CHAPTER FOUR

METHODOLOGY APPLIED IN ANALYSING SMALLHOLDER FARMERS' RELATIONSHIP WITH MILLERS

4.1 INTRODUCTION

The purpose of this study is to determine the factors affecting the performance of the smallholder cane growers, and hence the sugar industry supply chain and to present and test a model that identifies the relationship between these smallholder cane growers and millers in the Swaziland sugar industry. The hypotheses developed in this study are that:

- Social factors, such as trust are important mechanisms that can complement formal governance mechanisms in exchange relationships between smallholder cane growers and the millers
- Smallholder cane growers' perceptions on their relationship with millers can be explained by the detailed relationship structure outlined in Chapter three (Figure 3.3). The summary of the relationship proposed by the model is presented in Table 4.1
- The performance of smallholder farmers, hence the sugar industry supply chain, is a function of the farmers' perceived opportunistic behaviour by millers, trust, perceived cooperation and the growers' proximity to the mill. In addition to the relationship shown in Table 4.1, Table 4.2 shows the expected relationship of the cane growers' performance and its determinants. This chapter provides details of the methodology used in this study to answer the research objectives and testing the hypotheses.

Table 4.1: Summary of cane growers and millers' relationship (proposed Figure 3.3)

Relationship constructs		
Exogenous	Endogenous	Hypothesised sign
Opportunistic behaviour (F6)	Trust (F3)	-
Opportunistic behaviour (F6)	Cooperation (F4)	-
Opportunistic behaviour (F6)	Commitment (F8)	-
Relative dependence (F1)	Cooperation (F4)	+
Relative dependence (F1)	Influence by partner (F2)	+
Trust (F3)	Commitment (F8)	+
Trust (F3)	Cooperation (F4)	+
Trust (F3)	Certainty (F7)	+
Commitment (F8)	Cooperation (F4)	+
Cooperation (F4)	Certainty (F7)	+
Cooperation (F4)	Satisfaction (F5)	+
Influence by partner (F2)	Satisfaction (F5)	-
Certainty (F7)	Satisfaction (F5)	+

Note: F1 to F8 indicates the representation of the constructs in the analysis, and F stands for factor.

Table 4.2: Expected relationship between performance measures and their determinants

Dependent variable for performance	Independent variables	Expected sign
• Revenue per hectare (R) • Do you make profit (0=No, 1=Yes) • How much profit (R) • Satisfaction (1= vmds, 4= vms)[6]	• Transport cost per tonne (R)	-
	• Distance to the mill (km)	-
	• Percentage change in quota (%)	+
	• Yield per ha (tonnes/ha)	+
	• Average sucrose content (%)	+
	• Number of years in sugarcane farming (years)	+

4.2 RESEARCH DESIGN

Research can be either longitudinal or cross-sectional. Longitudinal research takes place over time and focuses on at least two or more "waves" of measurement. Cross-sectional research on the other hand takes place at a single point in time. Thus, it takes a 'slice' or cross-section of whatever it is being measured. Longitudinal research often poses the problem of response biases, obtaining a representative sample because of the need for cooperation of panels,

[6] Measured by four items in a likert-scale, where 1= very much dissatisfied (vmds), 2 = dissatisfied, 3 = satisfied, and 4 = very much satisfied (vms).

respondents' refusal to cooperate and panel mortality (Churchill, 1995; Malhotra, 1996; Parasuraman, 1991). It also requires a long period of data collection. As a result of the limitations in time series data and its availability, this study makes use of cross-sectional data.

4.2.1 Data collection

There are different methods of conducting a survey. These may include the use of telephone, Internet, mail and personal interviews. This study involved the use of personal interviews. Personal interviews involve face to face encounters with the respondent (Babbie, 1995). They tend to outperform the other methods in many ways, except for the interviewer control and bias, cost, and social desirability bias. The interviews were conducted by the researcher and one assistant who was provided training by the researcher before setting out for the data collection. Thus, the interviewer control was minimised. Interviewer bias was reduced by the use of a structured questionnaire, which was prepared in advance.

Data were collected between May and December 2001. Two sets of questionnaires were used to collect the data. One set was used for cane growers and another for millers' representatives. The interviews were conducted on a one-on-one basis. Cane growers were interviewed at the farm site, whilst millers' representatives were interviewed at the mill site. The questionnaires were constructed following an extensive review of the literature. Previously established scales were modified and utilised to measure some of the study constructs where possible.

4.2.2 Subject selection

When a unit of analysis is extended from dyadic relationship to a supply chain, sampling becomes a problem. Since a supply chain consists of multiple inter-connected firms, it is almost impossible to deal with all the constituent firms in a single study. Hence, in this study the supply chain is explored from the supplier-processor perspective. The target population of the study includes cane growers and millers in the sugar industry. A list of cane growers was obtained from the three sugar mills, Simunye, Mhlume and Ubombo (Big Bend).

4.2.3 Sampling procedure

This study employed a purposive method of sampling, which is part of nonprobability sampling (Figure 4.1). Although the disadvantages of nonprobability sampling in terms of statistical precision and generalisation are generally recognised (Parasuraman, 1991, Churchil, 1995), it was the appropriate method in this study. A list of all the farmers supplying each mill was secured from the millers, however it was not possible to know in advance whether the farmer operates as an association or as an individual within an association and whether the farmers has already started supplying the mill. Therefore, sampling had to be conducted in the field. Hence, purposive sampling was the most appropriate method.

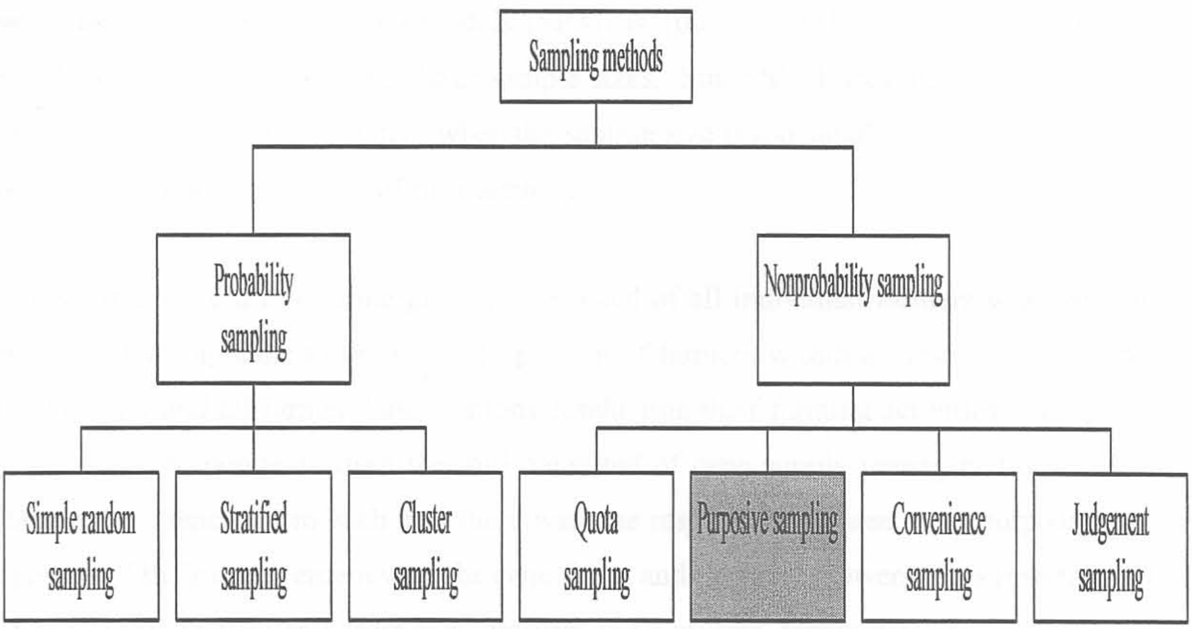

Figure 4.1: Types of sampling methods

Source: Adapted from Churchill (1995)

The most important criterion in selecting a sample is to increase the validity of the collected data (Carmines and Zeller, 1979, 1988). In this study, the data selection criterion was designed to increase validity, rather than to ensure that the sample was a representative of the given population. It is for that reason that the study used a purposive sampling, which is most desirable when certain important segments of the target population are intentionally represented in the sample. Purposive sampling is a deliberate non-random method of sampling, which aims to sample a group of people, or settings with a particular characteristic, such as where they live in society, or specific cultural knowledge. The power of purposive sampling lies in selecting cases with rich information for the study, such cases provide a great deal of insight into the issues of central importance to the research study (Patton, 1990).

In this study, farmers' respondents were selected on the basis of having sold sugarcane to the mill before. Those who were still going to sell sugarcane for the first time were not included in the sample.

4.2.4 Sample size

There is little theoretical guidance related to adequate sample size (Baumgartner and Homburg, 1996). However, it is generally accepted that the minimal sample size required when using structural equation models (SEM) is 100 to 150 (Hair *et al.*, 1995, 1998). Too small samples are as bad as too large sample sizes. Since SEM uses the maximum likelihood estimation method, it is sensitive when the sample size is too small or too large. As a result it tends to yield poor goodness of fit measures.

The sample structure for cane growers consisted of all individual farmers who have already started delivering cane to the mills, 10 percent of farmers within an association[7] but farming individually and all farmers' associations conducting their farming activities collectively as a group. The respondents from the mill consisted of cane supply managers from each of the three mills. Hence, from each mill there was one respondent. These were purposely selected because of their involvement with the cane flows and the cane growers. This resulted in a total of 124 usable respondents from cane growers and 3 millers' representatives.

[7] The farmers associations and schemes included in this study were: Nzama farmers Association; Vukani Association; Mankontshane association; Ntisheni farmers association; Makhabeni association; Lilanda farmers association; Lobovu farmers cooperative; Logoba Farmers association; Sukumani bomake farmers association; Maphobeni farmer association, Mavalela farmers association, Mbanana farmers association, Madlenya Irrigation scheme; Magwanyana farmers association; Mabhudlweni farmers association; Ntengenyane farmers association; Bambanani association; Hlomani association; Emadvodza association; Manyovu farmers association; Nsutumutwe farmers association; Mshumpula farmers association; Vulamehlo farmers association; Bambanani association; Mshumpula farmers association; Vulamehlo farmer association, Maphobeni farmer association; Mndobandoba farmers cooperation, Mdalantomb agric service; Yemshikashika farmers association; Phasentsaba farmers association; Vuvulane cooperative and vuvulane irrigation scheme.

4.3 STATISTICAL ANALYSIS

Data were analysed using descriptive statistics and multivariate analysis including logistic regression, multiple regression analysis and structural equation modelling.

4.3.1 Structural equation modelling

The most common way of estimating parameters in ordinary regression analysis is the ordinary least squares (OLS) method. In this method, the regression line is generated by trying to minimise the squared deviations of data points from a regression line that goes through the data. The straight line that generates the least squared deviations is said to have the best fit to the data. The coefficients that are generated to describe this regression line form the parameter estimates for this analysis. However, OLS is generally deemed to be inappropriate for generating parameter estimates in SEM studies. The most common method for estimating the best fitting parameters for SEM is the maximum likelihood (ML) method. This method generates a set of parameter estimates that are most likely to have been produced from non-chance relationships. The method is an iterative process in that a set of parameters is estimated and based on this first estimate a calculation of the "fit function", which is basically a coefficient describing the fit of the parameters to the data. Using this first estimate a second estimate is made in order to make the fit function smaller. This process is repeated until the fit function cannot be made any smaller. When this happens the model is said to have converged on a final set of parameter estimates.

Structural equation modelling evaluates how well a conceptual model that includes observed and latent (constructs) variables fit the obtained data (Bollen, 1989; Hoyle, 1995). The construct variable accounts for the inter-correlations of the observed variables that measure that construct (Bollen and Lennox, 1991). The basic formulation of structural equation modelling is in the form of:

$Y_1 = X_{11}+X_{12}+X_{13}+........X_{1n}$

$Y_2 = X_{21}+X_{22}+X_{23}+........X_{2n}$

$Y_m = X_{m1}+X_{m2}+X_{m3}+........X_{mn}$

The CALIS (Covariance Analysis Linear Structural) equations generate an estimate covariance matrix, using a hypothesised factor structure specified by the investigator as a guide. If only small differences are found to exist between the actual and estimated matrices, then the hypothesised factor structure is viewed as a plausible one. To test the proposed model of the relationship between cane growers and the millers, the study employed hierarchical regression and structural equation modelling using confirmatory factor analysis (CFA).

Structural equation modelling is a comprehensive statistical approach to testing hypotheses about relationships between observed and latent variables. It is an extension of multiple regression and factor analyses and allows separate relationships for each set of dependent variables. Hence, it is an appropriate and efficient estimation technique for a series of separate multiple regression equations estimated simultaneously (Hair *et. al.*, 1995). It consists of the structural model (path model) and the measurement model (factor analysis model) and hence is useful when one dependent variable becomes an independent variable in subsequent dependence relationships. It is characterised by estimation of multiple inter-related dependence relationships, and the ability to represent unobserved concepts in these relationships as well as accounting for measurement error in the estimation process (Hair *et. al.*, 1995). Therefore, one can assess the contribution of each scale item as well as how the scale measures the concept (reliability) into the estimation of the relationship between dependent and independent variables.

The measurement of the constructs is done indirectly through one or more observable indicator variables, such as responses to questionnaire items that are assumed to represent the construct adequately. Once the observable indicators define the theoretical constructs with theoretical guidance the inter-relationship between the constructs is then identified as dependent (endogenous) and independent (exogenous) constructs. Thus, the relationship between the indicator variables and the constructs constitute the measurement part of the model, whist the relationship between the constructs themselves constitutes the structural part (Joreskog, 1993).

The main advantages of structural equation modelling over other types of multivariate techniques are that; (1) it provides a straightforward method of dealing with multiple relationships simultaneously, whilst providing statistical efficiency, and (2) it has an ability to assess the relationships comprehensively and provides a transition from exploratory to confirmatory analysis (Bollen, 1989; Hair *et al.*, 1995, 1998).

A causal model as shown in Figure 3.3 was designed based on prior empirical research and theory. In order to test the causal assumptions the equations implied by the arrows were solved using the SAS PROCALIS procedure to give estimates of the magnitude of the linkages shown in Figure 6.2.

Factor analysis can be used to determine those variables, which measure relationship constructs (factors) for the perceptions of cane growers and the millers about their relationship. It is an interdependence technique in which all variables are simultaneously considered each related to all others (Hair *et. al.*, 1995). The factor loadings indicate the role each variable plays in defining each factor. They measure the degree of correspondence between the variable and the factor. Hence, a high factor loading means the variable is a representative of the factor. After conducting factor analysis, it is then that one can use the factors for regression analysis. However, due to the small number of items used to measure each construct, factor analysis was not used in the study, since during factor analysis some statements are lost as a result of low factor loadings to the constructs. Instead confirmatory factor analysis was used. Confirmatory factor analysis is a theory-testing model as opposed to a theory-generating method like exploratory factor analysis. In confirmatory factor analysis, the researcher begins with a hypothesis prior to the analysis. The hypothesis specifies which variables will be correlated with which factors and which factors are correlated. The hypothesis is based on a strong theoretical and/or empirical foundation (Stevens, 1996).

In addition, confirmatory factor analysis offers the researcher a more viable method for evaluating construct validity. The researcher is able to explicitly test hypotheses concerning the factor structure of the data as a result of having a predetermined model specifying the number and composition of the factors.

4.3.2 Data examination

4.3.2.1 Normality

The data were checked to verify that the assumptions of multivariate normality were met. In a strict definition of a normal distribution, the skewness and kurtosis of the data would be equal to zero. In a practical sense, normality is defined as a range of scores that span either side of zero. According to Monte Carlo studies, skewness values ranging from 2.0 to 3.0 and kurtosis values ranging from 7.0 to 21.0 indicate that the data should be considered moderately non-normal (Curran *et al.*, 1996). If values are less than these (i.e., 2.0 for skewness and 7.0 for kurtosis), data should be considered to be approximating a normal distribution. Other authors provide more rigorous guidelines, indicating mild non-normality when two-thirds of the observed variables exceed skewness or kurtosis values of +/- 1.0 and moderate non-normality when two-thirds of the observed variables have skewness values of about +/- 1.5 and kurtosis values around +/- 3 to 4 (Fan and Wang, 1998). In this study, skewness and kurtosis values ranged from -.52 to 0.34 and -1.2 to 3.5 respectively. Considering the above criteria for skewness and kurtosis scores, the portion of the data used in the model was moderately normally distributed (Table 4.3). Therefore, data were not transformed for non-normality in this study, as this would also introduce problems by changing the actual meaning of the responses (Gassenheimer *et al.*, 1998).

Table 4.3: Normality distribution of data for item scales used for cane growers respondents

Item	Skewness	Kurtosis
Commitment	-0.5171	-0.6177
Opportunistic behaviour	-0.4080	3.5799
Cooperation	-0.0827	-0.0221
Certainty	0.3434	0.3629
Influence by partner	-0.3447	1.2485
Satisfaction	0.0109	-0.383
Relative dependence	0.0295	-0.2838
Trust	0.1640	-0.0480

4.3.2.2 Reliability and validity

Reliability is concerned with the extent to which a measurement of a phenomenon provides a stable and consistent result (Hair *et al.*, 1995). There are two dimensions of reliability, repeatability and internal consistency (Hair *et al.*, 1995, 1998). Internal consistency measures the ability of a scale to correlate with other scale items intended to measure the same variable. In this study internal consistency was measured by the Cronbach's (1951) coefficient alpha and confirmatory factor analysis (CFA). Bollen (1989) argues that the most popular reliability coefficient used for internal consistency is the Cronbach alpha. Cronbach alpha estimates the degree to which the items in a scale are representative of the domain of the construct measured, whilst CFA on the other hand evaluates each item in the scale as well as any potential cross loading of items with others.

Validity refers to the relationship between a construct and its indicators. A construct is valid to the extent that it measures what it is supposed to measure (Hair *et al.*, 1995). Bollen (1989) identified three types of validity; face or content validity (verification of the content of the scale in measuring what it is supposed to measure), criterion validity (the degree of correspondence between a measure and a criterion variable, mostly measured by correlation) and construct validity (the ability of a measure to confirm a network of related hypotheses from theory based constructs). Content validity was determined through discussion with some farmers in the sugar industry and a review of the questionnaire and the scale items by professors in the Department of Agricultural Economics, Extension and Rural development at the University of Pretoria. The construct validity was assessed by analysing convergent validity and discriminant validity.

4.3.2.3 Variables aggregation

In SEM data abstraction for constructs may be conducted at three levels. These include total aggregation, partial aggregation and total disaggregation. Total aggregation involves the use of a single value for each construct as input in SEM by combining all indicator variables for that construct. Partial aggregation on the other hand involves the use of subsets of manifest items combined into various composites, which are then treated as multiple indicators of a particular construct. In total disaggregation, the true single manifest items are used as multiple measures of a construct. Due to the limited sample size for the cane growers and the requirement of at least 5 observations per estimate parameter, partial aggregation of indicator variables was used in this study. Bagozzi (1994) points out that partial aggregation also assists in reducing the variance of the items. Partial aggregation was done by aggregation of the items with the highest reliabilities with those with the lowest reliabilities (Table 4.4).

The issue of the number of indicators to use when measuring a construct is still not resolved in the literature (Baumgartner and Homburg, 1996). A general rule of thumb is that there should be three indicators per construct since less than three indicators increases the chances of infeasible solutions (Baumgartner and Homburg, 1996; Bollen, 1989; Hair *at al.*, 1998). While it is advantageous to use many indicators per construct, however, too many indicators may result in a non-parsimonious measurement model (Baumgartner and Homburg, 1996). Bollen (1989) argues that at least two scale items or composite indices should represent a construct. However, three or more is preferred. In this study some constructs were represented by an aggregate of two indicator variables, while others were represented by an aggregate of three indicator variables.

Table 4.4: Aggregated statements measuring construct variables

Items	Variable ID	Resulting items	Construct	Highest item corr to total
Dep33r + Dep22r = Dag1 Dep2 + Dep8 + Dep7 = Dap2	V1 V2	2	Relative Dependence	Dep7
Conf2 + Opp2 = Oag1 RConf3 + Opp1 = Oag2 RConf1 + Opp3 = Oag3	V14 V15 V16	3	Opportunistic Behaviour	Conf2
Cert4 + Cert5 = Cag1 Cert1 + Cert2 + Cert3 = Cag2	V17 V18	2	Certainty	Cert 5 Cert 3
Inflby2r + inflov3r + inflov1r = Iag1 Inflby1 + inflby4 + inflov4r = Iag2 Inflby3 + infov2r = Iag3	V3 V4 V5	3	Influence by partner	Inflov3r
Satis1 + satis2 = sag1 Satis3 + satis4 = sag2	V12 V13	2	Satisfied	Satis2
Trust4 + preleave4 + trust5 + trust6 = Tag1 Preleave3 +preleave2 + trust2 + trust3 = Tag2 Trust1 + preleave1 = Tag3	V6 V7 V8	3	Trust	Trust5
Comit2 + comit5 = Mag1 Comit3 + comit4 = Mag2	V19 V20	2	Commitment	Comit5
Coop1 + benefit5 + benefit2 + coop2 = Pag1 Coop4 + benefit3 = Pag2 Coop3 + coop5 + benefit4 = Pag3	V9 V10 V11	3	Cooperation	Benefit2
Total		20		

4.3.3 Data analysis

Several statistical procedures were employed to analyse the data in this study. In determining the reliability of the scale items for each construct in the model the confirmatory factor analysis (CFA) was conducted. Bollen (1989) states that CFA is a better method of analysis than exploratory factor analysis in situations where hypotheses about plausible models exist, as is the case in this study. Moreover CFA procedure can assist one to identify potential problems with multicollinearity between items within each scale and it can identify scale items that cross-load on other constructs in the model (convergent and discriminant validity).

The presence of multicollinearity between items is one criterion for eliminating items for SEM analysis.

CFA provides factor loadings, which represent the direct effects of the scale items on the measurement of the construct (Bollen, 1989). Though others recommend factor loadings of above 0.7 (Nunnally, 1978; Hair *et al.* (1995, 1998) argue that "factor loadings greater than ± 0.30 are considered to meet the minimal level; loadings of ± 0.40 are considered more important; and if the loadings are ± 0.50 or greater, they are considered practically significant. Thus the larger the absolute size of the factor loading, the more important the loading in interpreting the factor matrix. Because factor loading is the correlation of the variables and the factor, the squared loading is the variable's total variance accounted for by the factor; thus a 0.30 loading translates to approximately 10% explanation and a 0.50 loading denotes 25% of the variance is accounted for by the factor. The loading must exceed 0.70 for the factor to account for 50% of the variance" (Hair *et al.*, 1998: 111). They further state that factor loadings of 0.80 and above are not typical and that it is the practical significance of the loadings that is an important criterion. Moreover, the emphasis of this approach is on practical rather than statistical significance.

The squared multiple correlations are the measure of each item in the scale when it is regressed on the remaining items in the same scale (discussed in detail in Chapter six). Thus, it is a measure of the degree of collinearity of the scale item with the other items in the same scale and is considered a measure of reliability for each scale item (Bollen, 1989). The main objective of the CFA is to refine the scale items measuring the constructs, so that they are reliable and valid measures in the model.

The model was evaluated on the basis of goodness of fit indices to determine if the model is a representation of the proposed relationship between cane growers and the millers. There are a number of goodness of fit indices that could be used. These include likelihood-ratio Chi-square significance (χ^2), the goodness of fit index (GFI), the comparative fit index (CFI) and root square mean error (RMSEA). The (χ^2) value is the most important measure of the overall fit. Technically the χ^2 should be insignificant ($p > 0.05$) because an insignificant χ^2 shows a good model fit (Gefen, *et al.,* 2000). However, since χ^2 is sensitive to larger sample size and the power of test, it is often rare to satisfy this criterion. Therefore, the ratio of χ^2 to degrees of freedom is sometimes used. The recommended ratio of χ^2 to degrees of freedom is between 1 and 2 (Hair *et al.*, 1995, 1998). However, in some cases there has been some forgiving in that the recommendation would be a χ^2 as small as possible and the ratio of χ^2 to degrees of freedom smaller than 3:1.

The GFI measures the absolute fit (unadjusted for degrees of freedom) of the combined measurement and structural model to the data, while the adjusted goodness of fit index (AGFI) adjusts this value to the degrees of freedom in the model. The RMSEA on the other hand assesses the residual variance of the observed variables and how the residual variance of one variable correlates with the residual variance of the other items. Therefore, the closer the value of RMSEA is to zero, the better the model. The threshold for GFI, AGFI and RMSEA is 0.90, 0.80 and below 0.05 or at most 0.08 respectively (Gefen, *et al.*, 2000).

4.4 CONSTRUCT MEASURES

While the questionnaire structure also asked farmers to provide information about themselves and their farming practices, it was also divided into sections containing multiple item measures for each construct variable considered.

The measurement variables in a SEM represent the scale items for each construct to be measured. The conceptual model for the relationship between smallholder cane growers and millers in the sugar industry supply chain, presented in Chapter three, is represented by two exogenous variables (opportunistic behaviour and relative dependence) and six endogenous variables (commitment, trust, cooperation, influence by partner, certainty, and satisfaction). This section of the chapter details the scale items employed in the measurement of these constructs. The items measuring the constructs were validated by using confirmatory factor analysis (CFA), which is discussed in detail in Chapter six. The CFA statistical procedures were also used to reduce the number of scale items for measuring each construct used in the structural model testing. The number of items that remained in each construct were those that best represent the measurement of their respective constructs.

Most of the scales used were adopted from Morgan and Hunt (1994), Heide and John (1990) and Dwyer *et al.* (1987). However, they were modified to suit this specific study. Items used to measure constructs in the millers' questionnaire are presented in Appendix F.

4.4.1 Measurement of satisfaction

Satisfaction with an exchange relationship is regarded as an important outcome of buyer-seller relationships. Satisfaction was used as a proxy for relationship performance in this study. Four items were used to measure satisfaction (Table 4.5). Farmers were asked if they were satisfied with the statements used to measure satisfaction, using a 4-point likert type scale ranging from (1) = very much disatisfied to (4) = very much satisfied

Table 4.5: Items measuring satisfaction

1. Price received for sugarcane (satis1)
2. Procedures for testing sucrose content (satis2)
3. Time taken to receive payment after sugarcane has been delivered to the mill (satis3)
4. Technical assistance provided by the Sugar Association (satis4)

4.4.2 Measurement of commitment

Commitment has been considered an important element in business relationships. In this study commitment was measured using 5 items. The items were rated in a 4-point likert type scale ranging from (1) = strongly disagree to (4) strongly agree. Table 4.6 presents the items used to measure commitment.

Table 4.6: Items measuring commitment

1. Given a chance you would change to and supply another mill (comit1) (R)
2. You have invested a lot of capital in the sugarcane business (comit2)
3. You honour your quota as required by the mill (comit3)
4. You always try to satisfy your quota (comit4)
5. You do not care whether you meet your quota, as long as you make profit (comit5) (R)

R= reversed coding (The responses to these items were reversed before the analysis was conducted, i.e. responses such as 1 and 4 were switched over, and 2 and 3 were also switched over).

4.4.3 Measurement of influence by partner

Controlling behaviour among organisations in a contractual arrangement is a result of power imbalance and authority. The influence by partner implies that one partner's goals dominate the decisions made in the relationship. Hence, it affects the outcomes of the relationship. Eight items were used to measure the farmers' perception of influence by partner and are presented in Table 4.7.

Table 4.7: Items measuring influence by partner

1. The mill tries to control farmers (influby1)
2. Farmers can make farming decisions independently of the mill (influby2) (R)
3. Farmers take whatever the mill says because they do not have any bargaining power (influby3)
4. The mill has more bargaining power than farmers (influby4)
5. Farmers manage to have their concerns considered by the mill (Rinflov1) (R)
6. Farmers can influence the price of sugarcane offered in the industry (Rinflov2) (R)
7. Farmers and the mill have equal bargaining power (Rinflov3) (R)
8. Farmers have more bargaining power than the mill (Rinflov4) (R)

R= reversed coding (The responses to these items were reversed before the analysis was conducted, i.e. responses such as 1 and 4 were switched over, and 2 and 3 were also switched over).

4.4.4 Measurement of certainty

In today's fast-changing world it is inevitable that organisations involved in an exchange relationship are faced with uncertainty. It could be environmental uncertainty, how the environmental changes would affect each organization's business and how to react to such changes. Table 4.8 presents the items used to measure certainty in this study. The cane growers' perception of the degree of certainty in their relationship with millers was measured with 5 items rated in a 4 point likert-type scale.

Table 4.8: Items measuring certainty

1. Farmers are assured of a market (cert1)
2. Farmers know in advance the price at which the sugarcane will be bought (cert2)
3. Farmers have all the technical know-how on growing sugarcane (cert3)
4. Farmers can always get technical information from the SSA Extension department (cert4)
5. Now farmers know how to grow sugarcane (cert5)

4.4.5 Measurement of opportunistic behaviour

Opportunistic behaviour is a key concept in contract-centred approach to exchange relationships. Opportunism is defined as self-interest seeking with guile, which includes lying, stealing, and cheating. In general, it is the incomplete or distorted disclosure of information, especially to calculated efforts to mislead, distort, disguise, obfuscate, or otherwise confuse. Opportunistic behaviour was measured using 6 items, all rated in a 4 point likert-type scale (Table 4.9).

Table 4.9: Items measuring opportunistic behaviour

1. The mill takes advantage of the farmers' ignorance (opp1)
2. The mill is concerned with maximizing its own profits (opp2)
3. The mill cheats when testing farmers' sugarcane (opp3)
4. The difference in opinion between the mill and farmers is what strengthens the relationship between the two parties (Rconf1) (R).
5. The differences in opinions between the mill and farmers is an effort by the mill to cheat farmers (conf2)
6. Farmers regard conflict of opinion between the mill and farmers as a normal way of doing business (Rconf3) (R)

R= reversed coding (The responses to these items were reversed before the analysis was conducted, i.e. responses such as 1 and 4 were switched over, and 2 and 3 were also switched over).

4.4.6 Measurement of relative dependence

The perception of dependence of the parties in an exchange relationship is an important dimension. Dependence takes place when one partner does not control all of the conditions necessary for achievement of an action or when a desired outcome is performed by another partner (Handfield and Bechtel, 2002). A relative measure of dependence is imbalance in a relationship and the primary consequence of relative dependence is influence or power.

Relative dependence in this study was measured by 8 items rated in a 4 point likert type scale presented in Table 4.10.

Table 4.10: Items measuring relative dependence

1. If you want you can switch from growing sugarcane to another enterprise (dep1)
2. If this mill could close down, you would be forced to go out of business (dep2)
3. The mill makes an effort to assist farmers during emergencies (e.g. providing transport) (dep3)
4. Farmers can sell their sugarcane only to this mill (dep11)
5. The mill's output can be lowered without the farmers' involvement in sugarcane production (dep22R) (R)
6. Farmers can still do better by engaging in other businesses than sugarcane production (dep33R) (R)
7. Farmers are visited by the industry's extension agents on a frequent basis (dep7)
8. Farmers are invited to workshops by the SSA (dep8)

R= reversed coding (The responses to these items were reversed before the analysis was conducted, i.e. responses such as 1 and 4 were switched over, and 2 and 3 were also switched over).

4.4.7 Measurement of trust

Arrow (1973) asserts that there is an element of trust in every transaction. Parties to an exchange relationship in which past experiences and the shadow of the future emerge, will project their relationship into that future by focusing on the "relational quality" of the exchange (Arino and de la Torre, 1998). The critical determinant of relational quality is the experience of the parties with each other's behaviour as the exchange unfolds. Therefore, the direct experiences will influence the parties' views of each other's trustworthiness (Lewicki and Bunker, 1996; McKnight *et al.*, 1998). Trust in this study is measured by 9 items in a likert- type scale. Table 4.11 presents the items used to measure trust.

Table 4.11: Items measuring trust

1. The mill's decisions are meant to benefit both growers and the mill (trust1)
2. The mill treats cane growers with care (trust2)
3. There is a mutual understanding between the mill and the cane growers (trust3)
4. The mill can be relied upon for its technical ability (trust4)
5. The mill sometimes withholds some information that may be useful to cane growers (trust5R) (R)
6. The mill cheats on farmers (trust6R) (R)
7. One has to monitor and double check whatever information the mill gives to cane growers (trust7R) (R)
8. You sometimes think of quitting sugarcane farming (Rpleave1) (R)
9. The way farmers are treated by the mill one thinks of changing the mill (Rpleave2) (R)

R= reversed coding (The responses to these items were reversed before the analysis was conducted, i.e. responses such as 1 and 4 were switched over, and 2 and 3 were also switched over).

4.4.8 Measurement of cooperation

Cooperation is regarded as the starting point for supply chain management and as such it has become a necessary, but not a sufficient condition. The next important element is coordination, which ensures smooth flow of goods and resources among parties (Spekman *et al*, 1998). This study used 9 likert type scale items to measure the perception of cooperation between the cane growers and the millers. Table 4.12 presents the items measuring cooperation.

Table 4.12: Items measuring cooperation

1. Your activities with the mill are well coordinated (coop1)
2. Together with the mill you plan production and delivery schedules (coop2)
3. The mill seriously takes into consideration farmers' concerns (coop3)
4. The mill seeks farmers' opinions whenever it considers implementing changes that will affect farmers as well (coop4)
5. The mill is very much cooperative (coop5)
6. There are no hassles looking for a market (Benefit 2)
7. Subsidized transport by the mill (Benefit 3)
8. Loans provided by the mill to farmers (Benefit 4)
9. Use of mill equipment by farmers (Benefit 5)

4.5 SUMMARY

This chapter first introduced the hypotheses that guide the study. The second section addressed the methodology employed to gather the sample used in the study, and the third section presented the statistical procedures used to analyse the data. Finally, the measurement items used for the different construct variables used in the study were presented and discussed in this chapter.