Chapter 7

APPLICATIONS OF A CONTINGENCY APPROACH TO THE EXPLORATION OF AGRICULTURAL DECISION ENVIRONMENTS

7.1 Introduction

The evaluation of the contingency model developed in Chapter 6 will hinge on subjective judgements as to the contribution that the model makes to our understanding of the decision environment and producers' interaction with that environment, along with estimates of the model's ability to aid practicioners in the design of effective data/information/decision structures for agriculture.

Within this chapter two specific applications of the model will be considered. First the externalisation of components of the data/information/decision process will be discussed. Second, the model's structure will be used to develop the structured consideration of the potential for, and the limitations on, the aiding of inferencing.

However, prior to embarking on these more specific applications of the model, brief consideration is presented of the model's significance to both the prescriptive approach and the descriptive approach to agricultural decision theory.

A simplistic application of the model presented in Chapter 6, in its contingent form, would lead investigators to the conclusion that all agricultural decisions could be expected to be conducted at very low levels of cognitive complexity. This assertion can be based on the observation that market reporting and information services currently operating in the Australian agricultural environment generally fail to provide any objective market outcome distribution information. Hence, the application of decision structures applicable at the third, and possibly at the second level of problem conceptualisation, which are contingent on the availability of measures of variability, would be seen as impossible.

The radical alternative to this view is to confer upon the farmer, generally unaided by any form of computerisation and generally in the absence of the cognitive schemata of probability theory, the capacities of "Homo bayesian" and to assume the availability of the raw data necessary.

Even if we accept hypothetically the existence of such a species, the contingency model, as proposed, would then require the demonstration of the existence of an efficient objective data collection and transmission system which failed to elicit, to any major degree, ambiguity in "Homo bayesian" before it could be claimed that the "correct" environment for efficient "rational" decision making actually existed.

Hence, the question becomes whether farmers operate as simpletons, as Homo bayesians or somewhere in between? The answer to this, given the assumption that the most limiting factor will signify the point at which problem conceptualisation and or structuring is constrained , would be achieved through the regression along the problem conceptualisation sequence (Figure 6.9) until all the requirements for a particular decision structure were met. However, satisficing techniques, such as the subjective estimations of variables or the application of non-Bayesian inferencing techniques may overcome some of the constraints encountered. An example of such behaviour is the subjective estimation of triangular probability distributions as surrogate outcome probability distributions, as advocated by Mill and Longworth (1975a) in their development of "Stochastic Computerised Activity Budgeting".

With regard to the descriptive approach to modeling agricultural decision making, the placing of particular decision models within a contingency framework may aid in the understanding of the rationale for the observed behaviour of producers. However, a contingency approach, given a recognition of the dynamic nature of the decision environment and the impact of change in contingent limitations on decision making, will allow the practitioner to explore the potential change in decision behaviour.

Hypothetically, producers observed as being largely dependent on heuristic decision structures, having been exposed to basic education in a more structured decision conceptualisation, can be considered to have had one of the constraints on their behaviour removed. However, unless other environmental changes have occurred such as the development of appropriate data generation, summation and communication systems, observed behaviour may be predicted to remain unchanged.

As stated earlier, the identification of impediments or aids to the efficient utilisation of data/information in the information/decision process, as producers move towards a more structured approach to decision making, was seen as a primary goal for the development of a contingency model of market information utilisation in agricultural decision making. This avenue of application of the model is addressed in the following section, leaving aside questions as to whether a specific level of decision structuring or, in fact, the attainment of the economist's nirvana, rational decision making, is of economic benefit to the producer.

7.2 Decision Process Externalisation

An omnipotent body viewing agricultural data flows and decision making, within the framework of the model proposed, could rationalise the removal of parts of the process from producers' control and operation. Such constraints as limitations on memory capacity, stimuli differentiation, influences on cue saliency, limited learning capacities in probabilistic environments and a general preference to develop deterministic models of the environment would all provide a rationale for such an action. However, probably the most cogent argument for the provision of assistance in the acquisition and processing of economic data lies in the recognition of the time constraints faced by the average producer.

This omnipotence, in reality the "market", has already to an extent made this decision, as illustrated by the collective establishment of market data standards, data generation and data transformation in many industries. The opportunity costs associated with individual producers observing and reporting national markets has resulted in these parts of the process being external to the producer. Where such costs are reduced, in the case of local markets, the process may be undertaken by the producer, ie. internalised.

Additionally, in most cases movement away from unaided nonanalytical decision making towards more structured decision making increases both the data demand and the associated costs, subsequently increasing the economic imperative to externalise parts of the information/decision process as a way of gaining economies of scale.

The theoretical conceptualisation of data bases, management information systems, decision support systems and expert systems can be seen to allow the progressive externalisation of agricultural decision making. Detailed descriptions of the conceptual elements of automated information and decision structures are provided in Chapter 4, while Figure 7.1 provides an overview of the concepts and the functional format of these systems in a structure similar to that used in the model.

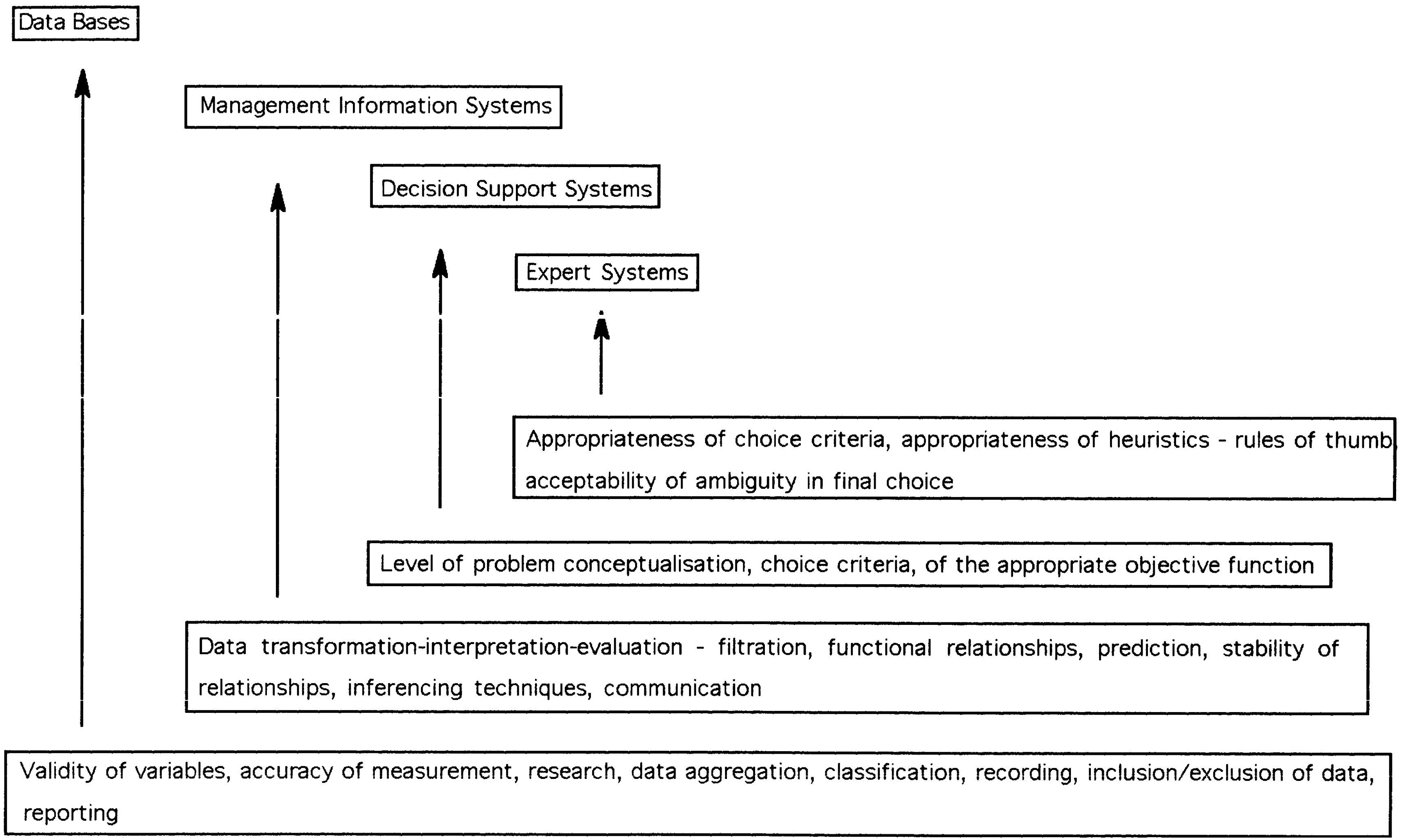
The conceptual significance of a progression from data bases to expert systems can be seen in the degree to which the system deals with questions relating to the environment, semantic memory, expectations and decision structures (Figure 6.1). The "function" (Gum and Blank 1990) of a data base can be seen to be associated entirely with the environment and the interface between the environment and the decision maker's semantic memory. Data Bases externalise such "processes" as search, data storage, message encoding, variable definition, sampling and recording.

The functions (prediction and inferencing) of Management Information Systems furthers the degree of externalisation as they undertake such processes as environmental modeling, selection of appropriate inferencing techniques and data processing. These functions involve the domains of semantic memory and expectations under the model proposed.

The Decision Support Systems functions of "value" and "choice" associated with the domain of decision structures, involve the externalisation of processes such as decision structuring, objective function selection and the cognitive processes associated with data processing within the decision structures.

The inclusion of "action" in the function associated with Expert Systems (Figure 4.3) extends the system beyond that under consideration in this model. As initially stated the primary interest of this study has been the scope of, and the meeting of the demand for, data/information of various decision structures. In effect, the study had been restricted to the fifth step or the fourth step in decision making as described by Barnett (1967) and Makeham and Malcolm (1988) respectively, action and responsibility-taking being additional steps in both models.

Figure 7.1 Concepts of Decision Automation



The recognition of the relationship between domains described (environment, semantic memory, expectations and decision structures)and the functions of Data Bases, Management Information Systems, Decision Support Systems and Expert Systems allows the systems engineer to identify some of the concepts and constraints which they must deal with in any attempt to aid the producer towards increased structuring of decisions. By way of illustration, a Data Base designer must address the fundamental data concepts and such constraint as limitations on data storage, scale, sampling techniques and the appropriateness of descriptive statistics (Figure 6.4) should they wish to develop an efficient system.

As with other systems (Data Bases, Management Information Systems, Decision Support Systems and Expert Systems), ultimately the external body must engage in communication with the producer serviced, such that they will also be required to consider the concepts and constraints associated with the act of communication (Figure 6.6). For example, a Data Base or other sources, of which producers hold low-level perceptions regarding source reliability or usefulness (5.6), may suffer in effectiveness regardless of the objective credibility of their output.

In the case of process externalisation the systems engineer is required to address questions relating to the domains of operation, functional concepts and associated environmental limitation. However, in addition, constraints beyond the operational system will need to be considered. A data and communication system, generating statistically correct measures of a stochastic environment is of little net value to producers who lack the appropriate cognitive schemata.

In such cases systems engineers will need to address the question of obtaining the best results given some major constraints down-stream of their involvement in the overall decision making process. Here, the contingency model is held to be of significant value. The following section, which deals with the use of the model in the aiding of inefficient (in a theoretical sense) inferencing structures, is an example of such an application of the model.

7.3 Aiding of Inferencing / Integration

To a traditional economist, inferencing efficiency is measured against the Bayesian standard. However, to a producer it is not the correctness of the integration technique that is of interest; it is the ability to forecast with an acceptable degree of accuracy that is of concern (4.3.2). In a producer welfare sense, a "rule of thumb" which is correct 90% of the time is probably as valuable as, if not more so than, the most statistically correct data integration and forecasting Management Information System. This is so especially if the latter has associated with it significant costs (financial and cognitive) or should it generate significant dissonance due to the producer's ignorance of the computative structures.

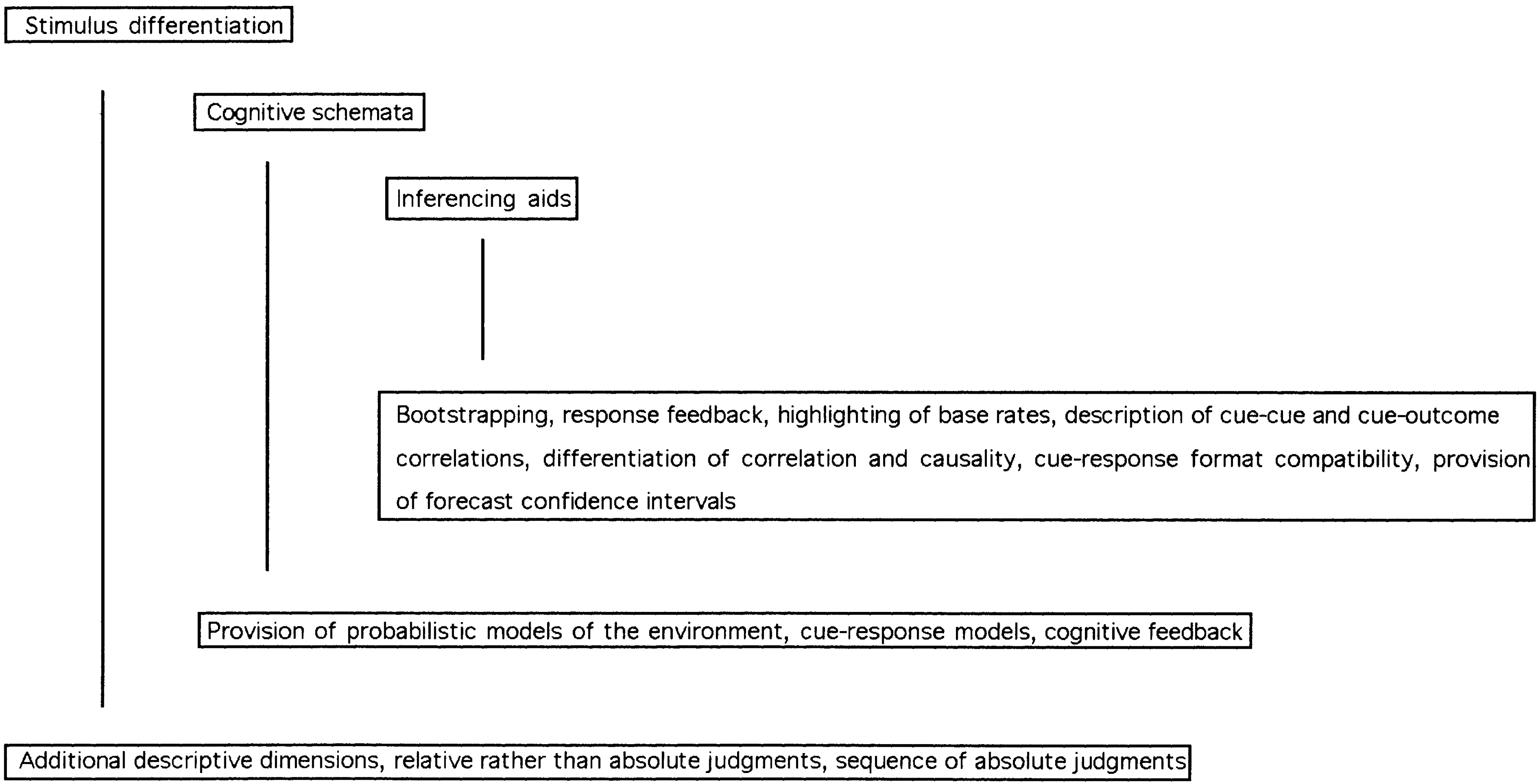
The omnipotent body struck with the desire to aid producers' inferencing may follow two paths. First, it may assist producers' cognitive activities or, second, it may relieve the producer of such activities, by externalising the activities through the provision of forecast information. The latter course, discussed in 4.3, is appropriate if the decision maker accepts such forecasts as information rather than data (as by the definitions adopted in this thesis) for direct entry into decision structures.

Where decision makers do not place utter faith in the forecasts of an external agency, such forecasts become yet another piece of data to be integrated in the producers' own forecasts. The systems engineer faced with this situation, must address questions relating to the nature of, and constraints on, the producers' inferencing capacities.

The selection of an inferencing technique becomes the entry point to the model, this act being contingent on a number of environmental factors (Howell and Burnett 1978, Nakajima and Hotta 1988). Down-stream questions relating to the optimal presentation of data/information, message encoding/decoding, internal (semantic memory) data storage formats, along with questions relating to the environmental constraints on the provision of data/information, require consideration. The selection of up-stream decision structure may be constrained by the inferencing structure selected and the format of the judgement generated (Beach, Barnes and Christensen-Szalanski 1986, McIntosh and Dorfman 1990).

The engineer's initial step would be to quantify the nature of the inferencing capacity exhibited by the producers concerned. The cognitive capacities and activities involved in human inferencing have been discussed in 3.3. The ability of producers to differentiate and process stimuli become the next concern on the down-stream side, while the

Figure 7.2 Aiding Of Integration/Inferencing



maintenance of cognitive control (Slovic and Lichtenstein 1971, Davis and Olson 1988)represents a major constraint on the up-stream side.

This interdependence of the process of selection amongst the cognitive schemata available for inferencing tasks, and the need to consider factors such as stimulus differentiation and external inferencing aids, is illustrated in Figure 7.2. The intent here is not to provide the definitive matrix of factors influencing the selection of inferencing techniques and ultimate success of the data integration step in the data/information/decision process. Rather, it is to illustrate the need for a holistic view of the data/information/decision process.

7.4 Summary

The use of the model format to aid in the consideration of the constraints on decision automation and the provision of assistance to producers in their inferencing tasks presented in this chapter is illustrative of the contingency approach to understanding decision behaviour.

The very environment, task and individual specificity of the approach makes it difficult to prove, or disprove, the validity of the approach in an empirical sense. However, some attempt at model validation is considered to be of value. The following chapter reports on some observations of a group of producers, their agricultural decision environment and their decision behaviour. The associated analysis is intended to examine the degree to which certain factors are associated with differences in observed behaviour.

The holistic model of the data/information/decision process presented in chapter six defies rigorous testing; however, a number of investigations have been undertaken in an attempt to partially validate the model. Descriptions of these investigations and discussions of the results obtained are presented in the concluding chapter of this thesis. The validation of the contingent approach taken to exploring producers' interaction with their decision environments can only be judged by its contribution to the improvement of producers' decision making efficiency. At this time we can only seek circumstantial evidence to support the notion that agricultural decision behaviour is in fact constrained by environmental factors associated with the concepts delineated.

Chapter 8

DESCRIPTION OF AN AGRICULTURAL DECISION ENVIRONMENT FROM A CONTINGENCY PERSPECTIVE

8.1 Introduction

The literature review undertaken in this dissertation has led to the development of a hypothesised holistic model of the data/information/decision chain as described in Chapter 6, with the application of this model to the aiding of inferencing and the externalisation of parts of the decision process being discussed in Chapter 7. The intent of this chapter is to report the findings of a survey of a group of producers which examined parts of the producers' decision environment, attitudes to factors determining production decisions, knowledge of decision aids, access to computing facilities, perceptions of their own and external agencies' predictive capacities and their exhibited decision behaviour.

The survey and analysis is essentially an exploration of the decision environment and the decision behaviour of a group of producers, conducted using the hypothesised holistic model of the data/information/decision chain as the frame of reference on which to conduct the investigation. As such the work reported is not considered to be a strict validation of the hypothesis; rather it was conducted in the hope of unearthing some confirmatory signs of constraint driven decision behaviour.

The issues of critical importance to this study are the differences in decision behaviour patterns exhibited by respondents and the relationship between such behaviours and the differences in individual respondents' capacities and the differences in their decision environments.

The survey results and analysis presented in this chapter, along with a general discussion presented in Chapter 9, represent nothing more than an attempt to identify signs, within a very limited data set, which are either confirmatory or disconfirmatory of the 'Contingency Approach' hypothesis put forward in this thesis. That is, the analysis asks of the data, are there signs of producers' decision actions being limited by their operating environment, or alternatively are there signs of producers' decision behavioural patterns being independent of their operating environment?

8. 2 Survey, Group and Procedure

A mail survey of producers in the Dubbo, Peakhill and Parkes regions of NSW was conducted in the Autumn of 1993. The questionnaire and covering letter (appendix 1) was sent to 1500 rural mailing addresses within this area. The utilisation of a direct mailing service provided by Australia Post enabled the random distribution of this material.

The questionnaire had previously (Spring 1992) been tested with 56 farmers, who make up the General Council of the NSW Farmers' Association. The feedback received resulted in major rewriting of the questions so as to make the intent of the questions more clear. The results from this trial were considered inappropriate for further analysis, as the group was considered to vary significantly from the general farming populace in both education and in their exposure to a far wider range of information sources.

The questionnaire was structured to gain a broad understanding of the individual's farming operation through questions relating to the scale and diversity of the operation, their sources of information, their exposure to other income generating exercises, their access to and knowledge of decision aids, their use pattern of these aids, the factors they considered influenced their production decisions, their confidence in price and production forecasts, their major sources of information and their education levels. The questionnaire was purposely structured to gain a broad understanding of the respondents' operations, capacities and behaviour and as such contained questions which could be considered redundant to the specific task of proving or disproving the contingency model proposed. The eliciting of this peripheral information was undertaken to allow for the exploration of potential significant drivers of decision behaviour, such as enterprise size, which were in themselves not seen to relate directly to the contingency model.

The questionnaire was sent by direct mail drop to all farm mail boxes in the survey area. This approach was adopted as it was considered that mailing lists derived from such sources as Stock and Station Agents, Banks or various publications would seriously bias the responses to questions relating to sources of information. The direct mailing approach provided an unbiased distribution of the questionnaire, however, the response rate was considered somewhat disappointing as only 94 surveys were returned in total, of which 89 were ultimately of use. The majority of the discarded surveys were returned blank.

A considerable disadvantage of the approach adopted was the inability to send reminder notices. It was not possible, due to the inability to trace responses and non-responses, to determine whether this low response rate has or has not introduced some bias into the sample.

The coded responses from sample (n=89) used in the further analysis undertaken have been reported in Appendix 2.

8.3 Analysis Method

A number of analytical approaches were used to explore the relationships between environmental variables and decision behaviour. The analysis of results presented below were conducted with the aid of the computer package "SPSS for Windows, Release 6.0" (Norusis 1993).

8.4 Decision Behaviour Groups

The initial concern of this analysis was to establish whether or not producers in the sample were utilising different decision aids/structure. Subsequent analysis concentrated on the delineation of any relationships between the decision behavioural groups observed and variations in the producers' decision environment.

Respondents were questioned as to their knowledge, utilisation, or past use of a number of decision aids/structures: gross margins (GM), cash flow budgets (CF), linear programming (LP) and decision theory (Dec)(Questions 12, 13 and 14; Appendix 1). Of these aids gross margins and cash flow budgets were the only ones to be used by a significant number of respondents (see Table 8.1).

Table 8.1

Decision Structuring Awareness / Utilisation

	GM	CF	LP	Dec
Percentage of Respondents; *				
Familiar with	79.8	89.9	13.5	14.6
Discontinued use of	5.6	2.2	3.4	0.0
Currently using	55.1	83.1	2.2	4.5

* % of total sample

Due to the very limited numbers of respondents using either linear programming or decision theory it was decided to concentrate the analysis on the factors influencing the utilisation, or rejection, of gross margins and cash flow budgets. Respondents were grouped on their current use of gross margins (CRGM = 0 (non-use), 1 (use)) and their current use of cash flow budgets (CRCF = 0 (non-use), 1 (use)).

The division of respondents, 89 in total, on the basis of decision structure use gave the following cell sizes: (CRGM = 0) 40, (CRGM = 1) 49, (CRCF = 0) 15 and (CRCF = 1) 74 .

Respondents' use of cash flow budgets was further differentiated by their reported frequency of review. Those who reported reviewing their budgets on a biannual basis, or more frequently, were classified as belonging to cash flow group one (CFG = 1), annual review resulted in allocation to CFG = 2 with non-users being allocated to CFG = 3 (note, this is the same group of respondents as CRCF = 0 (non-use)). The segregation of annual reporters was deemed necessary to enable the exploration of the hypothesis that many of these respondents may only be using cash flow budgeting as a means of reporting to financial institutions, a hypothesis supported by personal observations and Stevens's 1991 comments (4.2.6).

The division of respondents, 89 in total, on the basis of frequency of cash flow use gave the following cell sizes: (CFG = 1) 60, (CFG = 2) 14 and (CFG = 3) 15 .

It is recognised that there is significant redundancy in the presentation of results and analysis relating to CRCF groups where CFG groups 1,2 and 3 are reported. However, this division is maintained for the following reasons;

1) significant volumes of survey work have previously reported producers' use/non-use of cash flow budgets and as such the maintenance of the division here should allow more efficient comparisons with this work;

2) the descriptions of the constraints significant in the observed use/non-use of cash flow budgets behaviour is considered to be of critical importance to organisations such as banks, wishing to facilitate the adoption of cash flow budgeting amongst producers;

3) the reporting and analysis of the three CFG groups, enables a better understanding of the constraints relating to the non-use, the hypothesised use for reporting purposes and decision aiding use of this decision structure.

A cross tabulation analysis of the relationship between the utilisation of the various decision aids was performed. The results of this analysis and associated statistics are reported in Tables 8.2 and 8.3.

Table 8.2

Cross Tabulation Current Cash Flow (CRCF) x Current Gross Margins (CRGM)

	Count / Row Pct / Col Pct / Tot Pct	CRGM non-use	use	Row Total
CRCF	non-use	14 93.3 35.0 15.7	1 6.7 2.0 1.1	15 16.9
	use	26 35.1 65.0 29.2	48 64.9 98.0 53.9	74 83.1
	Column Total	40 44.9	49 55.1	89 100.0

Chi-Square	Value	DF	Significance
Pearson	17.07167	1	.00004

Minimum Expected Frequency 6.742

Table 8.3

Cross tabulation Cash Flow Group (CFG) x Current Gross Margins (CRGM)

	Count / Row Pct / Col Pct / Tot Pct	CFG 1	2	3	Row Total
CRGM	non-use	18 45.0 30.0 20.2	8 2.0 57.1 9.0	14 35.0 93.3 15.7	40 44.9
	use	42 85.7 70.0 47.2	6 12.2 42.7 6.7	1 2.0 6.7 1.1	49 55.1
	Column Total	60 67.4	14 15.7	15 16.9	89 100.0

Chi-Square	Value	DF	Significance
Pearson	20.45140	2	.00004

Minimum Expected Frequency 6.292

Significant associations between the use of gross margins and cash flow budgets were observed. Of the respondents who use gross margins only 2% failed to report some level of cash flow budget utilisation (Table 8.2). Similarly, those respondents who utilise cash flow budgets were far more likely to use gross margins than those who do not use cash flow budgets (Table 8.2).

It is clear from Tables 8.1, 8.2 and 8.3 that within this group the awareness of and utilisation of decision structuring aids is mainly to gross margins analysis and cash flow budgeting, with significant correlations existing between the use or non-use of these aids. Further the results indicate a limited level of problem conceptualisation to Humphreys and Berkeley's first level (Level 1) within the decision aids used.

Limited cell sizes observed for the higher conceptualisation level decision aids (linear programming and decision theory) utilisation made further analysis of these observations statistically problematic. Hence, the following analytical approach was adopted. An initial explorative phase of the analysis was undertaken, aimed at determining the between decisional behaviour grouping (CRGM 0 (non-use)/1(use), CRCF 0 (non-use)/1(use) and CFG 1/2/3) environmental differences. This phase of the analysis deals with measures associated with enterprise size (area of land, stock numbers, cropping area, etc), sources of income and complexity. Differences in producers' knowledge of decision structures and their capacity to utilise the decision structures under consideration were the next areas of interest. This was followed by consideration of the identity of the primary motivators of cash flow budgeting behaviour and the relationship between banks as primary motivators and respondents' indebtedness. Between-group differences in decision factor weights made up the fourth area of analysis. Next was consideration of producers' confidence in their own predictions and those of external forecasting agencies. Finally, differences in respondents' market and financial information sources were considered.

Subsequently, factor analysis and discriminant function analysis was applied to the data set in an attempt to gain some understanding of the association between observed or independent variables (IV) referred to as "predictors" (such as knowledge of decision aids, confidence in external forecasts, etc) and decision behaviour groupings (here : CRGM = non-use/use, CRCF = non-use/use, and CFG = 1/2/3)), the dependent variables (DV) referred to as grouping variables.

8.5 Enterprise Differences

The initial step was to determine whether or not there were any major enterprise differences between the various decision behaviour groups. The group means are reported in Table 8.4 and Table 8.5. The results presented have been derived from the answers to questions 1, 2, 3 and 4 of the questionnaire (Appendix 1).

Table 8.4

Variable (Enterprise Descriptive) Means by Current Gross Margins (CRGM)

Variable	crgm = non-use	crgm = use
Sheep	2068.4	2224.4
Cattle	88.2	72.3
Pigs	71.1	12.4
Goats	3.3	4.5
Scrp (ha)	13.8	17.0
Wcrp (ha)	205.6	452.0
prwool (%)	30.6	35.9
prsheep(%)	7.7	7.5
prlambs (%)	6.6	5.0
prcattle (%)	25.6	12.3
prwcrp (%)	24.1	34.2
prscrp (%)	0.5	3.8
farm (%)	80.1	86.0

Scrp (ha): area of summer crop; Wcrp (ha): area of winter crop; pr(wool, sheep, lambs, cattle, wcrp, scrp) (%): percentage of farm income derived from (wool, sheep, lambs, cattle, wcrp, scrp); farm (%): percentage of gross income derived from farming

Table 8.5

Variable (Enterprise Descriptive) Means by Cash Flow Group (CFG) and Current Cash Flow (CRCF)

Variable	crcf=use	cfg=1	cfg=2	cfg=3 (crcf =non-use)
Sheep	2315.6	2379.4	2283.0	1358.6
Cattle	73.1	74.9	72.1	111
Pigs	40.4	22.0	49.7	31.0
Goats	4.6	0.0	6.9	0.8
Scrp (ha)	18.0	16.9	18.5	3.7
Wcrp (ha)	379.9	572.1	281.8	150.6
prwool (%)	33.9	35.8	33.0	31.3
prsheep(%)	8.4	10.2	7.5	3.1
prlambs (%)	4.5	3.9	5.0	11.1
prcattle (%)	16.3	15.4	16.8	27.9
prwcrp (%)	31.7	29.9	32.6	19.7
prscrp (%)	2.7	2.8	2.6	3.3
farm (%)	8.5	90.2	81.6	77.7

Scrp (ha): area of summer crop
Wcrp (ha): area of winter crop
pr(wool, sheep, lambs, cattle, wcrp, scrp) (%):
percentage of farm income derived from (wool, sheep, lambs, cattle, wcrp, scrp)
farm (%): percentage of gross income derived from farming

Table 8.6 shows the level of significance, calculated on the basis of separate univariate F-tests, of observed between-group differences of means of the enterprise descriptive variables.

Table 8.6

Decision Behaviour Groupings x Enterprise Descriptors

Variable	CFGs (1/2/3)	CRCF (non-use/use)	CRGM (non-use/use)
Sheep	ns	ns	ns
Cattle	ns	ns	ns
Pigs	ns	ns	ns
Goats	**	ns	ns
SCRP(ha)	ns	ns	ns
WCRP (ha)	ns	ns	ns
PRWOOL (%)	ns	ns	ns
PRSHEEP (%)	ns	ns	ns
PRLAMBS (%)	**	*	ns
PRCATTLE (%)	ns	ns	*
PRWCRP (%)	ns	ns	*
PRSCRP (%)	ns	ns	ns
PROTH(%)	ns	ns	ns
FARM (%)	ns	ns	ns
ENT	ns	ns	ns

(**): significant at the 1% level
(*): significant at the 5% level
(ns): not significant

8.5.1 Enterprise differences between decision behavioural groups

Of the 15 enterprise description variables measured in the survey, only 3 of these variables exhibited significant differences (see Table 8.6) between decision behavioural groups (current gross margins non-user/user (CRGM 0/1), current cash flow non-user/user (CRCF 0/1) and cash flow groups (CFG 1/2/3)).

The very small means involved and the presence of two large holdings (outliers) suggests that, whilst a significant difference in the mean numbers of goats owned by the cash flow groups was identified, it would be difficult to suggest a causal relationship between goat ownership and decision behaviour.

The significantly higher percentage of gross farm income derived from lambs sales reported by cash flow non-users is difficult to explain. However, again the relatively small contribution of this source of income, relative to other enterprises, suggests that the value of the variable as either a behaviour predictor or a driver of decision behaviour would be very questionable.

The nature of the association between the observed significant difference in the percentage of income derived from cattle in the current gross margin non-user group compared to the current gross margins user group and the utilisation of this decision aid is difficult to ascertain from the data available. However, differences in predictive capacity associated with cattle enterprise do appear. These differences are discussed later.

Further, these results need to be treated with caution due to the potential for over inferencing on the basis of separate univariate F-tests, because of an inflated Type 1 error rate, a function of the testing of multiple related hypotheses. Multivariate tests of significance on this data produced Wilks values in excess of 0.05 for all three decision behavioural goupings, confirming the concern relating to over inferencing in the separate univariate F-tests.

In summary there appears to be little in these results to support any hypothesis suggesting any causal linkage between enterprise characteristics and between-group differences in voluntary analytical decision behaviour.

8.6 Capacity

One of the postulates of the hypothesised contingency approach centres around the adverse effects that excessive cognitive strain, generated by both the effort of conceptualisation and process calculations required, described as cognitive and computational effort by Bettman, Johnson and Payne (1990) (see section 2.3.4), has on the adoption of complex decision structures. If credence is to be given to this view it is rational to expect a greater degree of up-take of structured analytical decision aids by producers who possess or have access to greater computational and conceptualisation capacities.

The resources and time available were inadequate to examine thoroughly the potential for between-group variation associated with human capacities for information processing, problem conceptualisation and decision processing (see Chapter 3). However, some questions relating to features (indicative of decision processing capacities) of both the decision maker and their decision environment were included in the survey.

Respondents were questioned as to the highest level of education attained by any individual involved in their farm management (ELEV)(question 27 Appendix 1). Four levels of education were specified: primary school, secondary school, college and graduate, coded 1 to 4 respectively. Cumulative distribution data for CRGM non-use (0) and use (1) groups, CRCF non-use (0) and use (1) groups and CFGs are presented in Figures 8.1, 8.2 and 8.3 respectively.

Elev vs CRGM (cumulative distribution)

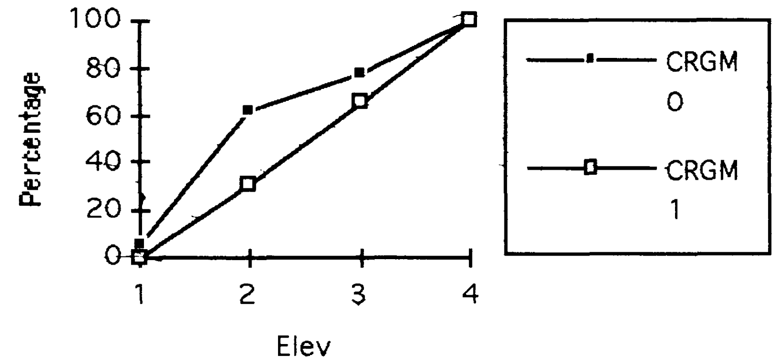


Figure 8.1 Cumulative Distribution of Education Groups by Current Gross Margins Non-use/use (CRGM 0/1) Groups

Elev vs CRCF (Cumulative distribution)

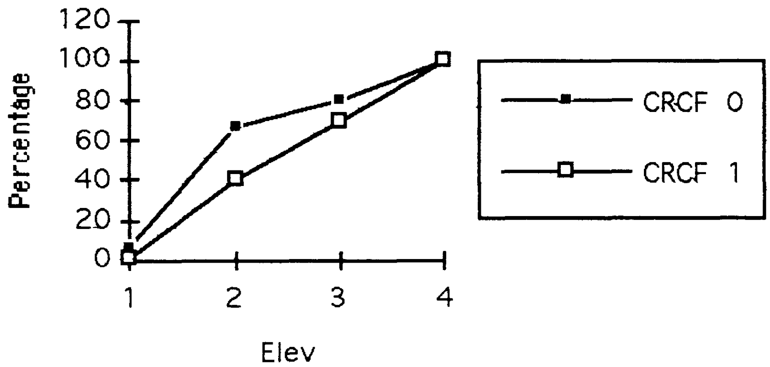


Figure 8.2 Cumulative Distribution of Education Groups by Current Cash Flow Non-use/Use (CRCF 0/1) Groups

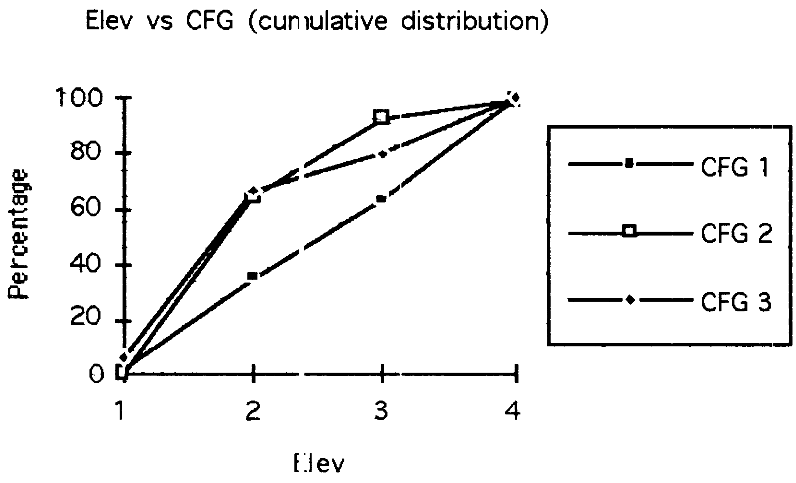


Figure 8.3 Cumulative Distribution of Education Groups by Cash Flow Groups (CFG)

Crosstabulation of the results showed an increased propensity for respondents in Elev groups 3 and 4 to be current users of gross margins and current users of cash flow budgets. The level of cash flow review also appears to be higher in Elev groups 3 and 4 with 73.9% and 84.6% (respectively) of these groups being in CFG 1.

However, the strength of the association between Elev and use of gross margins and cash flow budgets use is difficult to determine from this limited sample; the number of cells with expected frequency below 5 exceeded 20% in all cases, thus no cross tabulation statistics have been reported.

Apart from this general measure of education, producers were questioned as to their familiarity (unfamiliar = 0, familiar =1) with the following business planning aids, Gross Margins (GM), Cash Flow Budgets (CF), Linear Programming (LP) and Decision Theory (DEC) (question 12 Appendix 1). Cross tabulation of responses with respondents groupings CRGM non-use/use, CRCF non-use/use and CFG 1/2/3 and associated Chi-Squared statistics were calculated. The levels of significance of any association between decision structure familiarity and decision behaviour groupings are reported in Table 8.7.

Table 8.7

Decision Behaviour Groupings x Decision Structure Familiarity

Variable	CRGM (non-use/use)	CRCF (non-use/use)	CFG (1/2/3)
GM	**	**	**
CF	**	**	**
LIN	ns	ns	ns
DEC	ns	ns	*

Pearson Chi-Squared significance levels

(** significant at the 1% level, * significant at the 5% level, ns not significant)

Two factors, 1) availability of management staff and 2) availability of computer facilities on farm, were also considered potential influences on decision behaviour. No significant association between the number of people involved in the management of farms and the decision behaviour groupings was detectable in the sample.

Of the respondents, 31% owned computers (COMP = 1) with 67.7%, 87.1% and 80.6% of computer owners being in CRGM = use, CRCF = use and CFG =1 groups, respectively. It is of interest to note that only 6.5% and 12.9% of computer owners fell into CFG 2 and 3 respectively. However, the absence of on-farm computing facilities is clearly not a complete bar to the utilisation of these decision structures as 57.1%, 63.5% and 58.3% of respondents in CRGM = use, CRCF = use and CFG =1 groups respectively did not own a computer.

8.6.1 Capacity and analytical decision structure utilisation

The lack of knowledge of a particular decision structuring aid (which is taken to indicate the inability to conceptualise problems in terms of the particular decision aid) can be considered a primary constraint on producers adopting the particular aid. However, actual familiarity with an aid is no guarantee that the aid will be adopted in practice (see Table 8.1). The reported familiarity with gross margins and cash flow budgets was significantly higher than that of linear programming and decision theory with their reported use reflecting this pattern.

A positive association between familiarity with gross margins and cash flow budgets and the use of gross margins and cash flow budgets at the 1% level (Table 8.7) suggests that, where producers apply some form of analytical processing in their decision behaviour, they are inclined to become familiar with, and to utilise, gross margins and cash flow budget decision structures as a package. However, if cash flow budgets are used as a reporting tool, the use of gross margins as part of producers' management behaviour is less likely (Table 8.3).

The higher the general level of education, as measured in the survey, the higher the propensity for the individual to report the use of cash flow budgets and gross margin decision structures. Note the skewing to the right of the utiliser's lines in the cumulative distribution of education groups in Figures 8.1, 8.2 and 8.3.

These results, in conjunction with the positive association between computer ownership and the use of structured analytical decision aids (GM and CF), are held to support the view that it is rational to expect a greater degree of up-take of structured analytical decision aids by producers who possess or have access to greater computational and conceptualisation capacities. Hence, the possession of these conceptualisation and computational capacities can be said to remove some of the constraints on such decision behaviour. These results are held to indicate the possibility of a "capacity constraint" being significant in the voluntary decision behaviour of producers.

8.7 Equity and Cash Flow Motivators

Whilst this thesis is concerned in the main with the voluntary decision structuring behaviour exhibited by producers, it was recognised that some of the reported use of particular decision structuring techniques may not in fact be volitional behaviour. Table 8.3 indicated that there were apparent differences between groups differentiated on their frequency of review of cash flow budgets. It was hypothesised that banks and financial institutions were requiring producers to undertake cash flow budgeting as a reporting structure associated with the provision of loans.

This, if correct had the potential to corrupt and further analysis would be required should such compelled behaviour not be segregated from volitional behaviour.

Question 16 of the survey (Appendix 1) asked respondents to nominate the organisation that first encouraged them to use cash flow budgets. In considering these results, reported in Table 8.8 as the percentage of each group nominating a particular organisation, it is noted that several respondents nominated multiple organisations.

Table 8.8

Organisations Motivating Cash Flow Use by Decision Behaviour Groups
Percent Within Decision Structuring Group Nominating the Organisation as Prime Motivator

Motivators	CRGM = use	CRCF = use	CFG1	CFG2	CFG3
Department of Agriculture	10.2	9.5	8.3	14.3	0.0
Consultants	8.2	6.8	6.7	7.1	0.0
Banks/Financial Institutions	36.7	43.2	36.7	71.4	0.0
Accountant	24.5	25.7	28.3	14.3	0.0
Farmers	8.2	5.4	5.0	7.1	0.0
Education Institutions	14.3	12.2	15.0	0.0	0.0
Others	10.2	14.9	18.3	0.0	0.0

It can be observed in Table 8.8 that of all current cash flow users, 43.2% nominated banks as a prime motivator in their use of cash flow budgets and 71.4% of respondents in CFG = 2 nominated banks as being the first to encourage them to use cash flow budgets. Given this, it was considered fruitful to further explore the relationship between equity, decision behaviour and bank motivation of cash flow utilisation. Figure 8.4 presents the total sample percentages for each equity group (1 - no response to the question about equity levels, 2- equity less than 25%, 3 - equity between 25% and 50%, 4 - equity between 50% and 75%, 5 - equity between 75% and 100%, 6 - no debts) differentiated on the basis of Bank = 0 (banks not nominated as primary motivators of cash flow budget use) or 1(banks nominated as primary motivators of cash flow budget use).

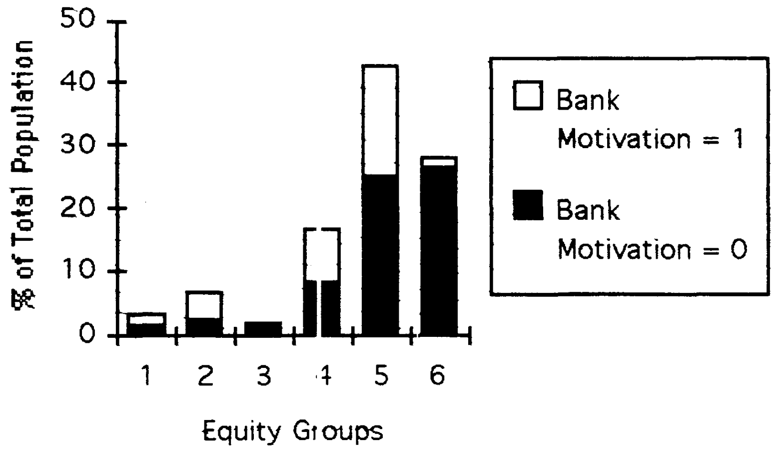


Figure 8.4 Bank Motivation of Cash Flow Budget Utilisation by Equity Group

The equity groups were collapsed into a bivariate variable debt (no debt/debt), to overcome analysis limitations imposed requirements to attain minimum expected frequencies within groups, with respondents in equity group 6 being assigned to debt variable = no debt and all other equity groups being classified as debt variable = debt. Cross tabulation of the data generated from this transformation and the Chi-Squared measure of association between debt classification and banks or financial institutions being nominated as the first to encourage the use of cash flow budgets is presented in Table 8.9.

Table 8.9

Cross Tabulation Bank x Debt

	Count Row Pct Col Pct Tot Pct	Debt no debt	debt	Row Total
Bank	non-motivator	23 40.4 92.0 25.8	34 59.6 53.1 38.2	57 64.0
	motivator	2 6.3 8.0 2.2	30 93.8 46.9 33.7	32 36.0
	Column Total	25 28.1	64 71.9	89 100.0

Chi-square	Value	DF	Significance
Pearson	11.79848	1	.00059

Minimum Expected Frequency 8.989

8.7.1 Banks, Debt and Compulsory Cash Flow Budgeting

Tables 8.8 and 8.9 along with Figure 8.4, clearly indicate that banks are significant initial motivators of the utilisation of cash flow budgeting by producers. Further, this motivation is positively associated with producers being in debt.

These results are taken to support the hypothesis that banks and financial institutions were requiring producers to undertake cash flow budgeting as a reporting structure associated with the provision of loans.

This is considered significant in the ongoing analysis of the impact of constraints on the decision behaviour exhibited by the portion of the sample representing the CFG =2 group.

The data generated relating to the primal motivation source for the adoption of these decision structuring aids is also considered significant in any attempt to change producers' behaviour; a subject outside the ambit of this work.

8.8 Decision Weights

There existed the potential to suggest that producers' voluntary use, or no use, of the decision structuring aids under consideration, was determined by the importance producers placed on a series of factors considered important in planning next year's production. That is, the level of importance placed on cash flow would be the sole determinant of the use or non-use of cash flow budgeting as a decision aid, irrespective of any other constraints or factors. In essence this is a potential predispositioning of producers to use particular decision aids.

Question 17 of the survey (Appendix 1) asked respondents to indicate on a scale of 1 to 10 (10 indicating the most important factors) the importance of a series of factors in the planning of next year's production. The scores indicated by individuals for each factor were divided by the sum of scores provided by the individual for all factors to give a weighted score, in the range 0 to 1 for the specific planning factor. (Not all factors were originally ranked by some respondents; where this occurred a score of 0 was placed on the unranked factor.) The average planning factor weights for CRCF =use, CFG=use, CFG=2 and CFG=3 (CRCF = 0) are recorded in Table 8.10.

Table 8.10

Planning Factors Means by Cash Flow Group (CFG) and Current Cash Flow (CRCF)

Variable	CRCF=use	CFG=use	CFG=2	CFG=3 (CRCF =non-use)
Rotation (weight)	0.173	0.153	0.183	0.186
Stock (weight)	0.169	0.147	0.180	0.203
Prices (weight)	0.151	0.119	0.167	0.113
Future prices (weight)	0.155	0.136	0.164	0.101
Current cash flow (weight)	0.167	0.165	0.167	0.105
Past production (weight)	0.154	0.116	0.174	0.174
Environment (weight)	0.128	0.099	0.144	0.073
Weather (weight)	0.088	0.054	0.105	0.060
Other factors (weight)	0.045	0.009	0.063	0.020

Table 8.11 presents the mean production planning weights for current gross margins = non-use and current gross margins = use groups.

Table 8.11

Planning Factors Means by Current Gross Margins (CRGM)

Variable	CRGM=non-use	CRGM=use
Rotation (weight)	0.1626	0.1477
Stock (weight)	0.1717	0.1404
Prices (weight)	0.1168	0.1287
Future prices (weight)	0.1175	0.1300
Current cash flow (weight)	0.1349	0.1358
Past production (weight)	0.1294	0.1320
Environment (weight)	0.0928	0.1015
Weather (weight)	0.0570	0.0647
Other factor (weight)	0.0173	0.0193

Table 8.12 shows the level of significance, calculated on the basis of separate univariate F-tests, of observed between-group differences of planning factor means by decision behavioural groups.

Table 8.12

Decision Behaviour Groupings x Planning Factors

Significance of Differences in Group Means

Variable	CRGM (non-use/use)	CRCF (non-use/use)	CFG (1/2/3)
Rotation	ns	*	ns
Stock	*	**	**
Prices	ns	ns	ns
Future Prices	ns	*	ns
Current cash flow	ns	*	*
Past production	ns	ns	ns
Environment	ns	*	ns
Weather	ns	ns	ns
Other factors	ns	ns	ns

significance levels

(** significant at the 1% level, * significant at the 5% level, ns not significant)

The data and analysis presented in Tables 8.10, 8.11 and 8.12 exhibits a pattern indicative of the potential predispositioning of producers, by reason of the importance they place on various factors influencing next year's production, towards the use or non-use of particular decision aids. On the basis of these patterns further analysis of the data was considered to be of benefit.

8.8.1 Factor analysis

To gain a further insight into the relationships underlying the decision weighting variables, Factor Analysis was considered to be an appropriate statistical technique. This technique attempts to explain observed correlations between a number of variables on the basis of a limited number of factors. The goal of using factor analysis is "to reduce a large number of variables to a smaller number of factors, to concisely describe (and perhaps understand) the relationships among observed variables, or to test theory about underlying processes" (Tabachnick and Fidell 1989, p. 600).

In the general model each variable is expressed as a linear combination of the factors generated. The model is written,

$$x_i = A_{i1} F_1 + A_{i2} F_2 + A_{i3} F_3 + \ \ldots\ + A_{ik} F_k + U_i$$

F's : are the common factors

U : is a unique factor

A's : are the coefficients used to combine the k factors.

> The factors are inferred from the observed variables and can be estimated as linear combinations of the variables (Norusis 1993, p. 49).

The four basis steps of factor analysis include (Norusis 1993, p. 50) :

> 1. In the first step, the correlation matrix for all variables is computed , ..
>
> 2. In the second step, factor extraction - the number of factors necessary to represent the data and the method for calculating them must be determined.
>
> 3. The third step, rotation, focuses on transforming the factors to make them more interpretable.
>
> 4. The fourth step, scores for each factor can be computed for each case. These scores can then be used in a variety of other analyses.

The decision weight data generated from the survey was subjected to factor analyses, using the computer program "SPSS for Windows Professional Statistics Release 6.0"

(Norusis 1993). The output generated is presented in Appendix 3.

Principal components analysis (PCA), a technique in which linear combinations of the observed variables are formed, was utilised as the method of factor extraction in this analysis .

> The goal of PCA is to extract maximum variance from the data set with each component. The first principle component is the linear combination of observed variables that maximally separates subjects by maximizing the variance of their component scores. The second component is formed from residual correlations; it is the linear combination of observed variables that extract maximum variability uncorrelated with the first component. Subsequent components also extract maximum variability from residual correlations and are orthogonal to all previously extracted components (Tabachnick and Fidell 1989, p. 626).

The number of factors used in the model was constrained to that number of factors that account for variances greater than 1 (eigenvalues greater than 1). Given the structure of the initial factors, it was not considered necessary to undertake any transformation of the factors for the purpose of interpretation. Therefore no factor rotation was undertaken. The scores for each factor were computed for each case and recorded in Appendix 2.

Four factors exhibited eigenvalues greater than 1, accounting for 69.6% of the variance in the original data. The individual case scores for these factors are recorded in Appendix 2 as Dwght-1, Dwght- 2, Dwght-3 and Dwght-4 respectively.

The factor loadings ("the coefficients use to express a standardized variable in terms of the factors" (Norusis 1993, p. 55)) for the three factors generated are presented in Table 8.13 .

Table 8.13

Decision Weight (Dwght) Factor Matrix

Variable	Factor 1 (Dwght-1)	Factor 2 (Dwght-2)	Factor 3 (Dwght-3)	Factor 4 (Dwght-4)
Rotation	-.68637	.07061	-.02961	-.53358
Stock	-.75437	-.45947	.00020	.11587
Prices	.47574	-.06245	.58024	-.17463
Future prices	.37418	.71796	.02515	-.33288
Current cash flow	-.09955	.67380	-.39331	.14717
Past production	-24277	.24470	.56023	.66571
Environment	.59562	-.07568	-.11397	.25881
Weather	.46565	-.60059	.12963	-.24135

The values in the Predictive Factor Matrix (Table 8.13) are the correlations between the predictive variables (Rotation, Stock, etc) and the factors. Tabachnick and Fidell (1989, p. 639) described the interpretation of such a matrix in the following terms, "the researcher decides on a criterion for meaningful correlation (usually .30 or larger), collects together the variables with loadings in excess of the criterion, and searches for a concept that unifies them".

8.8.2 Decision weight factors

The factor analysis of the decision weighting variables (Appendix 3) indicates that 4 factors account for 69.6% of the observed variation in the data.

The first factor generated exhibited high negative correlations with the Rotation and Stock variables and high positive correlation with the Price and Future price variables. High scores (Dwght - 1 variable Appendix 2) on this factor suggests a preparedness to change enterprise mixes in response to current and future price signals. Such individuals can be considered to be "economic maximisers".

The second factor exhibits high positive correlations with the Future prices and

Current cash flow variables. Individuals with high scores in this factor (Dwght -2 variable Appendix 2) can be considered to be producers constrained by cash flow problems.

Factor 3 (Dwght -3 variable Appendix 2) accounting for 15% of the variation in the data, exhibits high positive correlations with the Prices and Past production variables and a high negative correlation with Current cash flow. Producers with high scores on this factor could be considered to be non-cash flow dependent and reactive to their own experience, current (past) prices and past production experience.

The fourth factor (Dwght - 4), accounting for 12% of the variation observed, exhibits a high negative correlation with the Rotation and Future prices variables and a high positive correlation with the Past production variable. High scores on this variable are suggestive of a livestock producer, production orientated, reactive to past production experiences and realised prices.

The variables Environment, Weather and Other factor exhibited high (positive and negative) correlations with various factors; however, their absolute values, on average, were relatively low.

In summary the factor analysis approach adopted has enabled the representation of 8 variables by 4 factors, which provide a clearer insight to the drivers of production decisions purported by the producers surveyed. It is suggested that the first factor provides a measure of an individual propensity to be influenced by economic aspects in production decision making, the second by cash flow constraints, the third by past production experiences with the fourth factor identifying variance, in the data set, associated with animal production and an emphasis on past production experiences and realised prices in production decision making. These factors are used in the following analysis to explore the relative importance of this hypothesised predispositioning of producers to use particular decision aids.

8.9 Prediction Capacity

The application of structured decision aids is contingent on producers generating production and price forecasts to compile the requisite data sets. Chapter 3 discusses some of the constraints on human attempts at data integration and expectation formation, while Section 4.3 deals with the limitations on a range of forecasting techniques. It is suggested that should the individuals' perception of their capacity to generate or their acceptance of the validity of external predictions be positively associated with the utilisation of structured decision aids and vice versa, this would add to the evidence supporting the hypothesis contingent behaviour being exhibited by producers in their data/information/decision processing.

Question 18 of the survey (Appendix 1) asked respondents to indicate the degree of accuracy with which they believed they could predict a range of prices and input costs 12 months ahead. The costs specified in this question were; input costs sheep (INSH), input costs grain (INGR) and input costs cattle (INC). The levels of production specified were; production sheep (PSH), production gain (PGR) and production cattle (PC). Estimates of prediction of prices 12 months ahead included; wool prices (Wool), lamb prices (LMB), surplus sheep prices (CFA), grain prices (GR) and cattle prices (C).

Respondents were given four categories of accuracy from which to choose (plus or minus 5%, 10%, 15% and 25%). For the purpose of analysis, respondents indicating a belief in their accuracy of prediction were recorded as being in predictive categories 1 to 4, respectively. Where respondents failed to indicate a level of accuracy they were allocated to a fifth predictive category. Cumulative distribution graphs for each cash flow group (CFG = 1,2,3) are presented in (Figures 8.5 to 8.15).

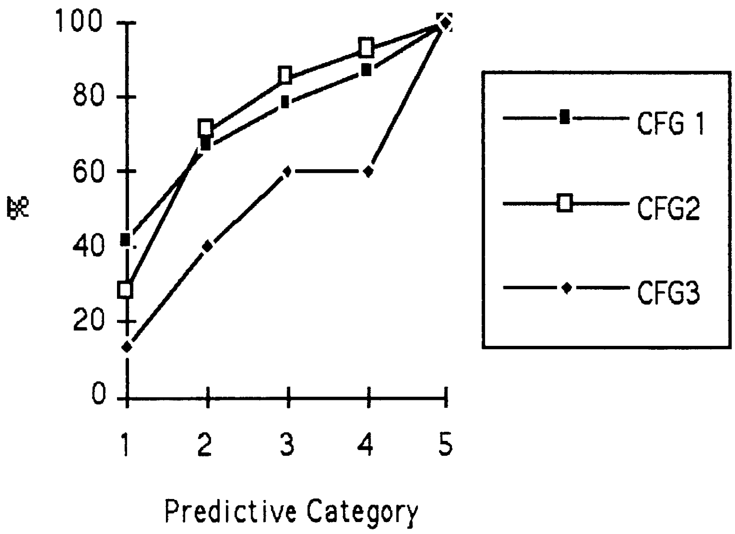


Figure 8.5 Predictive Capacity Input Costs Sheep (INSH) by Cash Flow Group (CFG)

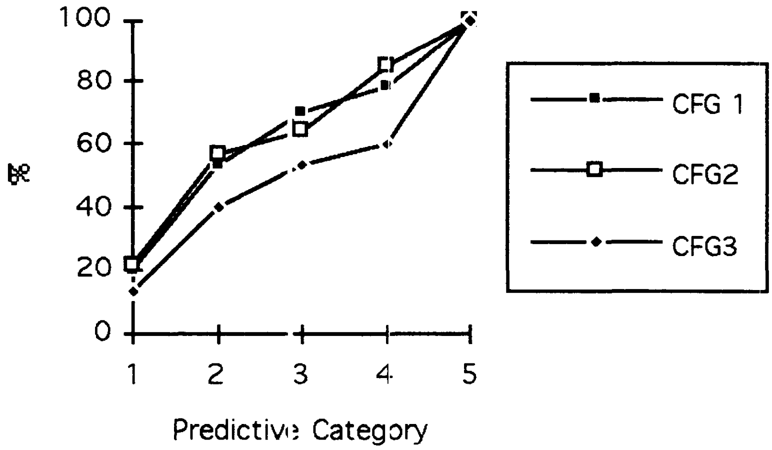


Figure 8.6 Predictive Capacity Input Costs Grain (INGR) by Cash Flow Group (CFG)

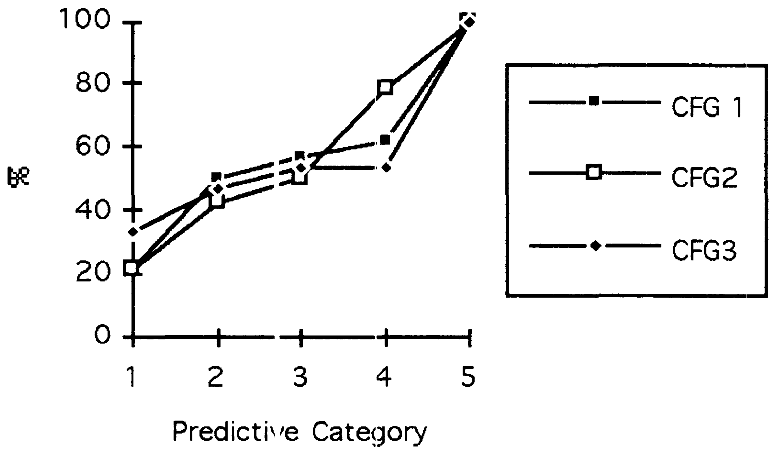


Figure 8.7 Predictive Capacity Input Costs Cattle (INC) by Cash Flow Group CFG

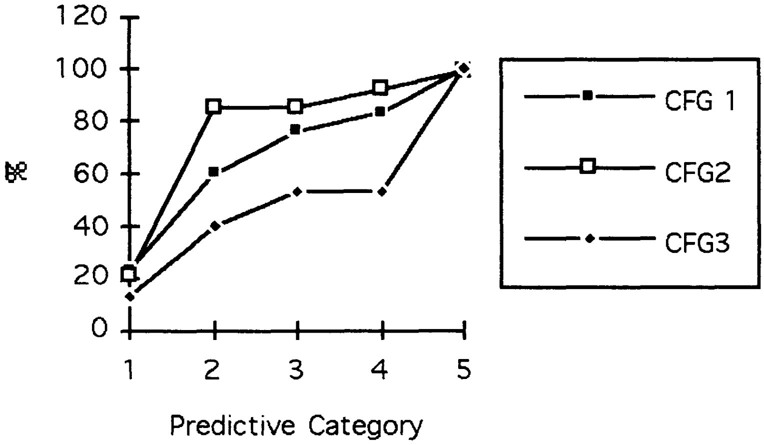


Figure 8.8 Predictive Capacity Production Sheep (PSH) by Cash Flow Group (CFG)

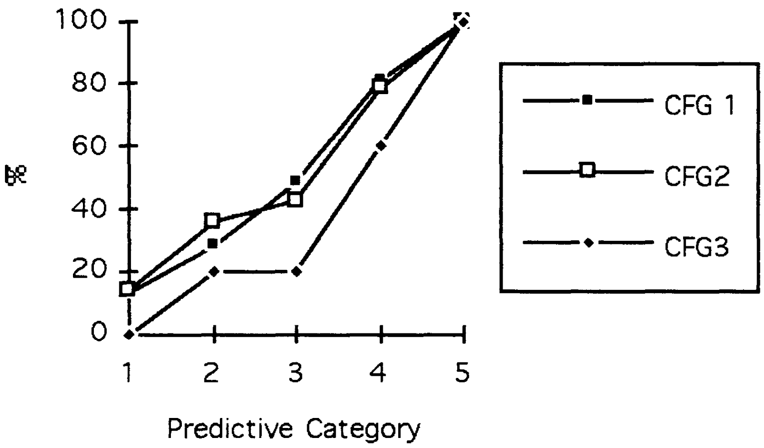


Figure 8.9 Predictive Capacity Production Grain (PGR) by Cash Flow Group (CFG)

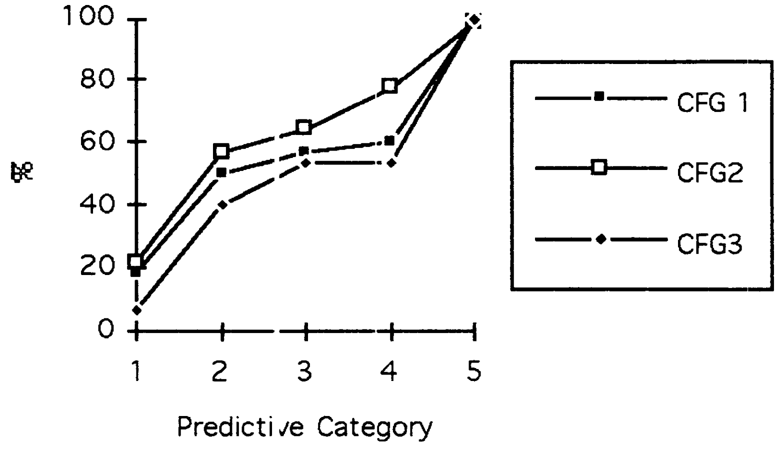


Figure 8.10 Predictive Capacity Production Cattle (PC) by Cash Flow Group (CFG)

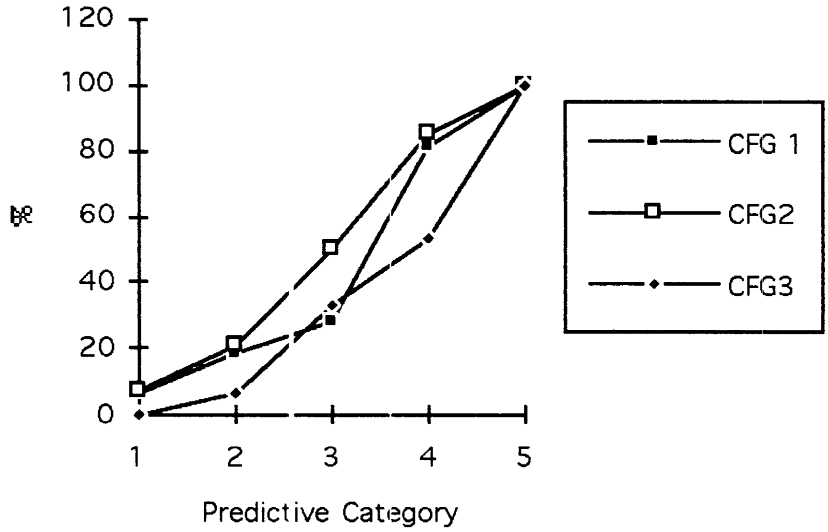


Figure 8.11 Predictive Capacity Wool Prices by Cash Flow Group (CFG)

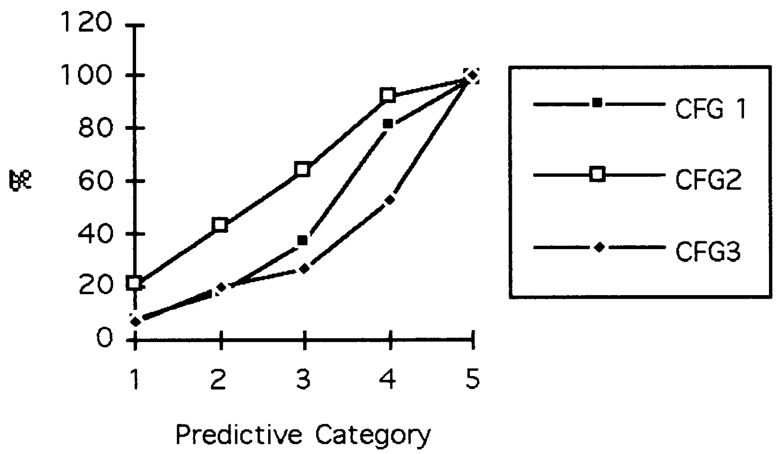


Figure 8.12 Predictive Capacity Cast For Age Sheep Prices CFA by Cash Flow Group (CFG)

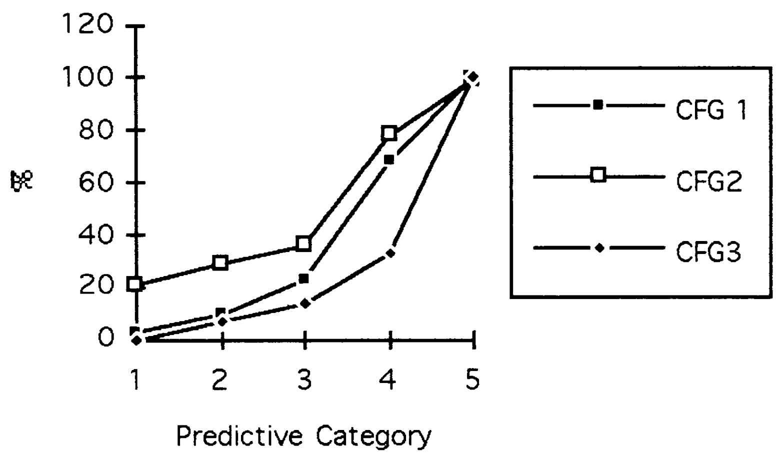


Figure 8.13 Predictive Capacity Lamb Prices (LMB) by Cash Flow Group (CFG)

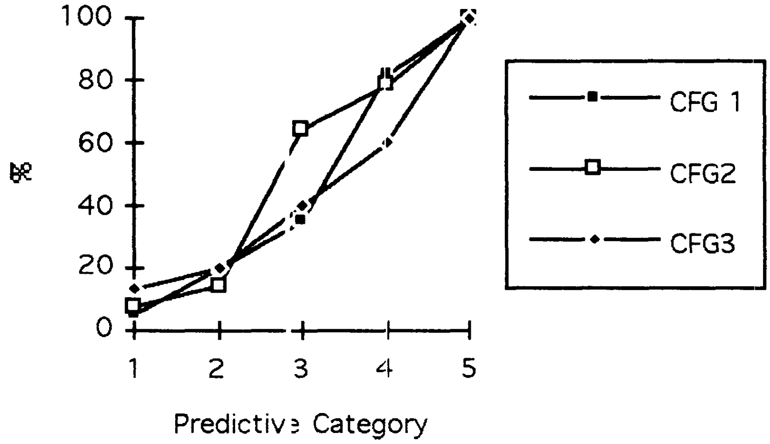


Figure 8.14 Predictive Capacity Grain Prices (GR) by Cash Flow Group (CFG)

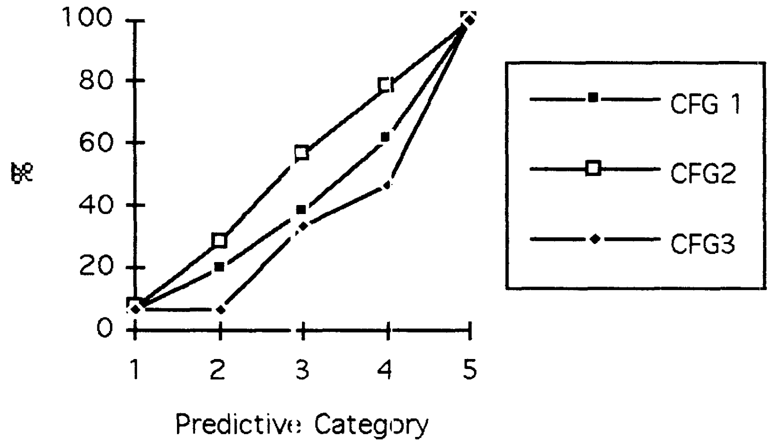


Figure 8.15 Predictive Capacity Cattle Prices (C) by Cash Flow Group (CFG)

Whilst producers' overall belief in the accuracy of their own predictive capacities was low, Figures 8.5 to 8.15 indicate that different decision groups believe that they can predict price, input costs and production levels to varying degrees of accuracy. However, in general all groups have greater confidence in their ability to predict production and input costs than prices. Further, in general CFG 1 and 2 groups reported greater confidence in their predictive capacities than CFG 3.

The limited sample size prohibited the application of cross-tabulation and associated statistical techniques to the analysis of the significance of this hypothesised predictive capacity constraint on volitional decision behaviour aspect. To gain a better understanding of the variation evident in the data it was considered advantageous to apply factor analysis to this data.

8.9.1 Predictive variable factor analysis

A factor analysis, using "principle components analysis" as the factor extraction method and the attainment of eigenvalues equal to or greater than 1 as the criterion for the acceptance of factors, was applied to the data relating to producer's perceptions of the accuracy of their own forecasts. Factor rotation was considered unnecessary in this case.

This analysis was conducted using "SPSS for Windows Professional Statistics Release 6.0" (Norusis 1993). The output of this analysis is presented in Appendix 3.

Three factors exhibited eigenvalues greater than 1, accounting for 73.3% of the variance in the original data. The individual case scores for these factors are recorded in Appendix 2 as pdict 1, pdict 2 and pdict 3 respectively.

The factor loadings for the three factors generated are presented in Table 8.14.

Table 8.14

Pdict Predictive Factor Matrix

Variable	Factor 1 (Pdict 1)	Factor 2 (Pdict 2)	Factor 3 (Pdict 3)
Input costs sheep	.71430	-.15154	.38490
Production sheep	.74576	-.20364	.40631
Wool prices	.73484	-.26423	-.39145
Lamb prices	.63219	-.35966	-.31686
Cast for age sheep prices	.74724	-.30532	-.42497
Input costs grain	.62198	-.07023	.61354
Production grain	.71027	-.01882	.10851
Grain prices	.70345	-.13025	-.05111
Input costs cattle	.38934	.86187	.04634
Production cattle	.46198	.81788	.00051
Cattle prices	.59507	.57989	-.35864

This analysis resulted in the identification of three principal factors (see Table 8.13 and Appendix 3). Factor 1 (pdict-1), accounting for 42.5% of the variation, with its high correlation to all variables, is taken to represent the underlying belief of producers in their ability to predict. Producers exhibiting high scores on this factor have a low regard for their own ability to predict input costs, production levels and product prices.

The second factor (pdict-2)(19.3% of the variation) clearly differentiates sheep/grain producers from cattle producers. High scores on this factor indicates a lack of confidence in predicting input costs, production levels and prices associated with cattle.

The third factor (pdict-3) (11.5% of the variation) identifies the disparity in the accuracy with which producers believe they can predict input cost and production as opposed to product prices. Producers' lack of confidence in their ability to predict sheep and grain input costs and production in sheep are positively associated with this factor.

8.10 Perceived Forecast Reliability

Producers confronted with the need to generate forecasts for inclusion in a decision structuring aid, yet exhibiting concern as to their own ability to generate such forecasts, have the alternate approach of adopting external forecasts available to them. Such a course of action would be seen to overcome the hypothesised predictive/forecasting constraint on the application of such decision aids.

Questions 19, 20, 21 and 22 of the survey (Appendix 1) were designed to gain some understanding of producers' perception of the reliability of the forecasts issued by major statutory bodies active at the time in Australian agriculture. These included the Australian Wool Corporation (AWC), the Australian Meat and Live Stock Corporation (AMLC), the Australian Wheat Board (AWB) and the Australian Bureau of Agricultural and Resource Economics (ABARE).

Respondents were asked to indicate the accuracy with which they believed that the body in question could predict prices 12 months ahead. Respondents were provided with 6 accuracy rankings to choose from plus or minus 5%, 10%, 15%, 25%, 50%, 100% and a category "do not know" to indicate their lack of knowledge on the subject. These response categories have been numbered 1 to 7 respectively for the purposes of recording and analysis.

The results obtained are presented as cumulative distribution graphs, Figures 8.16 to 8.19.

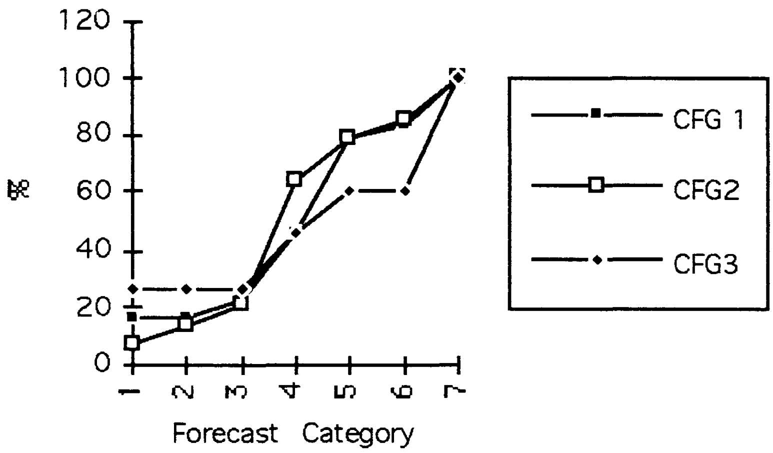


Figure 8.16 Producers' Perceptions of Australian Wool Corporation (AWC) Forecasts by Cash Flow Group (CFG)

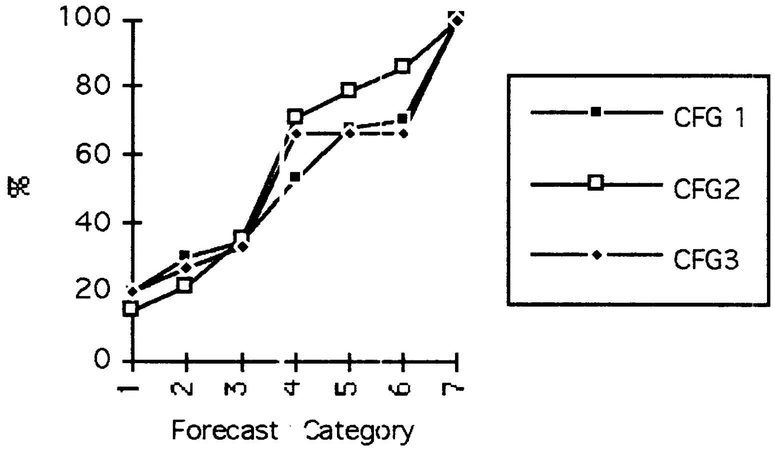


Figure 8.17 Producers' Perceptions of Australian Meat and Livestock Corporation (AMLC) Forecasts by Cash Flow Group (CFG)

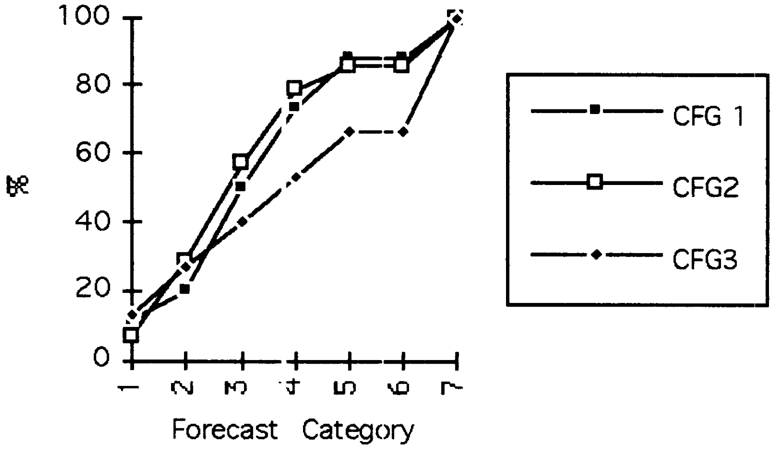


Figure 8.18 Producers' Perceptions of Australian Wheat Board (AWB) Forecasts by Cash Flow Group (CFG)

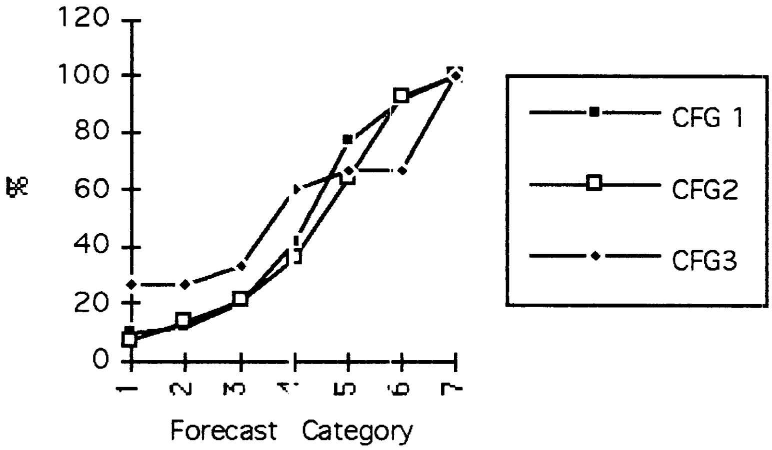


Figure 8.19 Producers' Perceptions of Australian Bureau of Agricultural and Resource Economics (ABARE) Forecasts by Cash Flow Group (CFG)

A comparison of producers' perceptions of AWC, AMLC, AWB and ABARE forecasts (Figures 8.16 to 8.19) with producers' perceptions of their own forecasting abilities, indicates that they , in general, viewed external forecasts as being less reliable than individual own estimates.

Examination of the cumulative distributions of cash flow groups perception of forecasts from AWC, AMLC, AWB and ABARE (Figures 8.16, 8.17, 8.18 and 8.19) show between-source differences in perceptions of forecast accuracy. These differences may reflect the nature of the market being forecast, factors such as the collapse of the "Reserve Price Scheme" for wool immediately prior to the survey or difficulties associated with the communication of the forecasts generated by different agencies.

As there was superficial indication of between group differences in the validity attached to external forecasts, factor analysis was again utilised in an attempt to further understand the nature of the relationships embedded in this set of data.

8.10.1 Forecast variables factor analysis

A factor analysis, using "principal components analysis" as the factor extraction method and the attainment of eigenvalues equal to or greater than 1 as the criterion for the acceptance of factors, was applied to the data relating to producer's perceptions of the accuracy of external forecasts. No factor rotation was considered necessary in this situation.

The output of this analysis is presented in Appendix 3.

A single factor attained the eigenvalue criteria (eigenvalue = 2.48195), accounting for 62.0% of the variation in the original data. Scores for the factor were computed for each case and recorded in Appendix 2 as the variable "forecast". The factor matrix is presented in Table 8.15.

Table 8.15

Forecast Factor Matrix

Variable	Factor 1 (forecast)
AWCF	.72698
AMLCF	.78035
AWBF	.81329
ABAREF	.82647

It is apparent from this analysis that producers exhibit a degree of consistency in their perceptions of external forecasts. The factor analysis of the data for all four sources indicates that the great majority of the variation could be accounted for by a single factor. Producers with high scores ("Forecast" variable Appendix 2) on this factor have a low regard for the ability of external agencies to predict prices.

8.11 Sources of Financial and Market Information

It was considered of interest to examine producers' preferences in sources of financial and market information not only for any additional light it may throw on the factors influencing decisional behaviour but also because it may be of potential interest to those who wish to package and deliver information for any particular decision structures through the most appropriate sources/channels.

Respondents to the survey were asked to indicate their three most useful sources of market and financial information (Questions 24 and 25 Appendix 1 respectively). A significant number of respondents solely indicated the membership of a source in the top three failing to rank the sources. To overcome this problem, results were recorded on the basis of sources being identified as belonging to the respondent's preferred group of three sources (=1) or as not belonging (=0).

A range of market information sources were provided for respondents to choose from including: NSW Department of Agriculture (Ag MI); ABARE (ABARE MI); Statutory Authorities (AWC, AMLC, AWB, CALM etc) (SMAs MI); Pastoral Firms, Agents and

Merchants (Past MI); Private Consultants (Con MI); Weekly Papers (The Land, Weekly Times etc) (W Pap MI); Local Paper (L Pap MI); Radio Broadcasts (Radio MI); Television Programmes (TV MI); Local Sales and direct sales (Sales MI); Other Farmers (F MI); and other sources (Ot MI). The percentage of producers nominating a particular source as being one of their three most useful sources of market information is shown in Figure 8.20.

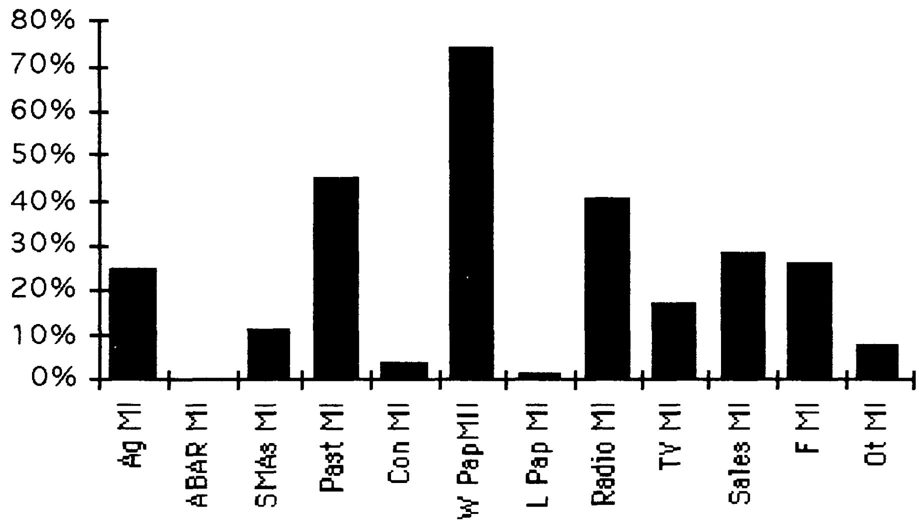


Figure 8.20 Sources of Market Information

The sources of financial information provided for selection included: NSW Department of Agriculture (Ag FI); Rural Counsellors (Csl FI); NSW Farmers Financial Referral Service (NSW FI); Pastoral Firms & Stock Agents (Past FI); Accountant (Acct FI); Bank or Financial Institution (Bank FI); Private Consultants (Con FI); Weekly Rural Papers (The Land, Weekly Times etc) (W Pap FI); Metropolitan Papers (Financial Review, The Australian, etc) (M Pap FI); Local Paper (L Pap FI); Radio Broadcasts (Radio FI); Television Programmes (TV FI); NSW Farmers 008 number (NSWF FI); Other Farmers (F FI); and other sources to be specified (Ot FI) (see Figure 8.21)

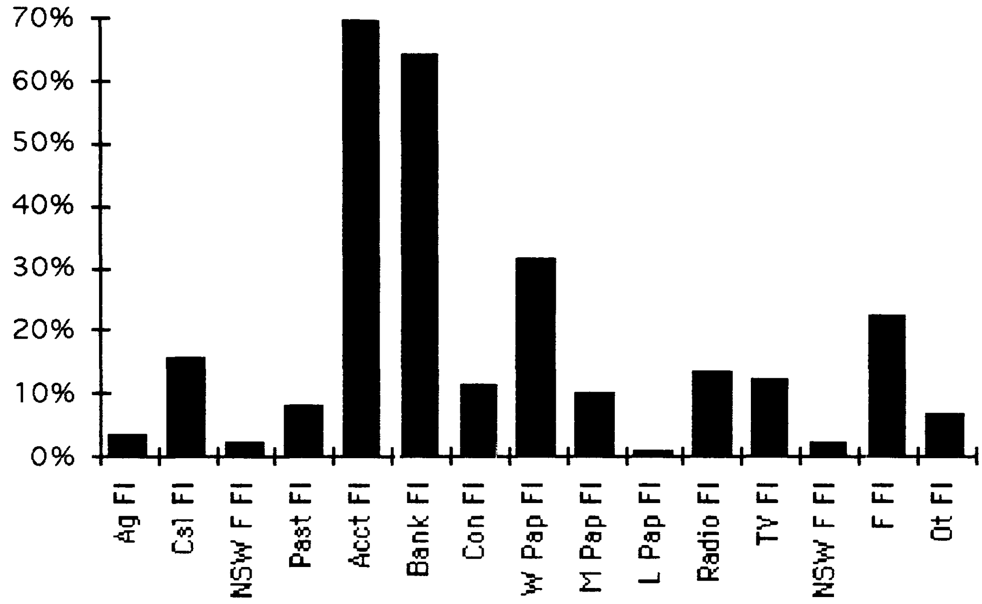


Figure 8.21 Sources of Financial Information

Analysis of this data indicated that no significant relationship between market or financial information sources and the adoption of decision structuring aids could be found. Generally the survey population relied heavily on pastoral houses, weekly papers and radio for market information. Financial information was predominantly sourced from accountants, banks and financial institutions. These findings are consistent with Bock's (1976) and Bardsley's (1982) observations.

It is very difficult to draw any conclusions from this work as to the significance of any or all of the source or channel constraints, identified in Chapter 5, as constraints on the adoption of structured decision aids.

8.12 Discriminating Between Decision Behavioural Groups

The analysis to this point has clearly shown that the decision structuring groups (GRGM 0/1, GRCF 0/1 and CFG 1,2, & 3) exhibit some significant differences on a number of the factors examined. However, there appears to be no single causal factor in producers' use or non-use of the decision aids studied. That is to say, there appears to be no single constraint upon which the producers' behaviour is contingent.

This is not to say that the factors studied may act in concert to generate constraints significant enough to ultimately influence producers' volitional decision behaviour. This is analogous to the difference between dominant/recessive and additive gene action.

To further explore this possibility discriminant function analysis has been used.

The use of discriminant analysis has been adopted here for two reasons. First, the discriminant functions produced many provide some understanding of the relationship between multiple predictor variables (independent variable) and producers' membership of the decision structuring groups (dependent variable). Second, it has the potential to provide a mechanism by which information providers, interested in the structuring of their operations to service producers using particular decision structures, may segregate their market.

Discriminant analysis was considered to be an appropriate statistical technique to achieve such aims, as the goal of discriminant analysis is to "find dimensions along which groups differ and to find classification functions to predict group membership" (Tabachnick and Fidell 1989, p. 507). In this technique emphasis is on the simultaneous consideration of a number of variables.

The canonial discriminating functions provide the means by which individuals may be allocated to decisional behaviour groups. Further, the pooled within-groups correlations between discriminating variables and these canonial discriminating functions aid in the understanding of the relationship between the independent variables and the observed decisional groups.

8.12.1 Discriminant function analysis

Individual cases are allocated to groups (often imperfectly) on the basis of scores generated by discriminant functions which are linear combinations of the observed independent (or predictor) variables. With more than two groups, multiple discriminant functions can be generated.

The linear discriminant equation

$$D = B_0 + B_1X_1 + B_2X_2 + \ldots\ldots + B_pX_p$$

is similar to the multiple linear regression equation. The X's are the values of the independent variables and the B's are coefficients estimated from the data (Norusis 1993, p. 7).

The coefficients (B's) are chosen to maximise the ratio of between-group sum of squares and the within-group sum of squares.

For the discriminant analysis presented in Appendices 4 and 5 the standard (direct) method of analysis was used. Here, all predictors (variables) enter the equation at once and "the variance shared among predictors contributes to the total relationship, but not to any one predictor" (Tabachnick and Fidell 1989, p. 527). In discriminant analysis the maximum number of discriminating functions is limited to the lesser of either the degrees of freedom for groups or equal to the number of predictors. The discriminant functions are generated so that the ratio of the between-groups sum of squares and the within-group sum of squares is maximised subject to the constraint that the functions themselves are uncorrelated.

"The eigenvalues associated with discriminant functions indicate the relative proportion of between-group variability accounted for by each function"(Tabachnick and Fidell 1989, p. 536).

Having developed the discriminant functions, discriminant scores are calculated for each case. On the basis of these scores and the application of Baye's theorem, it is possible to obtain a rule for the classification of each case. For a more detailed explanation see Tabachnick and Fidell (1989). To aid in the interpretation of the functions generated, the individual scores and their centroids (the average scores for each group) can be presented in histograms and discriminant function plots. "Groups are spaced along the various discriminant functions according to their centroids"(Tabachnick and Fidell 1989, p. 536). However, while "Plots of centroids tell how groups are separated by a discriminant function, ... they do not reveal the meaning of the discriminant function" (Tabachnick and Fidell 1989, p. 538).

To further aid the interpretation of the discriminant functions a loading matrix is calculated in which the pattern of the correlations between the functions and the predictors is recorded.

> The correlations between predictors and functions are called loadings in both discriminant function analysis and factor analysis. If predictors X_1, X_2, and X_3 load (correlate) highly with the function but predictors X_4, and X_5 do not, the researcher attempts to understand what X_1, X_2, and X_3 have in common with each other that is different from X_4, and X_5 ; the meaning of the function is determined by this understanding (Tabachnick and Fidell 1989 p. 538).

However, "consensus is lacking regarding how high correlations in a loading matrix must be to be interpreted. By convention, correlations in excess of 0.30 (9% of variance) may be considered eligible while lower ones are not" (Tabachnick and Fidell 1989, p. 538).

8.12.2 Discriminating between current gross margins (CRGM) groups

The direct discriminant analysis utilising Debt, Comp, GM, CF, Elev, Dwght-1, Dwght -2, Dwght-3, Dwght-4, Pdict-1, Pdict-2, Pdict-3 and Forecast as predictor variables and current gross margins non-use/use (CRGM 0/1) as the grouping variable is presented in Appendix 4.

A single function was generated with the following statistics (Table 8.16).

Table 8.16

Current Gross Margins (CRGM) Canonical Discriminant Function

Fcn	Eign-value	Pct of Variance	Cum Pct	Canonical Cor		After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.602359	40.299	13	.0001
1*	.6601	100.00	100.00	.6306	:					

* Marks the 1 canonical discriminant functions remaining in the analysis.

The standardised canonical coefficients of the function are presented in Table 8.17.

Table 8.17

Standardised Canonical Coefficients of the Current Gross Margins (CRGM) Discriminant Function

Debt	.16794
Comp	.11891
GM	.86910
CF	-.05955
Elev	.20773
Dwght-1	.13904
Dwgth -2	.01868
Dwght-3	-.07351
Dwght-4	-.24107
Pdict-1	.01894
Pdict-2	.08334
Pdict-3	-.11106
Forecast	.35721

The pooled within-groups correlations between discriminating variables and the canonical discriminant function are presented in the structure matrix (Table 8.18).

Table 8.18

Current Gross Margins (CRGM) Structure Matrix

GM	.85029
CF	.50304
Elev	.36126
Pdict-3	-.31963
Debt	.31722
Dwght-1	.26584
Comp	.22398
Forecast	.18339
Dwght-2	.10485
Pdict-1	-.08148
Dwght-3	.07809
Pdict-2	.02440
Dwght-4	-.00557

This discriminant function successfully classified 77.27% of cases with the greatest error being non-users predicted to be users of GM. From Table 8.18 it can be seen that there is a very high correlation between the predictors GM and CF (familiarity predictors) and the discriminant function. This clearly indicates the need for familiarity with the decision aid prior to its application. The inverse is held to support a hypothesised "knowledge constraint" which can be seen to be supportive of the general concept of contingent behaviour.

Further from this analysis it can be said that producers who utilise gross margins are likely to have higher general education, be in debt and to have greater confidence in the prediction of input costs and production outcomes as seen by the negative correlation between the Pdict-3 variable and the Current Gross Margins (CRGM) discriminant function (Table 8.18)

On the basis that the strength of the association between these familiarity predictors and the discriminant function was thought to have over shadowed some of the other predictors, an alternate discriminant function excluding the GM and CF variables was generated.

8.12.3 Alternate discriminating function current gross margins (CRGM) Groups

The direct discriminant analysis utilising Debt, Comp, Elev, Dwght-1, Dwght -2, Dwght-3, Dwght-4, Pdict-1, Pdict-2, Pdict-3 and Forecast as predictor variables and current gross margins non-use/use (CRGM 0/1) as the grouping variable is presented in Appendix 5.

A single function was generated with the following statistics (Table 8.19).

Table 8.19

Alternate Current Gross Margins (CRGM) Canonical Discriminant Function

Fcn	Eign-value	Pct of Variance	Cum Pct	Canonical Corr		After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.762198	21.860	11	.0255
1*	.3120	100.00	100.00	.4876	:					

* Marks the 1 canonical discriminant functions remaining in the analysis.

The standardised canonical coefficients of the function are presented in Table 8.20.

Table 8.20

Standardised Canonical Coefficients of the Alternate Current Gross Margins (CRGM) Discriminant Function

Debt	.50173
Comp	.08301
Elev	.53883
Dwght-1	.35482
Dwgth -2	.14131
Dwght-3	.03385
Dwght-4	-.04400
Pdict-1	-.09322
Pdict-2	.07006
Pdict-3	-.32079
Forecast	.49730

The pooled within-groups correlations between discriminating variables and the canonical discriminant function are presented in the structure matrix (Table 8.21).

Table 8.21

Alternate Current Gross Margins (CRGM) Structure Matrix

Elev	.52548
Pdict-3	-.46493
Debt	.46143
Dwght-1	.38669
Comp	.32580
Forecast	.26676
Dwght-2	.15251
Pdict-1	-.11852
Dwght-3	.11359
Pdict-2	.03549
Dwght-4	-.00810

The percentage of cases correctly classified by this alternate function fell to 71.6%, with the majority of missclassification, being the classification of non-users as users. However the removal of the familiarity predictors has allowed the significance of other predictors to show through.

The significance of Elev, Pdict-3 and debt variables in predicting the use of gross margins remains high but the impact of the Dwght-1 and the Comp variable becomes more evident.

Individual high scores on the Dwght-1 predictor variable have been taken to suggest a preparedness to change enterprise mixes in response to current and future price signals. The positive correlation between this variable and the Alternate Current Gross Margins (CRGM) Canonical Discriminant Function (Table 8.21) links this observation of management reactivity to the use of gross margins.

The presence of computer capacity with an associated reduction of computative load, alternatively seen as the removal of constraints arising from computational and cognitive effort on the application of analytical decision structures, is positively associated with the use of gross margins.

8.12.4 Discriminating between current cash flow (CRCF) groups

The direct discriminant analysis utilising Debt, Comp, GM, CF, Elev, Dwght-1, Dwght -2, Dwght-3, Dwght-4, Pdict-1, Pdict-2, Pdict-3 and Forecast as predictor variables and current cash flow non-use/use (CRCF 0/1) as the grouping variable is presented in Appendix 4. A single function was generated with the following statistics (Table 8.22).

Table 8.22

Current Cash Flow (CRCF) Canonical Discriminant Function

Fcn	Eign- value	Pct of Variance	Cum Pct	Canonical Corr		After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.356820	81.927	13	.0000
1*	1.8025	100.00	100.00	.8020	:					

* Marks the 1 canonical discriminant functions remaining in the analysis.

The standardised canonical coefficients of the function are presented in Table 8.23.

Table 8.23

Standardised Canonical Coefficients of the Current Cash Flow (CRCF) Discriminant Function

Debt	.14632
Comp	.01104
GM	.62361
CF	.65588
Elev	.03669
Dwght-1	.10771
Dwgth-2	.10540
Dwght-3	-.11931
Dwght-4	-.21314
Pdict-	-.08235
Pdict-2	.20303
Pdict-3	.22597
Forecast	.03675

The pooled within-groups correlations between discriminating variables and the canonical discriminant function are presented in the structure matrix (Table 8.24).

Table 8.24

Current Cash Flow (CRCF) Structure Matrix

CF	.83085
GM	.67070
Dwght-1	.24270
Dwght-2	.19277
Debt	.19274
Pdict-1	-.18091
Elev	.13616
Comp	.06071
Pdict-3	-.04555
Pdict-2	.04015
Dwght-3	-.03996
Forecast	-.02966
Dwght-4	.01668

Using this discriminant function it was possible to accurately classify 92.1% of cases, however the interpretive power of the function was again seen to be limited by the dominance of the familiarity predictors (GM and CF). Hence it was considered productive to pursue the generation of an alternate function excluding these variable.

8.12.5 Alternate discriminating function current cash flow (CRCF) groups

The direct discriminant analysis utilising Debt, Comp, Elev, Dwght-1, Dwght -2, Dwght-3, Dwght-4, Pdict-1, Pdict-2, Pdict-3 and Forecast as predictor variables and current cash flow non-use/use (CRCF 0/1) as the grouping variable is presented in Appendix 5.

A single function was generated with the following statistics (Table 8.25).

Table 8.25

Alternate Current Cash Flow (CRCF) Canonical Discriminant Function

Fcn	Eign-value	Pct of Variance	Cum Pct	Canonical Corr		After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.749741	23.186	11	.0166
1*	.3338	100.00	100.00	.5303	:					

* Marks the 1 canonical discriminant functions remaining in the analysis.

The standardised canonical coefficients of the function are presented in Table 8.26.

Table 8.26

Standardised Canonical Coefficients of the Alternate Current Cash Flow (CRCF) Discriminant Function

Debt	.41295
Comp	-.07505
Elev	.39592
Dwght-1	.57400
Dwgth-2	.53739
Dwght-3	-.10704
Dwght-4	.00619
Pdict-1	-.34232
Pdict-2	.13631
Pdict-3	.13453
Forecast	.24200

The pooled within-groups correlations between discriminating variables and the canonical discriminant function are presented in the structure matrix (Table 8.27).

Table 8.27

Alternate Current Cash Flow (CRCF) Structure Matrix

Dwght-1	.56398
Dwght-2	.44797
Debt	.44790
Pdict-1	-.42041
Elev	.31642
Comp	.14108
Pdict-3	-.10586
Pdict-2	.09330
Dwght-3	-.09285
Forecast	-.06892
Dwght-4	.03877

With the exclusion of the familiarity predictors (CF and GM) which are clearly dominant in the Current Cash Flow (CRCF) discriminant function presented in Section 8.12.4, the predictive power of the Alternate Current Cash Flow (CRCF) discriminant function fell to 85.2%, with the majority missclassification being the allocation of non-users to the users group.

Similar to the alternate Current Gross Margins function, emphasis on current and future price signals in planning next year's production is associated with the use of cash flow budgeting, as evidenced by the positive correlation between the Alternate Current Cash Flow (CRCF) discriminant function and the Dwght-1 variable.

The predictor variable Dwght-2, with its high positive correlations with the Future prices and Current cash flow variables indicating the level of cash flow constraint on future production plans, is also positively correlated with the Alternate Current Cash Flow (CRCF) discriminant function. This indicates that producers find this decision-structuring aid of benefit in the analysis of production plans where future cash flows are of critical importance.

Similar to the association between debt, education and GM use, the presence of debt and higher general education levels are also associated with the use of cash flow budgets.

High scores on the predictive variable Pdict-1 are associated with producers who have a low regard for their own ability to predict input costs, production levels and product prices. This variable is negatively correlated with the Alternate Current Cash Flow (CRCF) discriminant function, indicating that a lack of confidence in personally generated expectations is a significant constraint on producers utilisation of cash flow budgets. To the extent that a linkage can be drawn between constraints on data/information generation, message encoding, message decoding, semantic memory, human inferencing and the level of validity assigned by producers to their own expectations, these constraints can be seen to be associated with the use or non-use of this decision structure.

8.12.6 Discriminating between cash flow groups (CFG)

The direct discriminant analysis utilising Debt, Comp, GM, CF, Elev, Dwght-1, Dwght -2, Dwght-3, Dwght-4, Pdict-1, Pdict-2, Pdict-3 and Forecast as predictor variables and cash flow groups (CFG 1/2/3) as the grouping variable is presented in Appendix 4.3.

Two functions were generated with the following statistics (Table 8.28).

Table 8.28

Cash Flow Groups (CFG) Canonical Discriminant Function

Fcn	Eign-value	Pct of Variance	Cum Pct	Canonical Corr		After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.263280	105.428	26	.0000
1*	1.8433	84.59	84.59	.8052	:	1	.748593	22.875	12	.0288
2*	.3358	15.41	100.00	.5014	:					

* Marks the 2 canonical discriminant functions remaining in the analysis.

The standardised canonical coefficients of the function are presented in Table 8.29.

Table 8.29

Standardised Canonical Coefficients of the Cash Flow Groups (CFG) Discriminant Function

	Function 1	Function 2
Debt	-.18711	-.39826
Comp	.06597	.53031
GM	.64520	.26603
CF	.64514	-.16534
Elev	.08246	.44733
Dwght-1	.06133	-.45322
Dwgth-2	.14974	.42928
Dwght-3	-.08655	.31109
Dwght-4	-.23149	-.15658
Pdict-1	-.03225	.48028
Pdict-2	.21935	.13879
Pdict-3	.22006	-.05256
Forecast	.000060	-.35156

The pooled within-groups correlations between discriminating variables and the canonical discriminant functions are presented in the structure matrix (Table 8.30).

Table 8.30
Cash Flow Groups (CFG) Structure Matrix

	Function 1	Function 2
CF	.81629*	-.21860
GM	.68859*	.16185
Dwght-1	.23235*	-.20558
Forecast	-.02822*	.02662
Dwght-4	.01586*	-.01517
Elev	.15786	.37779*
Comp	.07913	.35473*
Debt	.17806	-.33654*
Pdict-1	-.16669	.32021*
Dwght-3	-.02593	.29467*
Pdict-3	-.05819	-.25231
Dwght-2	.20476	.21644*
Pdict-2	.03711	-.05882*

*denotes largest absolute correlation between each variable and any discriminant function.

Using these functions it was possible to accurately classify 79.6% of respondents to the survey. Due to the dominance of the familiarity predictors in the first canonical discriminant function (Table 8.30) it was again considered potentially fruitful to generate alternate functions excluding the CM and CF variables.

8.12.7 Alternate discriminating functions cash flow groups (CFG)

The direct discriminant analysis utilising Debt, Comp, Elev, Dwght-1, Dwght -2, Dwght-3, Dwght-4, Pdict-1, Pdict-2, Pdict-3 and Forecast as predictor variables and cash flow groups (CFG 1/2/3) as the grouping variable is presented in Appendix 5.

Two functions were generated with the following statistics (Table 8.31).

Table 8.31

Alternate Cash Flow Groups (CFG) Canonical Discriminant Function

Fcn	Eign- value	Pct of Variance	Cum Pct	Canonical Corr		After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.572270	44.651	22	.0029
1*	3606	55.92	55.92	.5148	:	1	.778634	20.017	10	.0291
2*	.3358	15.41	100.00	.5014	:					

* Marks the 2 canonical discriminant functions remaining in the analysis.

The standardised canonical coefficients of the function are presented in Table 8.32.

Table 8.32

Standardised Canonical Coefficients of the Alternate Cash Flow Groups (CFG) Discriminant Function

	Function 1	Function 2
Debt	.51309	-.03210
Comp	-.35482	.39592
Elev	-.01377	.71075
Dwght-1	.68253	.01143
Dwgth-2	.15950	.71526
Dwght-3	-.28399	.23278
Dwght-4	.06157	-.08042
Pdict-1	-.52366	.17206
Pdict-2	.01668	.21960
Pdict-3	.16590	-.00814
Forecast	.37982	-.13060

The pooled within-groups correlations between discriminating variables and the canonical discriminant functions are presented in the structure matrix (table 8.33).

Table 8.33

Alternate Cash Flow Groups (CFG) Structure Matrix

	Function 1	Function 2
Dwght-1	.52282*	-.23075
Debt	.51644*	.03245
Pdict-1	-.48681*	.02624
Dwght-3	-.23412*	.19341
Pdict-2	.10031*	.01589
Forecast	-.06457*	-.02669
Dwght-4	.03643*	.01484
Elev	.02049	.57415*
Dwght-2	.20354	.52405*
Comp	-.09669	.42117*
Pdict-3	.06558	-.30281*

*denotes largest absolute correlation between each variable and any discriminant function.

The absence of the familiarity predictors from this set of discriminant functions resulted in the level of correct classification falling to 71.59%.

8.12.8 Cash flow group discriminant functions

Both the Cash Flow Group (CFG) canonical discriminant functions (Section 8.12.6, Appendix 4) and the Alternate Cash Flow Group (CFG) canonical discriminant functions (Section 8.12.7, Appendix 5) successfully predicted group membership on the basis of two discriminant functions. The first functions (Function 1 in both cases) are the most effective in segregating cash flow group 3 (non-users) from cash flow group 1 and cash flow group 2 (frequent reviewers, and annual reviewers respectively). The second functions (Function 2) are the most effective in segregating cash flow group 1 group from cash flow group 2 group in both sets of discriminant functions. Group means for the second function of the Cash Flow Group (CFG) canonical discriminant functions are 0.27332, -1.30475 and 0.14269 for cash flow groups 1, 2 and 3 respectively. Group means for the second function of the Alternate Cash Flow Group (CFG) canonical discriminant functions are 0.36615, -.82259 and -.67243 for cash flow groups 1, 2 and 3 respectively.

The familiarity predictor variables (CF and GM) again dominated the first function of the Cash Flow Group (CFG) discriminating functions, which exhibited the greater degree of accuracy in classification than that shown by the Alternate Cash Flow Group (CFG) discriminating functions. Removal of these variables sees the Dwght-1 and Debt predictors variables as positively correlated with the first function and Pdict-1 negatively correlated (Table 8.33). This can be viewed in the same terms as the association between these variables and the Alternate Cash Flow Group (CFG) discriminant function.

Function -2 in the Cash Flow Group (CFG) canonical discriminant functions (section 8.12.6) is positively correlated with Elev, comp, Pdict-1 and negatively correlated with the Debt predictor (Table 8.30). The positive correlation between Pdict-1 and function - 2, suggesting that "annual reviewers" of cash flow budgets have higher levels of confidence in their forecasts than "frequent reviewers", may be viewed as a stimulus response feature. That is, the more often forecasts in general (input costs, production and prices) are compared with actual achievements the more salient forecast errors become, hence reducing producers' perceptions of their own ability to forecast. The negative correlation between Debt and function-2 relates to the association between the occurrence of debt, bank or financial institution motivation of cash flow behaviour and the utilisation of cash flow budgets in the annual reporting function.

The second function of the Alternate Cash Flow Group (CFG) canonical discriminant functions (Section 8.12.7) is positively correlated with Elev, Comp, Dwght-2 and negatively correlated with Pdict-3 (Table 8.33). As the predictor variable Dwght-2 exhibits a high positive correlation with the Future price and Current cash flow variables, the positive correlation between Dwght-2 and the second function suggests that frequent cash flow reviewers find this decision structure (cash flow budgets) to be an aid in the analysis of production plans constrained by current cash flow requirements. The relationship between Pdict-3 and the second function of the Alternate Cash Flow Group (CFG) canonical discriminant functions suggests that frequent reviewers of cash flows believe themselves to be better predictors of input costs and production levels but poorer predictors of prices than annual cash flow producers. In this case the stimulus/response argument may still hold if it is accepted that producers are better at predicting costs and production levels rather than product prices and that frequent reviewers become more aware of their actual predictive capacities.

8.13 Summary

A general discussion of the results of the limited survey work conducted and presented in this chapter is undertaken in Chapter 9, concentrating on its implication for the hypothesised "Contingency Model of Market Information Utilisation in Agricultural Decision Making". This is followed by some concluding remarks relating to the overall conduct and outcomes of the complete study presented in this dissertation, along with some suggestions for further research opportunities in Chapter 10.