Management of a Top Processing Firm and Demand for Wool at Auction

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In this paper the impact of management of top processing operations on the transmission of demand at auction is investigated. Of particular interest is the impact of management activities such as stockholding, the backlogging of orders, production of top and the purchasing of raw wool supplies. In undertaking this investigation, a monthly simulation model of a topmaking firm was constructed using a System Dynamics approach. It is concluded that the management of processing operations does impact upon the transmission of demand for raw wool in the short term and that the significance of these impacts has repercussions for the specification of demand functions for wool at auction.

The transmission of final demand for wool, from woollen consumables through the various stages of the textile chain to demand for wool at auction, is a highly complex process. While this is well illustrated by the concept of the 'textile pipeline' rarely has any attempt been made to incorporate this process in any detail in models of wool demand. As a consequence, the impact of management of wool processing operations on demand for wool at auction has largely been overlooked in past studies of wool demand.

This paper reports an analysis of the impact of the operations and management practices of topmaking firms on demand for raw wool, with a view to contributing to a better understanding of the transmission of demand for top to demand for wool at auction. On the basis of this analysis it is hoped that some insights may be gained into how future models of demand for wool may be more fully specified so that a more detailed and informed analysis of the processes of demand transmission may be considered.

Background

Concepts such as the textile pipeline, in depicting the process of derived demand, do not adequately take account of certain management practices undertaken by wool processors, such as forward ordering and the judicial use of order backlog and inventories. Yet Durbin (1975) in a study of the European wool processing sector argued that the management of backlog, production and physical stocks does influence the purchasing of additional wool supplies and thereby, the transmission of demand for raw wool.

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Other researchers have attempted to incorporate various aspects relating to the management and operations of topmaking firms into models of wool demand (e.g. Wallace, Naylor and Sasser 1968; McKenzie, Philpott and Woods 1969; Smallhorn 1973; Carland and Pagan 1979 and Campbell, Gardiner and Hazler 1980). However, the extent to which these models depict the nature of the inter-relationships between management activities and wool demand is varied.

A lack of industry data has further restricted efforts to construct more representative models of wool processing firms. This aspect was noted in particular by Durbin (1975). Durbin considered the unavailability of data relating to the distribution of new orders for top by month-of-delivery to be a major constraint in constructing a model of a topmaking firm. Durbin claimed that the placement of new orders by delivery date directly influences topmakers raw wool purchasing decisions over time. Consequently, if data on the distribution of new orders for top by month-of-delivery could be collected from industry sources or alternatively estimated, then it may be possible to more accurately estimate purchasing requirements for raw wool at auction and, hence, more accurately describe the transmission of demand for wool through the top processing sector.

Initial attempts were made to estimate econometrically new orders for top by delivery date from aggregated industry data, however these proved unsuccessful due to the requirement to fix both the length and shape of the monthly lag structure in relation to the distribution of orders. In the course of estimation it became apparent that the distribution of orders for top was not fixed over time, rather, the proportion of prompt (delivery within two moths) and forward (delivery after two months) orders fluctuated considerably. A more appropriate modelling approach was therefore sought, the basis of which was the construction of a simulation model of the management of a topmaking firm.

Modelling Management Behaviour

The complex nature of the relationships between processing operations and management practices within the wool industry adds to the difficulties experienced in modelling the behaviour of wool processors. As an example, the operations performed by a wool top processor may include purchasing greasy wool, holding physical stocks of both raw wool and finished top and processing orders for spinners and weavers. Each of these operations is in turn bound by the practices of maximising plant utilisation, reducing variability in output, minimising inventory investment and avoiding delays in delivery. Invariably, in attempting to manage these various activities in a collective manner conflicts arise. A constant level of plant utilisation is clearly at odds with minimising inventory investment, but then high inventories of raw and finished materials improve the quality of service offered to clients by minimising delays.

Recognising the complex nature of the operations of a top processor suggests that it would be unrealistic to model these operations independently of one another. Rather, such complexity suggests that a systems approach to modelling processor behaviour would be more appropriate. A systems approach may more adequately capture the dynamics of the various interactions both within and between processing operations. To this end, a simulation method was sought that used existing industry data to investigate the interactions between the various operations and management practices of a top processing firm. Work in the area of systems engineering provided the impetus for the development of such a method for depicting the dynamics of components within a system. This method is known as System Dynamics (Forrester 1961).

The method of System Dynamics is based on the identification of key variables that influence the flow of resources within a firm. Once identified, decision rules reflecting the management of these key variables are constructed to form a model of the firm's decision processes. The resulting model depicts the management of the firms' operations in terms of a series of decision rules. Quantitative expressions of these decision rules may then derived such that these expressions may subsequently be employed to construct a simulation model of the management of the firm.

Using this approach, a model could be constructed which incorporates the major processing activities of the firm and the decision rules which control the level of these activities. Such a model, by encapsulating the management of a topmaking operation, may provide insights as to the behaviour of wool processors in response to changing order demand conditions. Exposing such a model to a range of market conditions not only allows the appraisal of processor responses but also permits an assessment of the manner in which each decision rule influences those responses. The identification of these influences is of prime importance in this study as these may indicate appropriate model specifications for describing demand for raw wool at the processing level.

System Dynamics was preferred to an optimising approach, such as exemplified by the inventory control models that appear in the operations research and economics literature, on the grounds that in modelling the management of a topmaking firm the assumption of optimisation was deemed to be inappropriate; given that the fundamental role of management is the resolution of conflicts between processing operations and management practices under unpredictable and variable demand conditions. In such highly dynamic situations, where adaptive mechanisms continuously influence decision making, models must be developed that can both describe these mechanisms, and reflect the ways in which they interact within a system.. In contrast to the typical inventory control models, System Dynamics characterises the decision making process as an adaptive mechanism.

As method of system enquiry, System Dynamics incorporates both qualitative and quantitative components into its overall operational framework. The initial system description phase is based on identifying the flow of information and resources within the system and ascertaining the nature of the feedback loops that exist between system components. Tracing the various feedback loops that link decisions to actions, resulting in new information and giving rise to new decisions, is facilitated by the construction of a series of influence diagrams (Wolstenholme 1982; Coyle 1983). These influence diagrams in turn provide the basis for the specification of a quantitative model.

On formulating a mathematical model of the relevant interactive mechanisms and decision processes, based on the system descriptions provided during the qualitative stage, a history of system behaviour may be generated. The time dynamic nature of the model may be further investigated by simulation. The key to operationalising this overall approach is to work backwards from observed outcomes to identify what information actually influences decisions, and hence, outcomes. This contrasts with the more common approach economists have tended to follow whereby pre-conceived ideas, albeit theoretically based, are formulated as to what information is actually required when modelling management behaviour.

Development of the Model

The operations of a topmaking firm can be divided into four main activities:

(a) the management of orders received from spinners and weavers;
(b) the management of inventories of greasy wool and processed top;
(c) the production of wool top in response to orders received; and
(d) the purchasing of additional raw wool supplies.

The inter-relationships between these operations are illustrated in Figure 1. In undertaking these operations the firm attempts to:

(a) limit capital investment in finished stocks while maintaining sufficient stocks to enable prompt delivery;
(b) limit capital investment in raw wool stocks;
(c) control variability in the rate of production; and
(d) maintain order backlog subject to capacity constraints.

The key variables of greatest concern to the processor are therefore the level of stocks, the volume of order backlog and the rate of top production. Identifying the policies or practices topmakers follow in controlling these key variables is the aim of the first phase of the System Dynamics approach.

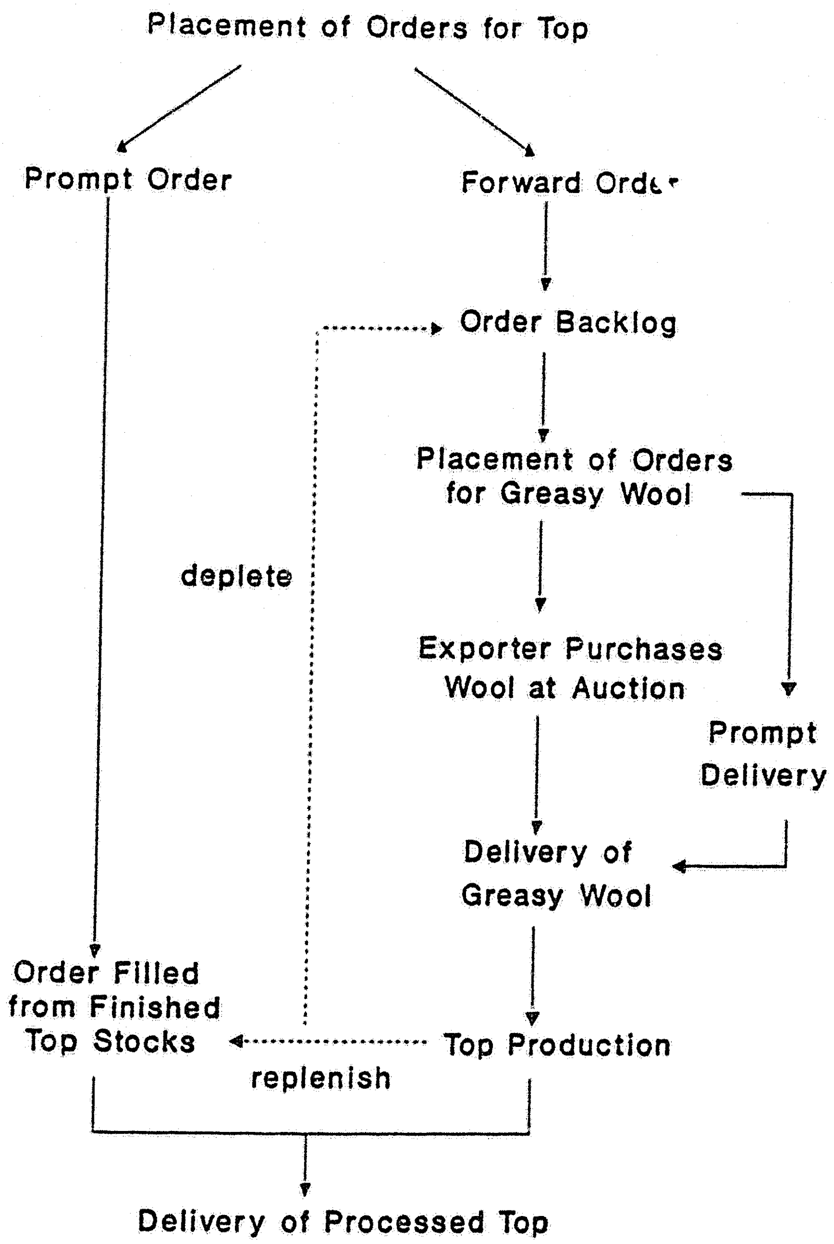


Figure 1 : Operations of a Topmaking Firm

The System Description Phase

The qualitative component of Systems Dynamics is based on the recognition that the fundamental process within any managed system is the conversion of resources, and as such, all management decisions serve to convert or transfer resources from one form or state to another (Wolstenholme and Coyle 1983). Therefore, the starting point of the analysis is the description of the systems' physical processes as they relate to the transformation of resources. In this study the conversion process of interest is the manufacture of wool top from raw wool.

The key variables which encapsulate the problem of managing a topmaking firm are inventories of stocks and unfilled orders and production of top. With the exception of production, it is the level of these activities that is of concern. Production, on the other hand, is a flow variable and hence the focus of attention is a rate, not a level. The management problem can then be redefined as one of matching the rate of one operation to the levels of other operations, subject to the constraints imposed by variable demand for top.

The conversion process of interest in relation to orders received is the transformation of new orders into either processed orders (prompt delivery) or unfilled orders (forward delivery). The process of accumulating new orders into a backlog of unfilled orders and an inventory of processed orders is shown in Figure 2. The diagram in Figure 2, termed a flow module, indicates the influences which orders have on the behaviour of other resources or key variables in the processing system. The positive sign on the flow between New Orders and Order Backlog indicates that new orders have a positive influence on the size of backlog. In a similar fashion, the negative sign between Production Rate and Order Backlog indicates a depletion in the size of backlog in response to an increase in production rate.

The other flow modules relating to the management of raw wool stocks and the production of top are represented in Figures 3 and 4. The difference between these flow modules and the module depicted in Figure 2 is the incorporation of a delay effect between the placement and arrival of raw wool orders and between the start and the completion of production.

The set of flow modules outlined above may in turn be combined to form a representation of the top processing system, depicting the production, purchasing and stockholding functions of a topmaking firm. Such a representation is called an influence diagram and is depicted in Figure 5. At this stage in the analysis four flow rates have been identified which influence other variables but which are not yet influenced by variables presently included in the system. These are New Orders, Production, Raw Wool Orders and Sales. The flow of New Orders and Sales are not under the direct control of the firm and are therefore treated as exogenous

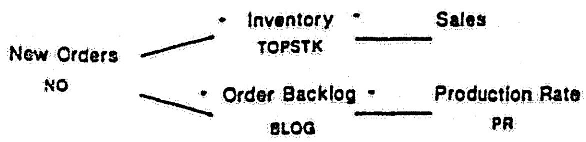


Figure 2 : Accumulation of New Orders in Backlog

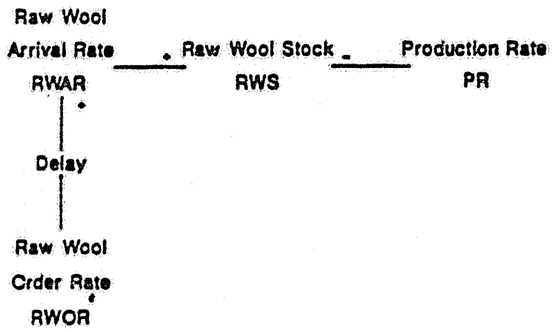


Figure 3 : Management of Raw Wool Stocks

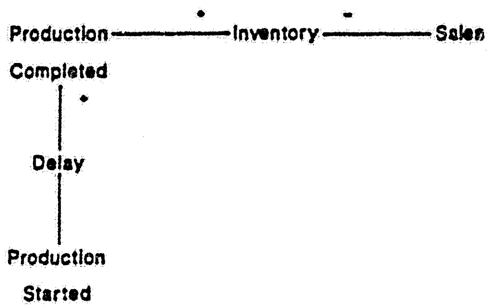


Figure 4 : Production of Wool Top

to the system. This leaves the flow of wool through the production process and the flow of raw wool orders.

Control of the flow of production is illustrated in Figure 5. As an adaptive decision-making mechanism is assumed in System Dynamics, control policies concerning key variables are defined in terms of differences between actual and desired states for these variables. As an example, the production manager attempts to eliminate differences between actual and desired inventories and backlog. This decision rule is effectively a control policy. In a similar fashion, the purchasing manager attempts to eliminate Raw Wool Stock Differences.

In short, the dynamics of the inventory, production and raw wool sub-systems depend on the exogenous variables (new orders and sales), the decision rules on control policies governing them, and the structure of the processing system as a whole. The significance of feedback in each sub-system, and the system as a whole, is clearly evident in Figure 5. For example, orders and inventory levels influence production, which in turn affects subsequent backlog and inventory levels. Concurrently, production influences the purchasing and inventory of raw wool supplies. Past production, through its influence on past purchasing, also determines the arrival of raw wool supplies which in turn influences current purchases and inventory levels.

The construction of an influence diagram of the top processing system signifies the completion of the system description phase. This influence diagram symbolises the flow and regulation of orders and materials and identifies the nature of feedback mechanisms. On the basis of this diagram a quantitative simulation model of the management of a top processing firm will be constructed.

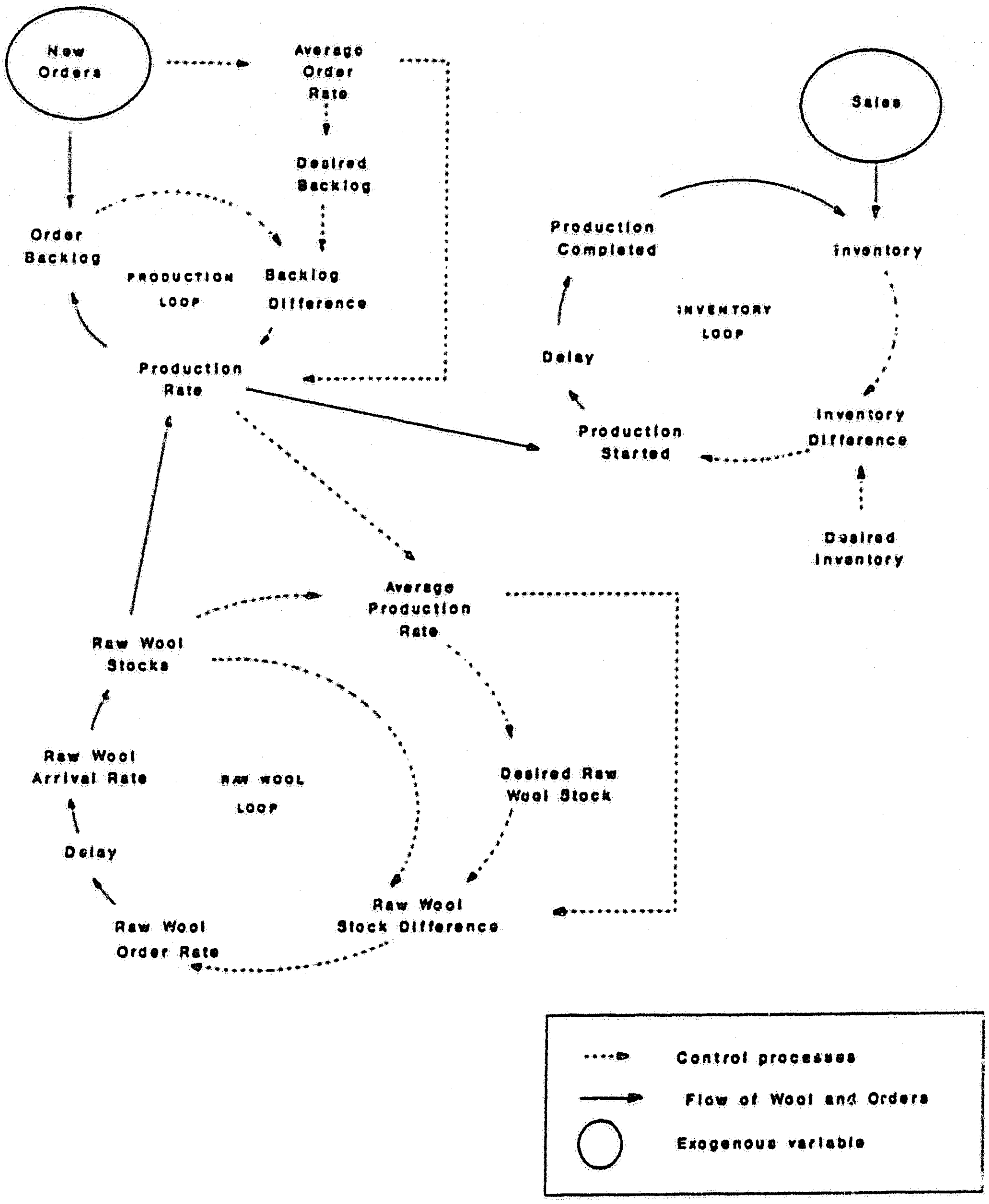
The Model Construction Phase

The emphasis on constructing the model is on specifying the decision rules which govern or regulate the flow or transformation of orders and materials within a topmaking firm. The two decisions of particular interest in this study are the production and raw wool ordering decisions. In Figure 5 it was revealed that both these decisions are associated with feedback mechanisms and a set of control rules. The control rules are:

(a) equate the difference between actual and desired backlog by adjusting the production rate;

(b) equate the difference between actual and desired raw wool stock positions by adjusting the raw wool order rate; and

(c) equate the difference between actual and desired levels of finished-good inventories by adjusting the production rate.



Adapted from Coyle (1983)

Figure 5 : Influence Diagram of Top Processing System

The specification of these control rules will now be discussed in detail.

Production Rate (PR)

In setting the rate of production, managers are typically faced with cost and capacity constraints. It is therefore hypothesised that in order to introduce an element of longer-term stability into the production decision.managers attempt to match the current rate of production to anticipated demand, which is assumed to be formulated on the basis of the immediate past pattern of order placement Another aspect that managers invariably consider is the ability to limit the volume of order backlog to a level which conforms to client delivery schedules and yet ensures an acceptable level of machinery utilisation. Attainment of this desired level of backlog is sought by minimising the difference between actual and desired unfilled orders allowing for a suitable production delay.

On the basis of these observations it is possible to algebraically represent the production rate decision rule as;

(1) $PR = (UFO - DBLOG)/TABL + AOR$

with

(2) $UFO = BLOG_{-1} - TOPSTK_{-1}$

(3) $DBLOG = K1 * AOR$

where

UFO is volume of unfilled orders,
BLOG is backlog of unfilled orders,
TOPSTK is inventory of finished stocks on hand awaiting delivery,
DBLOG is desired backlog of unfilled orders,
K1 is months of average orders (or production) held in backlog,
TABL is time to adjust backlog,
AOR is average new order rate,

This production rule has the following implications. If actual backlog of orders exceeds the desired volume, then capacity is not being efficiently utilised and there is a risk that delivery schedules may not be met. In this situation, production will be increased in an effort to reduce the volume of unfilled orders. On the other hand, if desired backlog is greater than actual backlog, the rate of production will be reduced. This enables a build-up of unfilled orders which ensures continuity of production, at a lower level of capacity utilisation. In essence, the decision rule reflects an attempt to balance the desire to contain variability in capacity utilisation (through the inclusion of the average order rate) while maintaining control over the backlog of unfilled orders.

Raw Wool Order Rate (RWOR)

The decision as to the rate at which orders for raw wool are to be placed at auction is similar, in form, to the production rate decision. Orders for greasy wool must be placed at a rate which ensures that sufficient stocks are on hand to maintain current production. Expected raw wool requirements are in turn determined on the basis of the average rate of production over recent months, with the effect of injecting some stability into the procurement of raw wool supplies.

Purchasing managers must also consider whether current holdings of raw wool stocks are at an acceptable level. Sufficient stocks must be held to meet immediate processing requirements, yet at the same time management will strive to minimise total capital investment in stocks. In this sense, the desired level of greasy wool stocks is defined in terms of months of average production.

The raw wool decision rule is as follows;

(4) $$RWOR = (DRWS - GWSTK_{-1}) / TARWS + APR$$

with

(5) $$DRWS = K4 * APR$$

where

DRWS is desired raw wool stocks;
GWSTK is raw wool stocks;
K4 is months of average production covered by raw wool stocks;
TARWS is time to adjust raw wool stocks;
APR is average production rate.

This rule implies that if actual stocks of raw wool are greater than desired, then the order rate will be reduced, and similarly, if actual stocks are less than desired, the placement of raw wool orders at auction will increase.

Having formulated control rules relating to the production of top and the ordering of raw wool an effort was made to express these two rules in terms of the production to order:production to stock distinction (Belsley 1969). The management orientation of a topmaking firm will differ depending on whether production is primarily to order or to stock. Firms that produce to order rely on order backlog to reduce variability in throughput, in contrast, firms producing to stock use output stocks to stabilise production. It was hoped that by attempting to incorporate this distinction in the model the simulated outcomes would more closely approximate the real system.

In short, the decisions relating to the rate of top production and the rate of raw wool ordering regulate the transmission of top orders into demand for wool at auction. Having formulated decision rules for these two key variables the remaining variables were derived on the basis of simple identities (see Appendix A).

In order to assess the value of the model as a representation of the management of a topmaking firm a baseline simulation was performed over a period of eighty months using aggregated industry data provided by Interlaine Secretariat Statisque (details in Grace 1991). The purpose of this baseline solution, designated BASE, was to assess the ability of the model to track historical trends in the data, and most importantly, to evaluate the dynamic stability of the model.

Assessment and Validation of the Model

The validation of a simulation model is typically assessed in terms of the model's ability to replicate historical data. However, the extent to which a model fits the real system is but one dimension of validity. In validating any model attention should focus primarily on the purpose for which that model was constructed. In this paper the model was developed to identify the dynamic relationships underlying the management of a top processing firm and, more specifically, to examine the extent to which inter-relationships between processing operations affect demand for raw wool at the top processing level. Accordingly, validity of the model was assessed both in terms of the realism of the simulated outcomes over time and the extent to which the model's various management components portrayed a high degree of dynamic stability when subjected to varying order demand. Evidence of a degree of dynamic stability would seem to authenticate the structure of the model and would suggest that the appropriate feedback mechanisms had been correctly incorporated within the model.

Without knowledge of the actual distribution of orders for top by delivery date and given that this order distribution varies over time, the comparison of historical data with simulated data for an individual 'representative' firm operating under a fixed distribution of new orders and a constant level of stocks coverage, would not be expected to represent a true test of goodness-of-fit. However such comparisons may be of some value in highlighting the exclusion of relevant feedback mechanisms.

Graphical and Statistical Assessment

Figures 6 through 9 contain a comparison of the time paths of the actual data and simulated outcomes for the four endogenous variables of especial interest - top stocks, order backlog, top production and raw wool stocks. Subjective assessment of the validity of the model on the basis of these graphical comparisons is however bound by the constraints outlined above. In particular, fixing the distribution of new orders over the entire simulation period was expected to severely constrain the predictive ability of the model. Yet despite these limitations, the simulated series appear to duplicate the general trends in the level and variability of the observed data with a reasonable degree of accuracy.

A range of simple measures of predictive performance are also presented in Table 1. These coefficients indicate that backlog and to a lesser extent top production, are both reasonably well predicted. The predictive accuracy of the two stocks series is low but is certainly adequate for the purposes of this investigation.

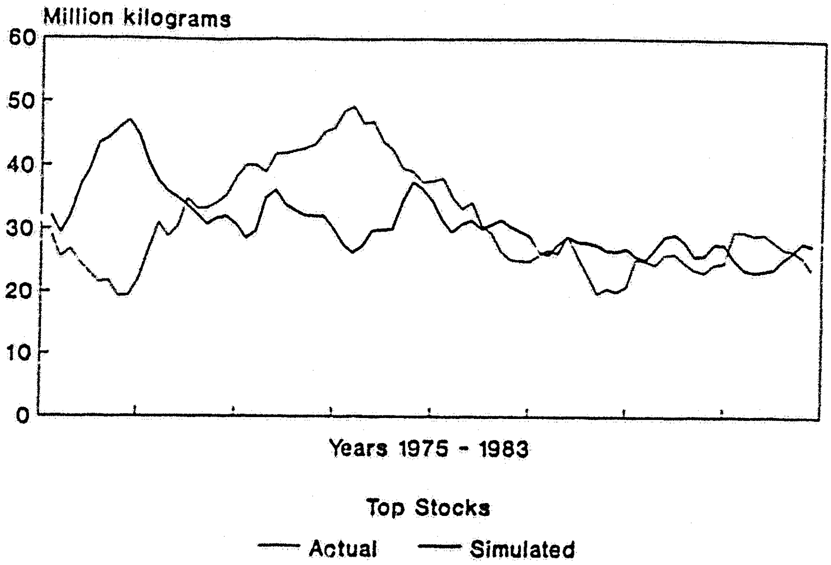


Figure 6 : Stocks of Finished Top

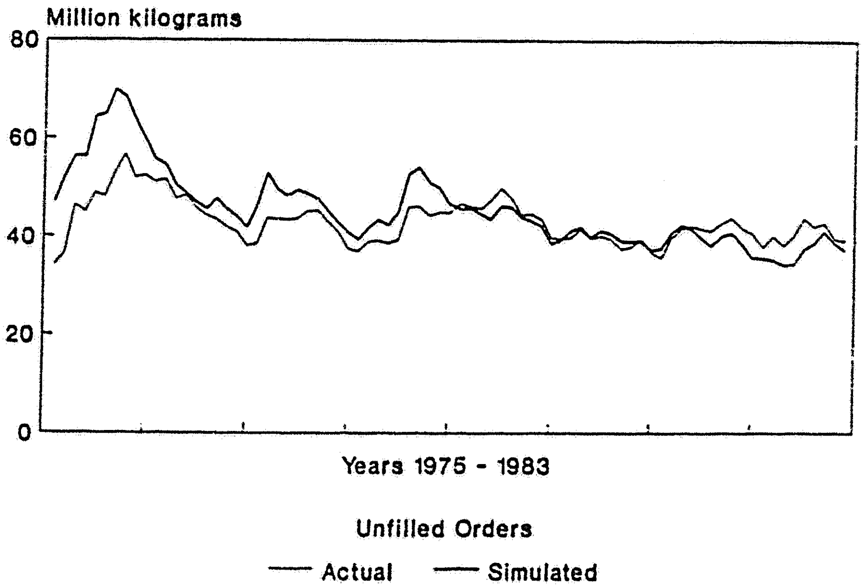


Figure 7 : Backlog of Orders

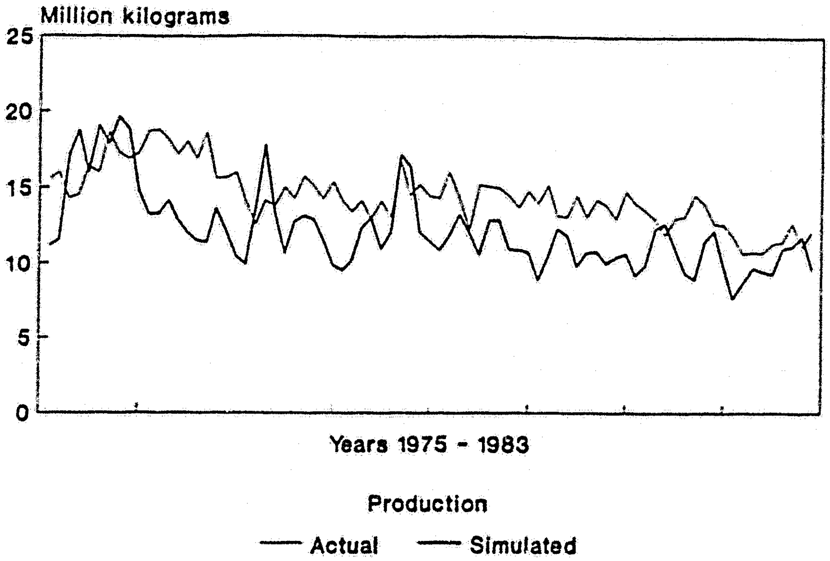


Figure 8 : Wool Top Production

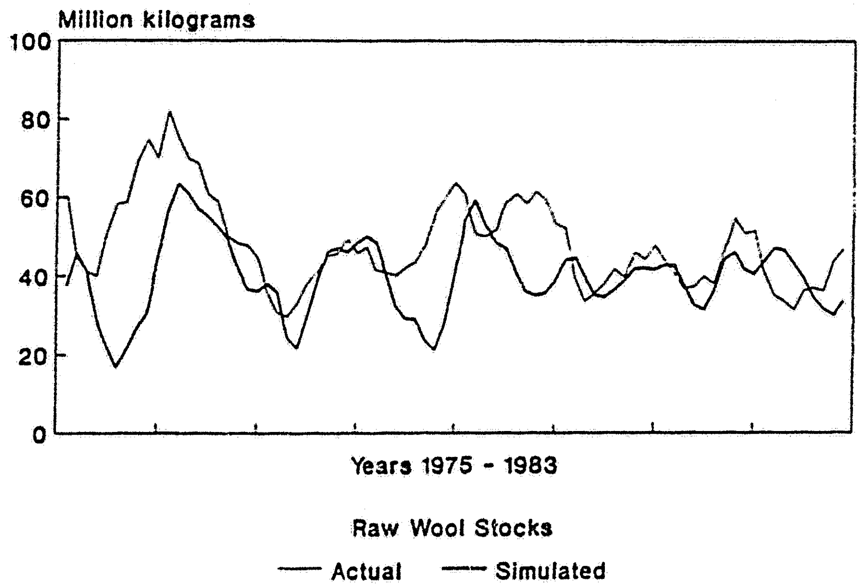


Figure 9 : Stocks of Raw Wool

Table 1: Measures of Predictive Performance

Variable	Gross Error[a] (n=79)	Turning Point Error[a]	Root Mean Percent Error	Theil Statistic
Top Stocks	43	44	37.2	0.31
Order Backlog	12	19	13.1	0.19
Top Production	50	39	22.2	0.23
Raw Wool Stocks	43	34	27.0	0.31

[a] errors are measured in % points and are defined as prediction errors of greater than 15%.

Dynamic Stability

To reiterate, the model developed in this paper depicts the management of a top processing firm operating under an environment of variable and unpredictable order demand. Consequently, the dynamic stability of the various components of the model which represent a wide range of management activities relevant to top processing is of prime concern.

Stability was assessed in terms of the dynamic response of the predicted endogenous variables to a ten-period change in the fixed distribution of new orders. The order distribution of the base simulation was altered, first to reflect an increase in the proportion of prompt orders for top, and second, to reflect an increase in forward top orders. It is important to stress however that the dynamic responses presented in Figures 10 to 19 in Appendix B are due solely to changes in the proportion of orders prompt and forward and <u>not</u> as a result of any increase in the aggregate level of the exogenous variable, new orders.

The complexity of these response patterns is clearly evident in Figures 10 to 19. Detailed interpretation of the relevant causal processes and inter-relationships as depicted in these figures is accordingly left to Grace (1991). Overall, the level of control displayed within the modelled system in response to changes in the distribution of new orders is encouraging. Once the altered distribution of new orders reverts to the original order distribution the processing system returns to the base levels of production, backlog, stocks and raw wool orders. It is therefore apparent that all the predicted endogenous variables exhibit a high degree of dynamic stability in response to changes in the pattern of order demand. The ability of the model to absorb shocks in demand would seem to suggest that the linkages and feedback mechanisms that exist between the management practices of a topmaking firm are reasonably well represented. It is concluded therefore that the model, in its present form, is adequate for the purpose of investigating the transmission of demand for wool at auction.

Investigation of the Transmission of Demand

The purpose of this section of the paper is to investigate whether or not changes in the placement of orders for top, in terms of prompt and forward, affects the placement of orders for raw wool by month-of-delivery. Four simulation experiments were conducted in which the relative proportions of prompt and forward orders for top were varied from 15 percent to 75 percent, and 85 to 25 percent respectively (see Table 2). Varying the proportion of prompt and forward is synonymous with varying the delivery requirements for top over time. It is important to note, however, that the aggregate level of demand for top remains unchanged for all the experiments; rather, it is the breakdown of demand into prompt and forward components that varies.

A range of comparisons were drawn between the base distribution and the experimental distributions, the details of which are reported in Grace (1991). In this paper the reporting of results focuses specifically on how the placement of orders at auction changes relative to the breakdown of aggregate demand for top. In the first experiment the proportion of forward top orders was set at 85% with prompt at 15%, reflecting an increase in forward ordering of top relative to the base distribution. As expected with such an increase in forward ordering, a greater proportion of top orders tend to be accumulated in backlog, the significance of which is twofold. First, an increase in unfilled orders held in backlog buffers the production of top against fluctuations in order demand, thereby stabilising throughput. More importantly however, orders held in backlog may be filled forward over time thereby creating an opportunity for the firm to strategically purchase additional raw wool supplies. This particular aspect is evident in Table 2 where over 85 percent of raw wool purchases are made on a forward basis. Furthermore, although the monthly volume of raw orders does not change significantly compared to the base distribution the variability in raw wool purchases falls sharply (see Table 3). This would seem to suggest that total raw wool orders are more stable in response to an increase in forward ordering of top and that a rise in the volume of unfilled orders held in backlog promotes greater production control and flexibility in purchasing at auction.

In the subsequent set of simulation experiments the proportion of prompt orders for top was increased from 15% to 40%, 50% and finally 60%. In all cases the increase in prompt orders led to a greater volume of raw wool purchased on a prompt basis and a resultant increase in the variability of total raw wool purchases (see Table 3). Production of top and total stock holdings were also more variable as prompt top orders increased. Variability in the production of top is buffered to a large extent against variability in new orders by order backlog. With the increase in prompt orders, backlog is smaller and much of the variability in orders for top is transmitted directly through to the production system and invariably through to purchases at auction. This is reflected in the coefficients of variation for raw wool purchases presented in Table 3.

As the volume of prompt orders for top increases, the ability of the processing system to buffer variations in demand deteriorates as reflected by an increase in the variability of raw wool purchases. Although the average volume of raw wool purchases at auction is relatively stable, changes in the actual proportions of prompt and forward purchases, in accord with delivery requirements for top, alters the variability of total raw wool purchases.

Table 2: Proportion of Prompt and Forward Orders (%)

	Top Orders		Raw Wool Orders	
	Prompt	Forward	Prompt	Forward
Experiment One	0.15	0.85	0.13	0.87
Base Distribution	0.25	0.75	0.24	0.76
Experiment Two	0.40	0.60	0.40	0.60
Experiment Three	0.50	0.50	0.51	0.49
Experiment Four	0.60	0.40	0.61	0.39

Table 3: Volume and Variability of Prompt and Forward Orders

	Top Orders			Raw Wool Orders			
	Prompt (mkg)	Forward (mkg)	Total (mkg)	Prompt (mkg)	Forward (mkg)	Total (mkg)	C.V.
Experiment One	1.8	10.3	12.1	2.6	16.7	19.3	0.23
Base Distribution	3.0	9.1	12.1	4.7	14.7	19.4	0.31
Experiment Two	4.8	7.3	12.1	7.9	11.6	19.5	0.42
Experiment Three	6.1	6.1	12.1	10.0	9.6	19.6	0.50
Experiment Four	7.3	4.8	12.1	12.0	7.6	19.6	0.59

The relative monthly volumes and variability of prompt and forward top and raw wool orders are presented in Table 3. From Table 3 it is evident that as the volume of prompt (forward) orders for top increases the volume of raw wool orders placed for prompt (forward) delivery increases proportionately. This would seem to suggest that in the longer run, the distribution of raw wool orders placed by month-of-delivery closely follows, on average, the placement of orders for top by delivery date. This would imply that in the long run at least, processors tend to reflect top order demand directly in purchasing additional raw wool supplies at auction. In this sense, in the long run, the rate of raw wool purchases is directly related to the rate of placement of top orders, modified by the level of backlog and inventories held within the system. In the short term however, this relationship between orders for top and orders for raw wool may be more attenuated.

The nature of the short run relationship between top and raw wool orders was investigated on the basis of sample correlations between the volume of forward orders for top and raw wool and the volume of prompt orders for top and raw wool. These sample correlations are reported in Tables 4 and 5. The correlations between prompt orders for top and raw wool and the correlations between forward orders for top and raw wool are relatively weak. However, it is interesting to note that as the proportion of prompt orders for top increased the actual correlation between prompt top and prompt raw wool orders increased, while the correlation between forward top and forward raw wool orders decreased.

Table 4: Sample Correlation between Prompt Orders

		Prompt Top Orders
Prompt Raw Wool Orders	Experiment One	-0.01
	Base Distribution	0.21
	Experiment Two	0.31
	Experiment Three	0.34
	Experiment Four	0.33

Table 5: Sample Correlation between Forward Orders

		Forward Top Orders
Forward Raw Wool Orders	Experiment One	0.48
	Base Distribution	0.48
	Experiment Two	0.46
	Experiment Three	0.43
	Experiment Four	0.40

This would seem to suggest that in the short run, the relationship between the proportion of prompt orders for top and raw wool and the relationship between forward orders for top and raw wool is affected by the management functions performed by the topmaker. This was further investigated on the basis of an analysis of sample correlations between the level of new orders for top, order backlog, top stocks, top production, raw wool stocks and raw wool orders, the results of which are presented in Grace (1991).

In short, this investigation revealed that as the proportion of prompt and forward changed, the sample correlations between the v. .ous management variables also changed. This implied that, assuming that the distribution of new orders by delivery date is not constant through time, then the correlations between these variables will also vary over time. Accordingly, any attempt to model demand for wool at auction as a linear function of these variables is likely to prove difficult. Since the covariation between these explanatory variables (stocks, backlog, production etc...) varies through time then the partial correlations between these variables are also unlikely to remain constant. Consequently, for a linear demand equation, the parameter estimates for variables such as top stocks, backlog, greasy wool stocks and production are unlikely to be stable.

This would seem to suggest that parameter estimates, and therefore elasticities of demand, obtained from past models in which demand for wool has been expressed as a linear function of either mill consumption (e.g. Campbell et al. 1980) or stocks held by processors (e.g. McKenzie et all 1969; Smallhorn 1973; Carland and Pagan 1979; Richardson and Beynon 1980). are unlikely to be stable. Such models, in light of the results obtained in this study, would appear to be misspecified with respect to functional form.

In conclusion, it appears that in specifying demand functions for wool, a system of equations reflecting the management of orders and wool by the processing firm may be required to adequately capture the complexity of the process of transmission of demand. However, with the unavailability of data pertaining to the placement of orders by delivery date, the specification of such a system will prove difficult. In short, the collection of delivery dates for orders placed with wool processing firms appears to be a crucial pre-requisite to undertaking a more thorough investigation of demand for wool at auction.

Implications and Conclusions

The purpose of this study has been to provide some insights into how the distribution of new orders for top placed by month-of-delivery affects the volume, variability and distribution by delivery date of orders placed at auction. The results of the study indicate that as the proportion of prompt top orders increases relative to forward orders, the variability of total raw wool purchases also increases. Conversely, an increase in the proportion of forward top orders has the effect of reducing variability in the volume of raw wool purchases. This occurs despite the fact that the total volume of monthly purchases is unchanged.

Of particular interest was the discovery that in the long run, on average, the distribution of new orders by month-of-delivery closely approximates the distribution of raw wool orders in terms of the relative proportions of prompt and forward. However, in the short run, this relationship is weak. In a long-run analysis of demand for wool it may not be inaccurate to assume some fixed lag structure between orders for top and orders for greasy wool but, in the short-term, such an assumption would be erroneous. The results of this study clearly indicate that the relationship between orders for top and orders for greasy wool is neither linear, nor constant over time.

These results have important implications for the specification of demand functions for wool. The sample correlations between the volume of stocks, backlog, production and raw wool purchases vary as the distribution of new orders varies over time. Accordingly parameter estimates of these variables, when included in linear demand functions, are likely to be unstable. If an accurate description of short-term demand for wool at auction is to be contemplated, it is imperative that some consideration be given to incorporating aspects of the management of top processing operations in such work.

In conclusion, the level of demand for top, as depicted by the placement of new orders by month-of-delivery, may be modified to such an extent by existing management practices and processing operations that demand for raw wool at auction may be only weakly related to the demand for top. Consequently, the estimation of demand functions for wool will continue to be incomplete and somewhat naive if the impact of management continues to be ignored.

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Appendix A

Simulation Model of a Topmaking Firm

The simulation model that was used in the study is presented in this Appendix. Variable names are defined at the conclusion of the Appendix.

Total Production of Top

(A.1) $$PR = PR^{o} + PR^{s}$$

where,

Production Rate

(A.2) $$PR = (UFO - DBLOG) / TABL + AOR$$

Production to Order

(A.3) $$PR^{o} = (UFFO - DBKORD) / TABL + AOR^{o}$$

Production to Stock

(A.4) $$PR^{s} = (DTSTK - TSTK_{-1}) / TASTK + AOR^{s}$$

Total Purchases of Raw Wool at Auction

(A.5) $$RWOR = RWOR^{o} + RWOR^{s}$$

where,

Raw Wool Order Rate

(A.6) $$RWOR = (DRWS - GWSTK_{-1}) / TARWS + APR$$

Forward Raw Wool Order Rate

(A.7) $$RWOR^{o} = (UFFO - DFRWS) / TABL + APR^{o}$$

Prompt Raw Wool Order Rate

(A.8) $$RWOR^{s} = (DPRWS - GRSTK_{-1}) / TARWS + APR^{s}$$

Total Sales of Top

(A.9) $$SALES = SALES^{o} + SALES^{s}$$

where,

Forward Sales of Top

(A.10) $$SALES^{o} = PR^{o} - (TORD - TORD_{-1})$$

Prompt Sales of Top

(A.11) $$SALES^{s} = PR^{s} - (TSTK - TSTK_{-1})$$

Total Stocks of Finished Top

(A.12) $TOPSTK = TORD + TSTK$

where,

Forward Stocks of Finished Top

(A.13) $TORD = TORD_{-1} + PR^{o} - SALES^{o}$

Prompt Stocks of Finished Top

(A.14) $TSTK = TSTK_{-1} + PR^{s} - SALES^{s}$

Total Stocks of Raw Wool

(A.15) $GWSTK = GORD + GRSTK$

where,

Forward Stocks of Raw Wool

(A.16) $GORD = GORD_{-1} + ARRIVALS^{o} - USE^{o}$

Prompt Stocks of Raw Wool

(A.17) $GRSTK = GRSTK_{-1} + ARRIVALS^{s} - USE^{s}$

Backlog of Unfilled Orders

(A.18) $UFO = BLOG_{-1} - TOPSTK_{-1}$

Backlog of Forward Unfilled Orders

(A.19) $UFFO = BKORD_{-1} - TORD$

Usage of Raw Wool in Production to Order

(A.20) $USE^{o} = (1/0.625) * PR^{o}$

Usage of Raw Wool in Production to Stock

(A.21) $USE^{s} = (1/0.625) * PR^{s}$

Arrival of Forward Raw Wool Purchases

(A.22) $ARRIVALS^{o} = RWOR^{o}_{-2}$

Arrival of Prompt Raw Wool Purchases

(A.23) $ARRIVALS^{s} = RWOR^{s}_{-2}$

Desired Backlog of Unfilled Orders

(A.24) $DBLOG = K1 * AOR$ or APR

Desired Backlog Of Forward Unfilled Orders

(A.25) $DBKORD = K1 * AOR^{o}$

Desired Finished Top Stocks

(A.26) $DTSTK = K2 * AOR^{s}$

Desired Raw Wool Stocks

(A.27) $DRWS = K4 * APR$

Desired Forward Raw Wool Stocks

(A.28) $DFRWS = K3 * APR^{o}$

Desired Prompt Raw Wool Stocks

(A.29) $DPRWS = K4 * APR^{s}$

Variable Names

Endogenous variables

AOR	=	Average new order rate
AOR^{o}	=	Average rate of placement of forward orders
AOR^{s}	=	Average rate of placement of prompt orders
APR	=	Average production rate
APR^{o}	=	Average production rate to order
APR^{s}	=	Average production rate to stock
$ARRIVALS^{o}$	=	Arrivals of forward raw wool supplies
$ARRIVALS^{s}$	=	Arrivals of prompt raw wool supplies
BKORD	=	Backlog of unfilled forward orders
BLOG	=	Backlog of unfilled orders
DBKORD	=	Desired backlog of forward unfilled orders
DBLOG	=	Desired backlog of unfilled orders
DRWS	=	Desired raw wool stocks
DFRWS	=	Desired forward raw wool stocks
DPRWS	=	Desired prompt raw wool stocks
DTSTK	=	Desired prompt top stocks
GORD	=	Forward raw wool stocks
GRSTK	=	Prompt raw wool stocks
GWSTK	=	Raw wool stocks
K1	=	Months of average orders covered by backlog
K2	=	Months of average orders covered by top stocks
K3	=	Months of average production covered by backlog
K4	=	Months of average production covered by raw wool stocks
PR	=	Rate of production
PR^{o}	=	Rate of production to order
PR^{s}	=	Rate of production to stock
RWOR	=	Raw wool order rate
$RWOR^{o}$	=	Forward raw wool order rate
$RWOR^{s}$	=	Prompt raw wool order rate
SALES	=	Sales of top
$SALES^{o}$	=	Forward sales of top
$SALES^{s}$	=	Prompt sales of top
TABL	=	Time taken to adjust backlog
TARWS	=	Time taken to adjust raw wool stocks

TASTK	=	Time taken to adjust top stocks
TOPSTK	=	Inventory of finished stocks of top
TORD	=	Inventory of forward stocks of top
TSTK	=	Inventory of prompt stocks of top
UFFO	=	Forward unfilled orders held in backlog
UFO	=	Unfilled orders held in backlog
USE^o	=	Usage of greasy wool in production to order
USE^s	=	Usage of greasy wool in production to stock

Exogenous variables

NO	=	New orders for top

Appendix B

Dynamic Responses of Endogenous Variables to Changes in Order Demand

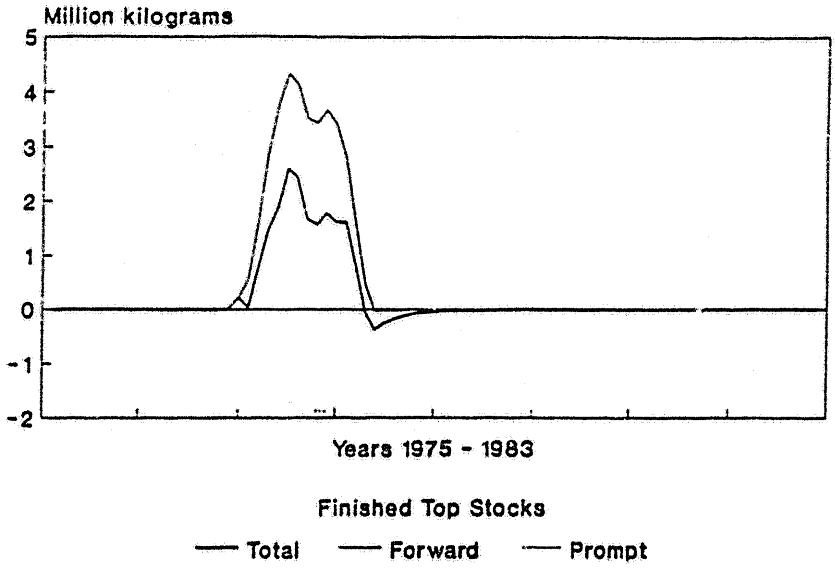

Figure 10 : Stocks Response to Increase in Forward Orders

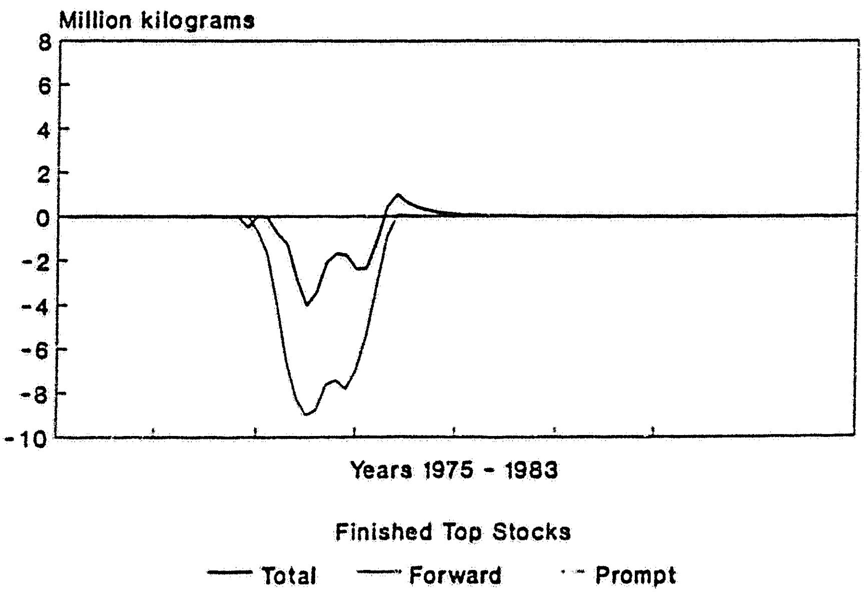

Figure 11 : Stocks Response to Increase in Prompt Orders

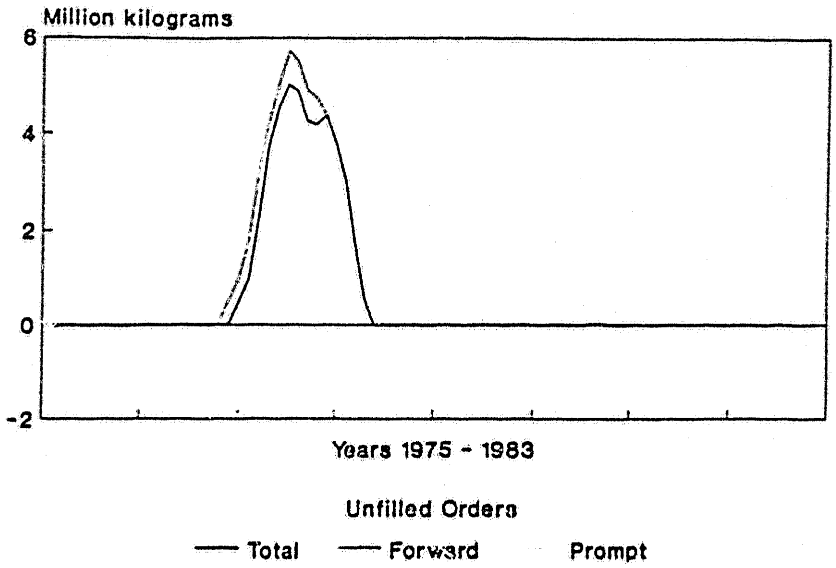

Figure 12 : Backlog Response to Increase in Forward Orders

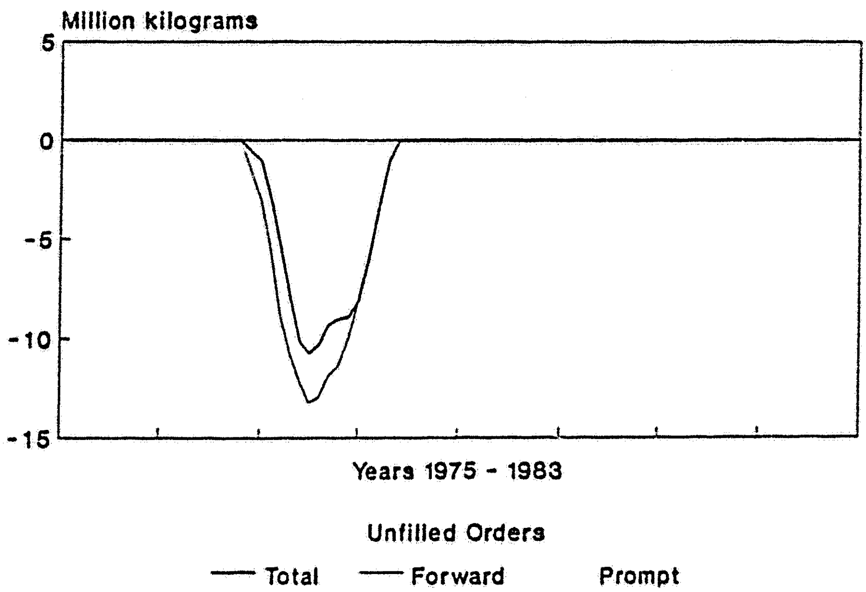

Figure 13 : Backlog Response to Increase in Prompt Orders

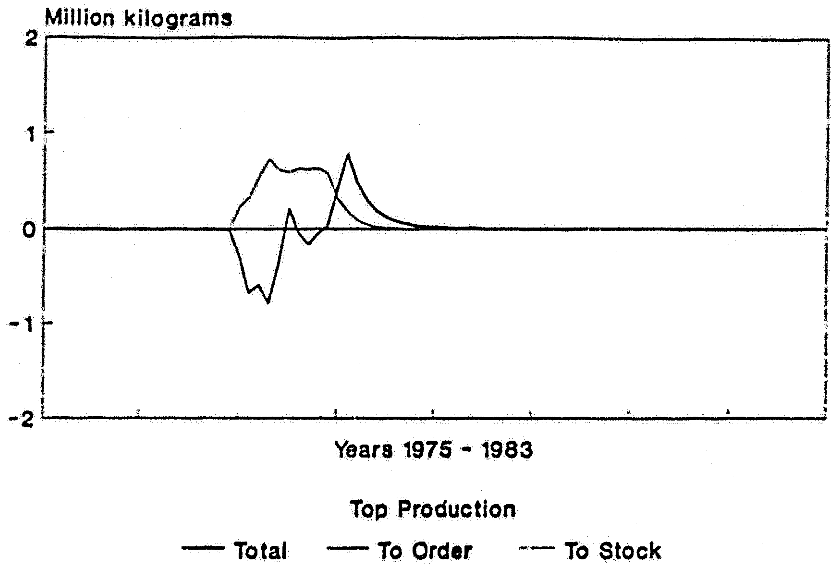

Figure 14 : Output Response to Increase in Forward Orders

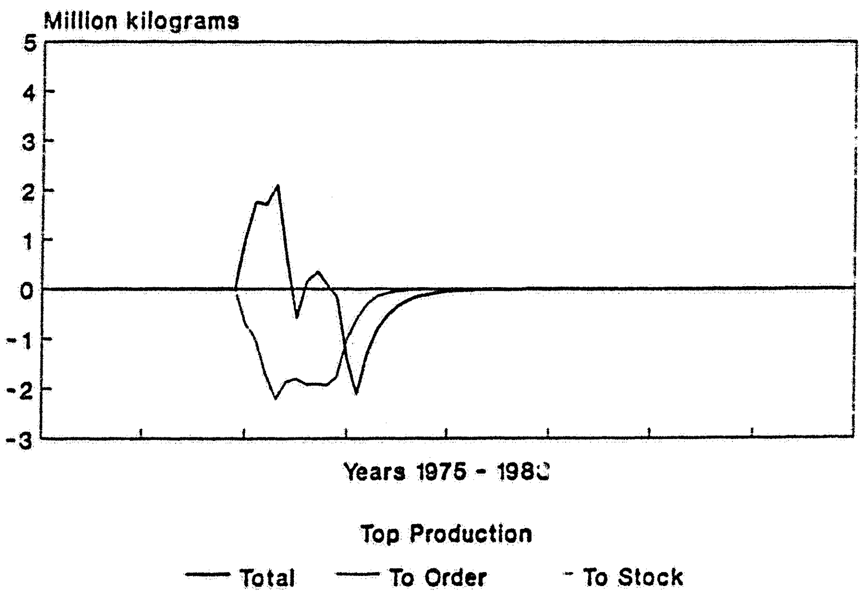

Figure 15 : Output Response to Increase in Prompt Orders

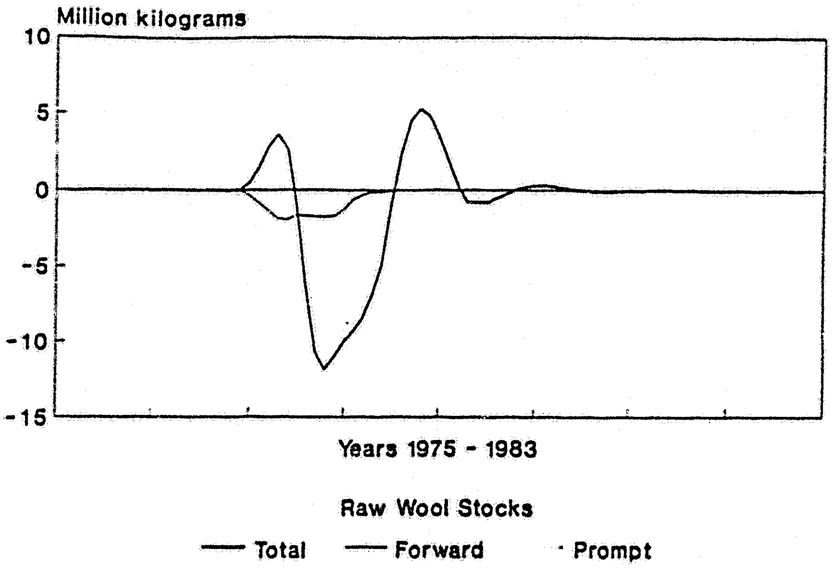

Figure 16 : Stocks Response to Increase in Forward Orders

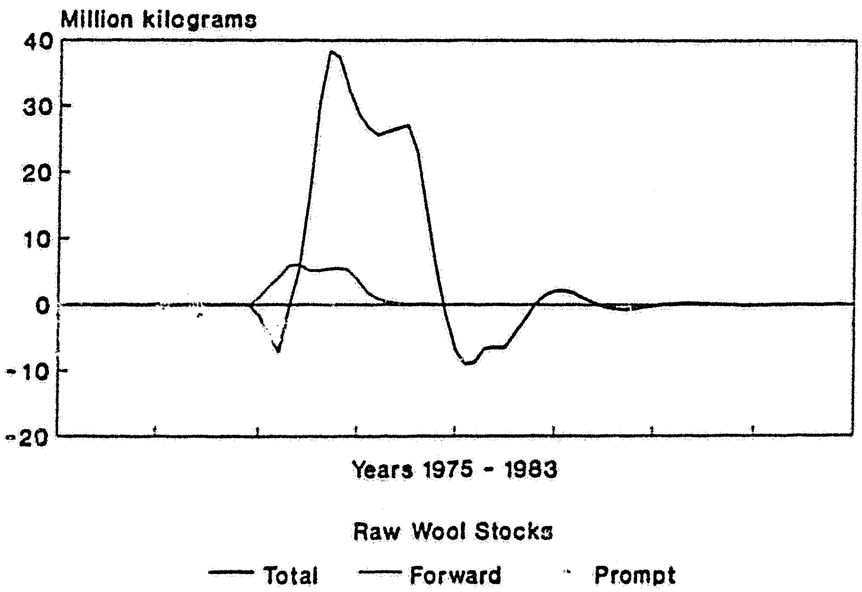

Figure 17 : Stocks Response to Increase in Prompt Orders

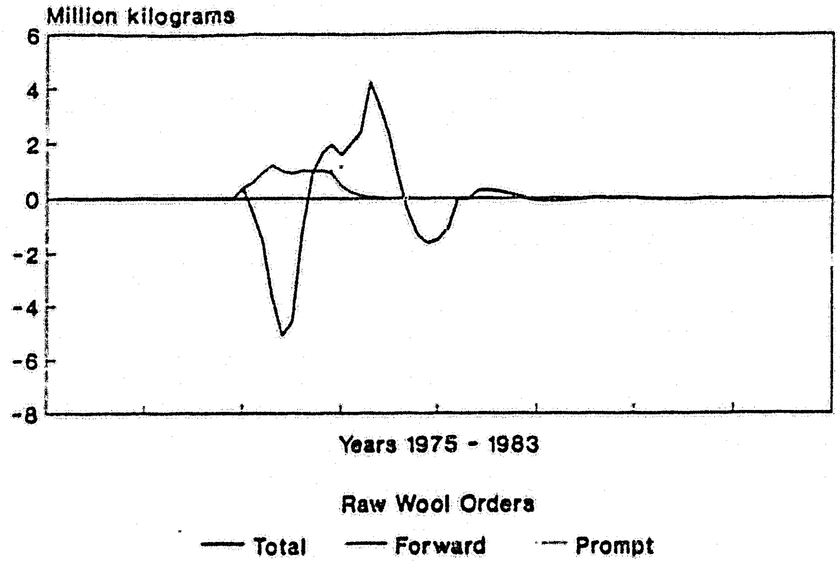

Figure 18 : Orders Response to Increase in Forward Orders

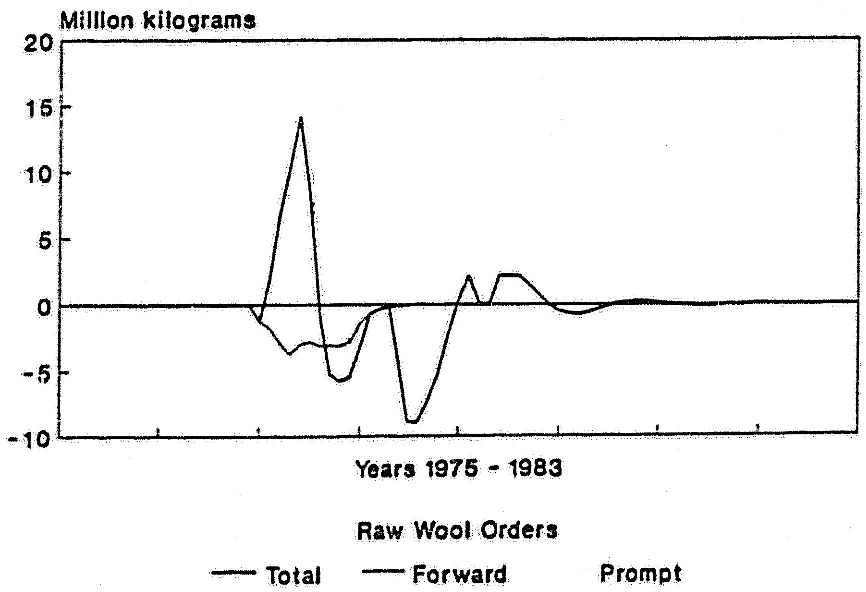

Figure 19 : Orders Response to Increase in Prompt Orders