supply and demand shift variables to simplify the analysis.

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

5. 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).

6. Estimation results in this paper were carried out on a microcomputer using a GAUSS routine for nonlinear optimisation.

7. 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.

8. 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.

9. 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 average price and revenue effects seem due to the stabilisation attributes of AWC policy causing a shift in demand.

10. Although policy *shocks* are at their historical values this does not mean that simulated AWC stocks will be at their historical levels. AWC stock levels respond to supply and demand shocks. Hence, setting all historical demand shocks to zero means that simulated AWC stock levels are much smaller that historical levels, because there are fewer market shocks that require neutralising.

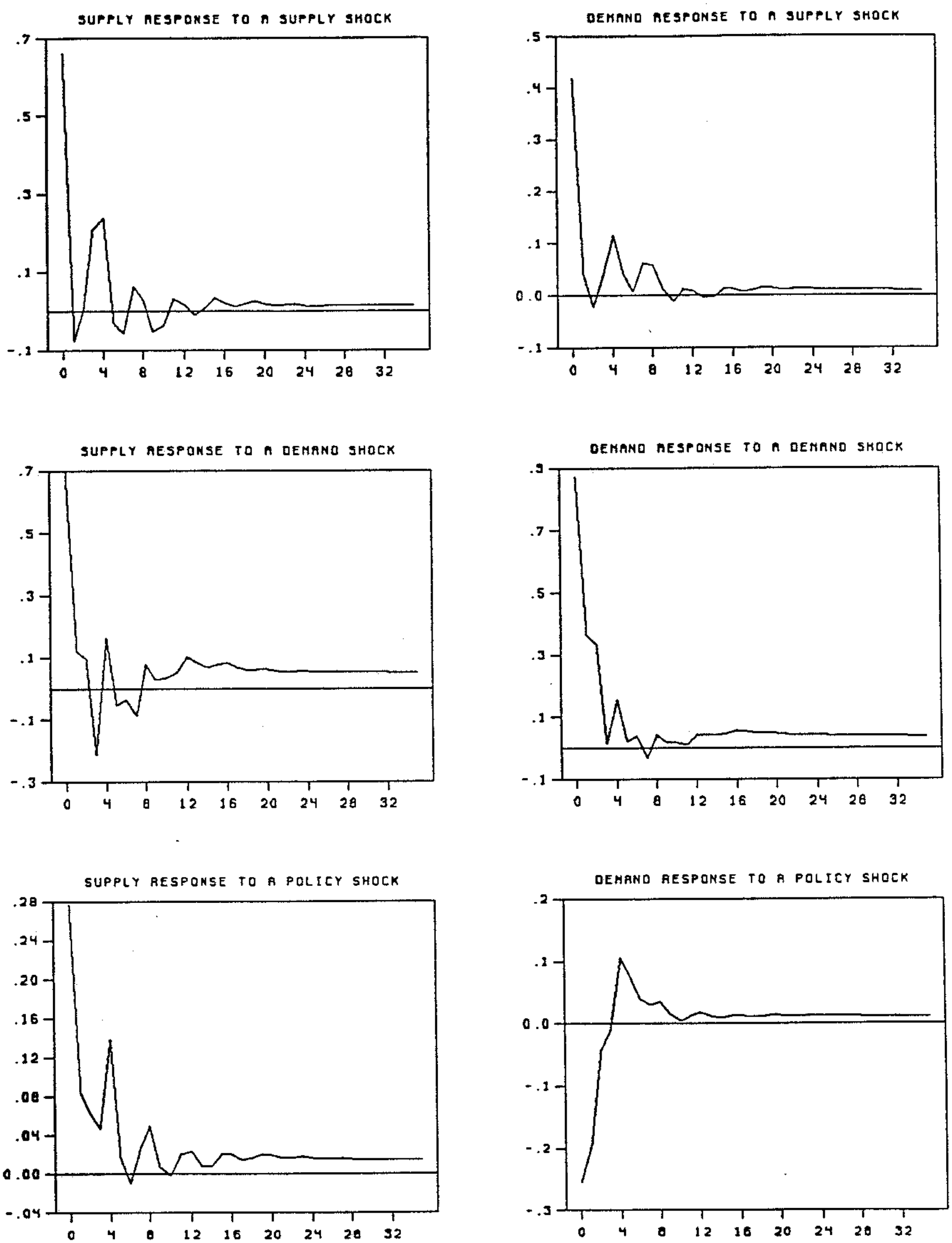


Figure 1. Impulse Responses for Quantity Supplied and Quantity Demanded

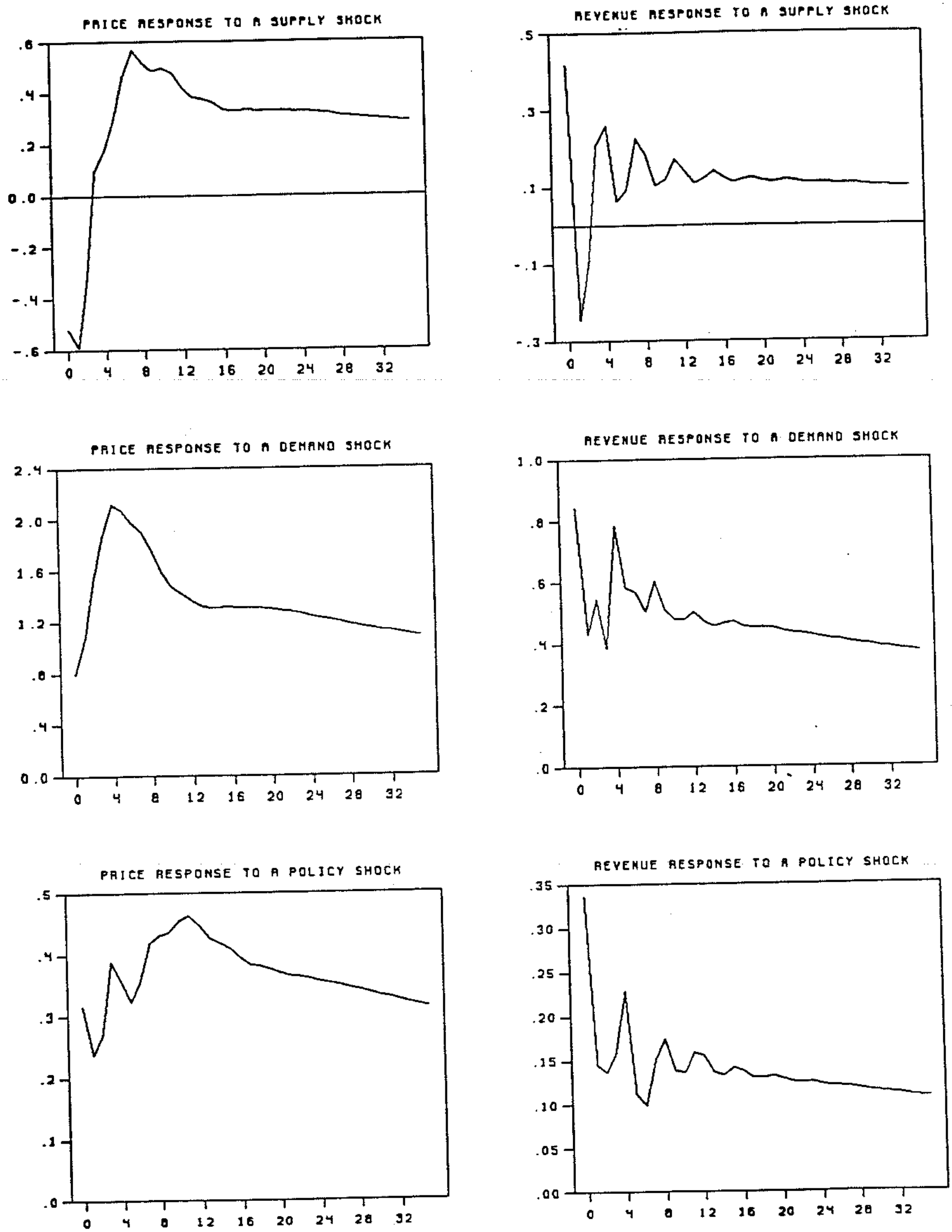
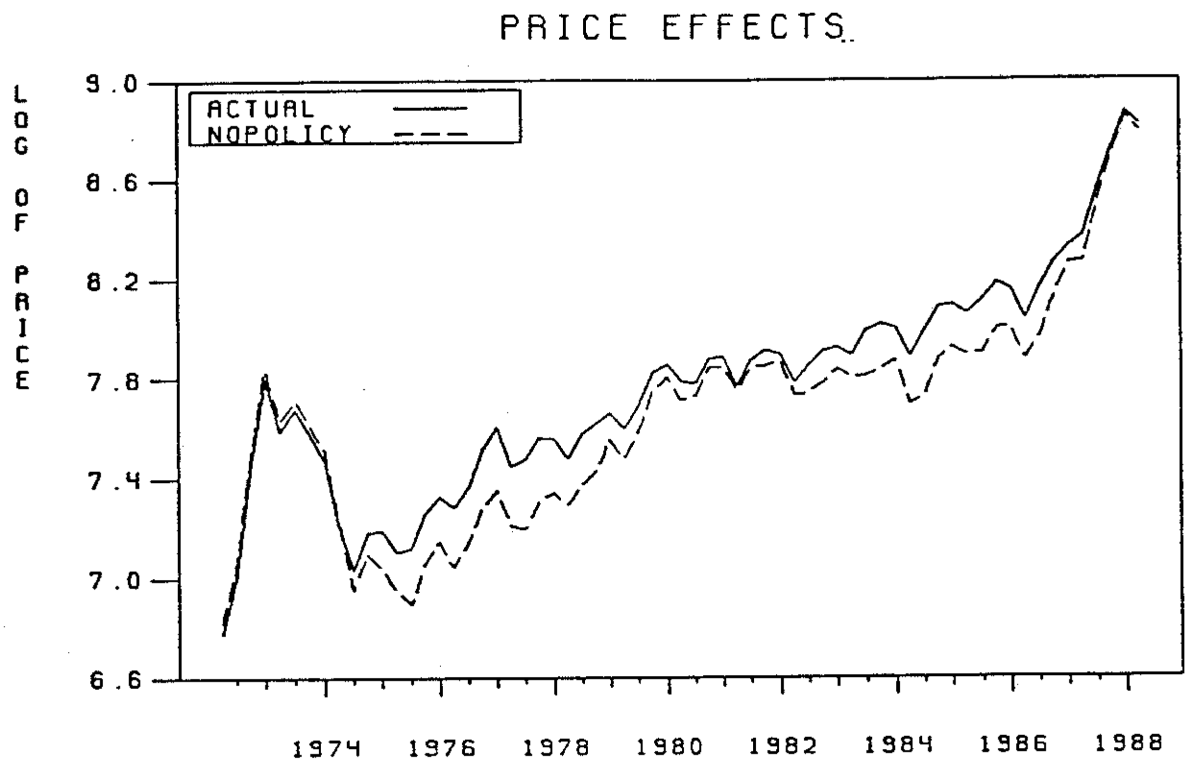


Figure 2. Impulse Responses for Price and Revenue



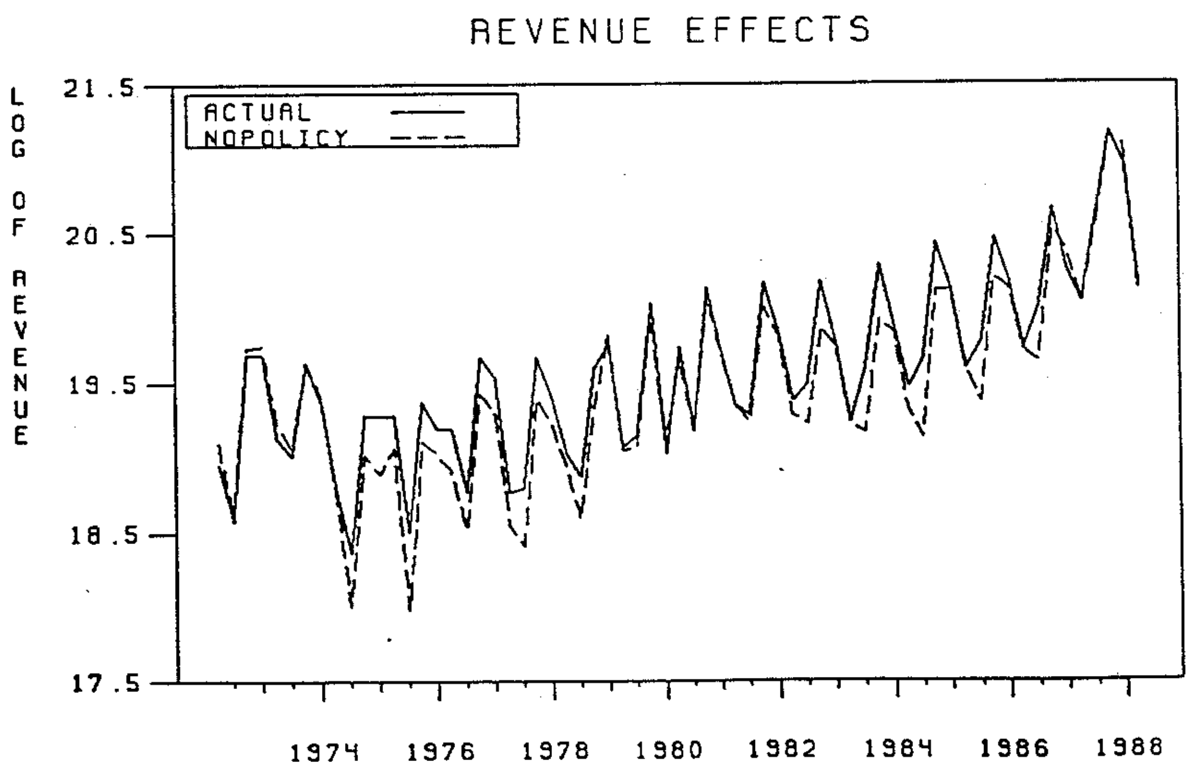
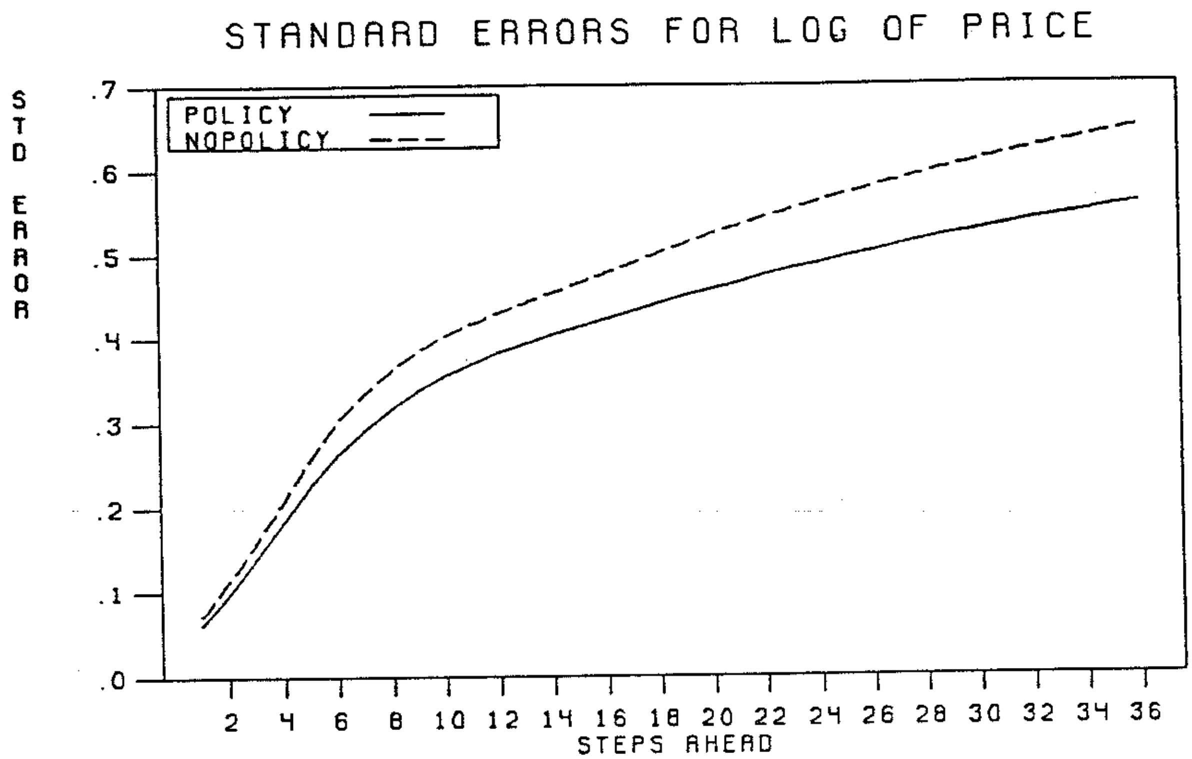


Figure 3. Actual Price and Revenue Paths Compared to Simulated Paths Under No AWC Buffer Stock (Nopolicy)



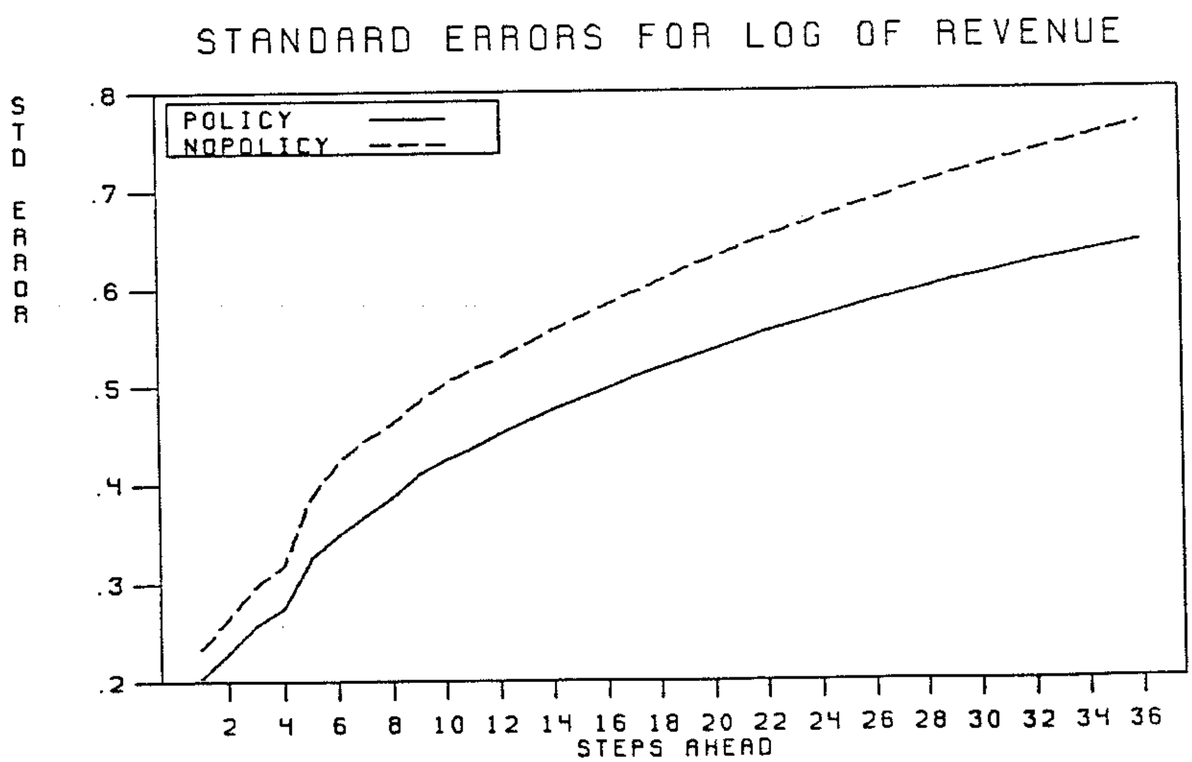
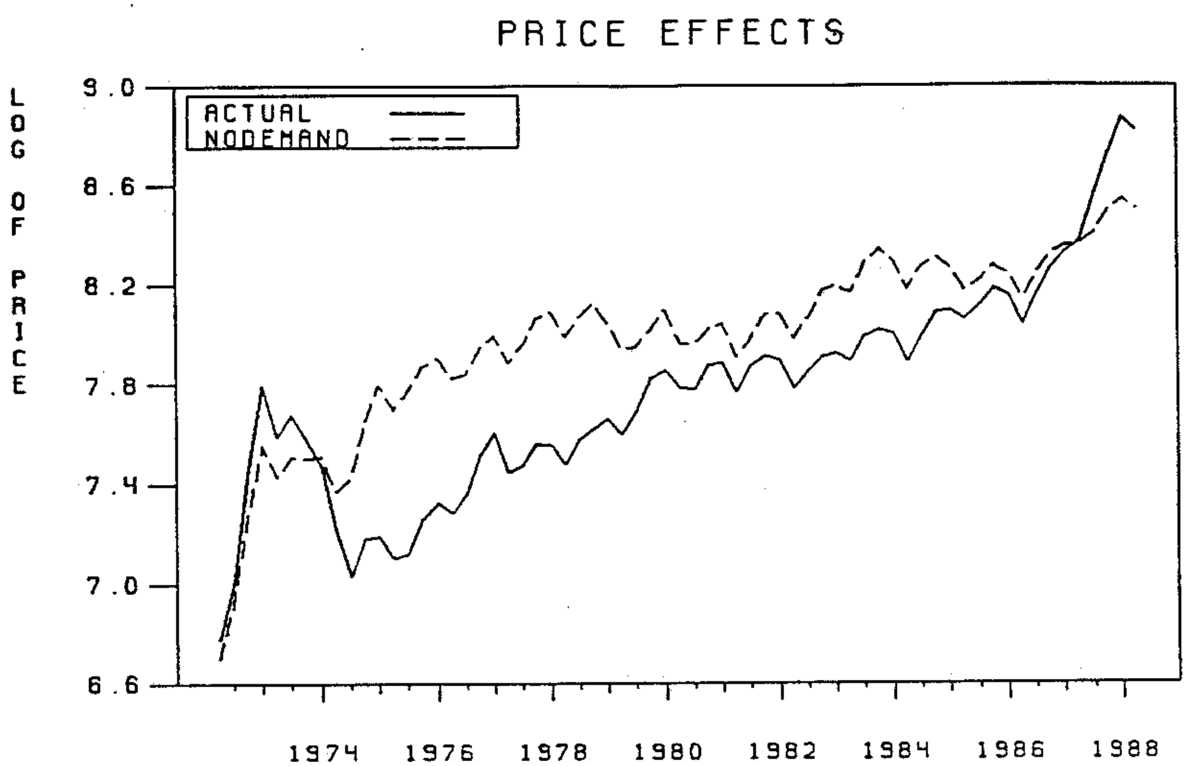


Figure 4. Standard Deviation of Forecast Errors With (Policy) and Without (Nopolicy) the Buffer Stock Scheme



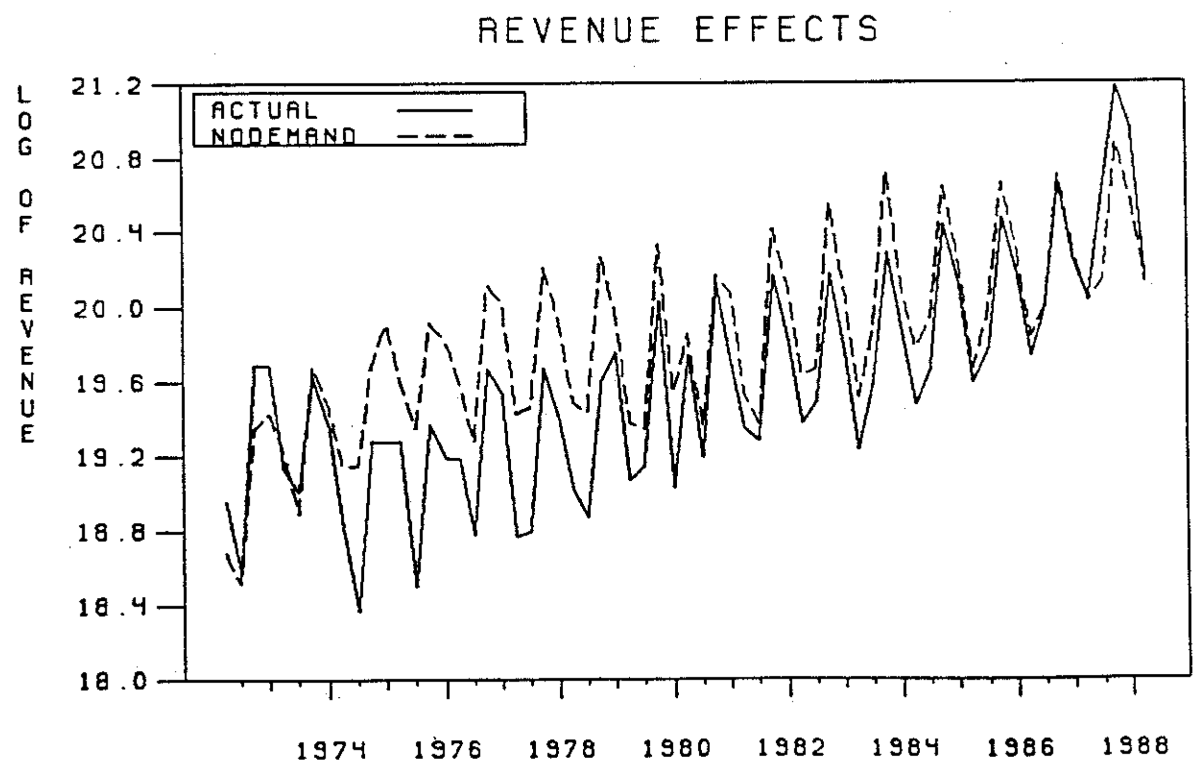


Figure 5. Actual Price and Revenue Paths Compared to Simulated Paths With No Demand Shocks (Nodemand)

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.

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.

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] Portmanteau test for autocorrelation in the residuals.

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
$\hat{\beta}_s$	4.611 (3.980)[a]	3.849 (4.467)	2.983 (4.933)	2.504 (5.014)	2.201 (4.931)	1.99 (4.789)
$\hat{\alpha}_s$	0.289 (4.545)	0.253 (5.555)	0.216 (7.202)	0.199 (8.360)	0.190 (9.148)	0.184 (9.685)
$\hat{\alpha}_d$	0.246 (11.393)	0.263 (11.395)	0.303 (11.397)	0.350 (11.399)	0.402 (11.399)	0.455 (11.400)
$\hat{\alpha}_c$	0.098 (10.952)	0.100 (11.089)	0.104 (11.256)	0.108 (11.329)	0.111 (11.362)	0.114 (11.378)
$\hat{\alpha}_{cs}$	0.032 (2.187)	0.029 (2.022)	0.025 (1.696)	0.021 (1.426)	0.017 (1.215)	0.016 (1.053)
$\hat{\alpha}_{cd}$	-0.087 (-5.853)	-0.086 (-5.770)	-0.083 (-5.477)	-0.079 (-5.014)	-0.075 (-4.836)	-0.071 (-4.572)
Log likelihood	-151.965	-151.965	-151.965	-151.965	-151.965	-151.965

[a] Values in parentheses are t-ratios.

TABLE 5

Forecast Error Variance Decompositions Under the Historical AWC Policy Regime

Steps ahead	Percent of forecast error variance due to:					
	Supply shocks	Demand shocks	Policy shocks	Supply shocks	Demand shocks	Policy shocks
	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

TABLE 6

Forecast Error Variance Decompositions Under
a Simulated No-Intervention Regime

Steps ahead	Percentage of forecast error due to:					
	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

Other Agricultural Economics Working Papers

No. 88-11	Estimating Endogenous Switching Systems for Government Interventions: The Case of the Dairy Sector	Donald J. Liu Harry M. Kaiser Olan D. Forker Timothy D. Mount
No. 88-12	Current Assessment Models for Farm Borrowers: A Logit Analysis	Lynn H. Miller Eddy L. LaDue
No. 88-13	The Economics of Sustainable Agricultural Systems in Developing Countries	Randolph Barker Duane Chapman
No. 89-1	Resource Economics: Five Easy Pieces	Jon M. Conrad
No. 89-2	Optimal Dairy Policy with bovine Somatotropin	Loren W. Tauer Harry M. Kaiser
No. 89-3	Environmental Standards and International Trade in Automobiles and Copper: The Case for a Social Tariff	Duane Chapman
No. 89-4	Optimal Fluid Milk Advertising in New York State: A Control Model	Donald J. Liu Olan D. Forker
No. 89-5	A Bioeconomic Model of the Harp Seal in the Northwest Atlantic	Jon Conrad Trond Bjorndal
No. 89-6	A Money Metric Measure of Welfare Change From Multiple Price and Income Changes	Jesus C. Dumagan
No. 89-7	The Strategic Role of Supermarket Buyer Intermediaries in New Product Selection: Implications for Systemwide Efficiency	Edward W. McLaughlin Vithala R. Rao
No. 89-8	Estimating Parameters in a Dynamic Open-Access Model With an Application to the Flemish Cap Ground Fishery	Nick Gomersall
No. 89-9	The Dynamic Effects of Agricultural Subsidy Programs in the United States	Harry de Gorter Eric O'N. Fisher