Attributes of dominant control: theoretical model and empirical tests

Keith Duncan

Follow this and additional works at: http://epublications.bond.edu.au/discussion_papers

Recommended Citation

http://epublications.bond.edu.au/discussion_papers/52
DISCUSSION PAPERS

"Attributes of Dominant Control: Theoretical Model and Empirical Tests"

Keith Duncan
Assistant Professor Accounting and Finance
Bond University

DISCUSSION PAPER NO 52

May 1994

University Drive, Gold Coast, QLD, 4229
AUSTRALIA
Bond University was established by Act of Parliament in 1987 as an independent, private University. The first student intake occurred in May 1989. The School of Business offers degrees in the undergraduate (BCom, BHospMgt and Diploma) and the graduate (MBA, MAcc, MCom, MTM and PhD) levels.

The School teaches and sponsors research in accounting, economics, econometrics, finance, marketing, management, organisational behaviour and related disciplines in hospitality and real estate fields.

The Discussion Paper series is intended to foster research and comments are invited. The views expressed in the papers are the opinion of the authors and do not necessarily reflect the views of the School or the University.

Lists of available Discussion Papers and copies of the papers (which are free of charge) may be obtained from:

The Senior School Administrator
School of Business
Bond University
GOLD COAST QLD 4229

Telephone: (075) 95 2244
Fax: (075) 95 1160
ATTRIBUTES OF DOMINANT CONTROL: THEORETICAL MODEL AND EMPIRICAL TESTS

by

Keith Duncan
Assistant Professor of Accounting and Finance

Acknowledgments: The research reported herein has benefited greatly from comments made by Professors Ray McNamara, Ken Moores, Ted Mock, Keith Shriver, Lester Johnson, and Don Stokes.
Abstract

This paper develops and empirically tests a predictive model of the attributes that give one entity dominant control over the decision making of another entity. Control is modelled to be a linear function of four key attributes: (1) the level of ownership; (2) the directness of ownership; (3) the dispersion of ownership; and (4) the level of board membership. The importance of each attribute is estimated through a conjoint experiment wherein subjects judge the degree of control that they feel pre-planned scenarios depict. Through conjoint analytic techniques these judgements are disaggregated to reveal the relative attribute weights for each individual, and for the respondent group as a whole.

The results indicate that ownership and board membership are perceived to be the most important attributes in assessing dominant control relations. Indirect ownership links and dispersion of ownership play a lesser role in the assessment of dominant control. The model is found to exhibit predictive ability within the estimation sample and for a set of holdout observations. Finally, the cross-cultural instability of the estimated parameters is found to be driven by the clustering of opinions within the two cultures in the sample (ie. US and Australia).
1. Introduction

The international trend in accounting regulation is to require consolidation of all entities where the 'group' controls the operating and financing decisions. Regulations are moving away from the uni-dimensional majority ownership test for group membership towards a broader control test which reflects that contemporary group structures include both ownership and other forms of inter-entity linkage. Such complex inter-entity structures cloud the control issue and allow non-consolidation of some controlled members of the extended group (Walker, Wilkins and Zimmer, 1982; Ma, Parker and Whittred, 1991; Mian and Smith, 1990a, 1990b).

Current US regulations (ie. SFAS 94) define control in terms of the uni-dimensional majority ownership measure. This contrasts with the broader control concept adopted in the international accounting standards (ie. IAS 27), the EEC Seventh Directive, and the recent regulatory changes (and pending changes) in the UK, Australia and New Zealand. Terminology differences aside, the IAS, UK, EEC, Australian and New Zealand provisions adopt a similar broad definition of control. In each case control is presumed to exist where the parent has majority ownership - the previous de jure test. Control can exist with less than majority ownership if the parent also has the "power to govern" (IAS), "dominant influence over" (UK, EEC), or the "capacity to dominate" (Australia and New Zealand) the operating and financing policies of the related entity.

The problem this paper addresses is how to operationalise the concepts of "power to govern", "dominant influence", and "capacity to dominate". Sections 2 and 3 develop a theoretical model of the attributes that give one entity dominant control over the decision making of another entity. Section 4 discusses the experiment design and section 5 presents the individual and aggregate level empirical control models. Sections 6 and 7 respectively explore the model's predictive ability and cross-cultural stability. The final section discusses the major results and conclusions.

2. Model of Control

Control can be thought of as a continuous concept \( C \) anchored at the points of no control and absolute control, as depicted in Figure 1. Financial reporting regulations arbitrarily trichotomise this continuum into three broad categories of partial or shared control: insignificant influence, significant influence, and dominant control. The boundaries between the control categories, labelled \( \theta_s \) and \( \theta_c \) in Figure 1, represent
the reporting decision points that confront directors, accountants, and auditors. The choice of accounting technology for investments is dependent on this judgement. Regulations and accounting practice have deemed lower of cost or market, equity method, and consolidation to be the appropriate accounting technologies for the respective control categories. There is, however, no research on how decision makers operationalise these "fuzzy" conceptual boundaries.

To model the control continuum depicted in Figure 1 it is first assumed that multiple attributes manifest in each control situation. Different combinations and levels of these attributes represent different points along the control continuum as follows:

\[ C_i = f(X_{i0}, X_{i1}, X_{i2}, X_{i3}, \ldots, X_{in}) + u_i \]  

The continuous variable \( C_i \) represents the degree of control an entity has over its \( i \)th related entity as a function of \( n+1 \) attributes \( (X_{ij}, j = 0,1,2,3 \ldots, n; \) where \( X_{i0} = \) unit vector for common fixed effects), and \( u_i \) non-systematic attributes that distinguish control relationship \( i \) from relationship \( k \) (\( i \neq k \)). To operationalise the model, it is assumed that control is a linear additive function that maps a multi-dimensional attribute set to a uni-dimensional overall control vector. This assumption rests on the research in psychology that has found simple linear models more closely approximate human judgements than lexicographic, satisficing or multiplicative choice models (see for example Goldberg, 1968; Hoffman, Slovic and Rorer, 1969; Dawes, 1971; Dawes and Corrigan, 1974; Berl, Lewis and Morrison, 1976, and Barron, 1977). To maintain generality the mapping function depicted in equation 2 is constrained to be linear in the parameters, but not the attributes:

\[ f(X_0) = \sum_{j=0}^{n} \beta_j g(X_0) \]  

Where \( \beta_j \) is the weight for the \( j \)th control attribute. The function \( g(\cdot) \) permits the attributes \( (X_{ij}) \) to enter the general model in linear or non-linear states. For tractability the theory is discussed in terms of a simple linear additive model. Equations 1 and 2 permit \( C_i \) to take on any real number value to reflect the strength of the control relation implied by the underlying attributes, at least some of which will also be real numbers (e.g. percentage ownership is non-negative real number variable). However the concept of control applied in accounting is trichotomous, not continuous. An entity either has insignificant influence, significant influence, or dominant control over related entity \( i \) for financial reporting purposes. This implies that there are values \( \theta_s \) and \( \theta_c \) for \( C_i \) that respectively define the boundaries between situations where there is insignificant
or significant influence, and where one entity does or does not have dominant control over another. This trichotomous view of concept in accounting is represented by defining $C_i^*$ as follows:

$$
C_i^* =
\begin{cases} 
-1 & \text{if } C_i < \theta_i; \\
0 & \text{if } \theta_i > C_i \geq \theta_2; \\
1 & \text{if } C_i \geq \theta_c.
\end{cases}
$$

In theory $\theta_c$ and $\theta_s$ are constants, albeit unknown at this stage. Empirically, however, these cut-off points may vary between either the control situations (ie. the $i$s), individual decision makers, or the cultural environment for the evaluation. Nevertheless modifying $C_i$ by some function $\kappa(.)$ transforms the cut-offs to known constants. For instance, defining $C_i' = \kappa(C_i)$ creates new boundaries $\theta_c'$ and $\theta_s'$ such that,$$
\theta_c' = \kappa(\theta_c) \quad \text{and} \quad \theta_s' = \kappa(\theta_s).$$

The problem that accounting practitioners and researchers face is to assess the probability that the relationship between an entity and its $i$th related entity falls into one or other of the three control categories. That is, do the attributes of the relationship indicate it is more probable that $C_i^* = -1$ (ie. insignificant influence), or $C_i^* = 0$ (ie. significant influence), or $C_i^* = 1$ (ie. dominant control)? Estimating these probabilities must be relative to the cut-off points, $\theta_s$ and $\theta_c$, and the probability function generating the observed values of $C_i$ as follows:

Insignificant Influence

$$\begin{align*}
\text{prob}(C_i^* = -1) &= \text{prob}(C_i < \theta_i \mid \theta_s' = 0) \\
&= \text{prob}(u_i < \theta_s - \sum_{j=0}^n \beta_j g(X_i)) \\
&= F(\theta_s - \sum_{j=0}^n \beta_j g(X_i))
\end{align*}
$$

The model depicts accountants, auditors and managers behaving as if they assign probabilities to whether one entity controls another. It is debatable, however, whether accountants, auditors and managers can articulate their probability assessment or even explicitly assign probabilities. To overcome this measurement problem a conjoint experiment is used to capture judgements.
**Significant Influence**

\[
\text{prob}(C_i^* = 0) = \text{prob}(\theta_c > C_i \geq \theta, | \theta_c' = 1, \theta_e' = 0) \\
= \text{prob}(\theta_c - \sum_{j=0}^n \beta_j g(X_{ij}) - u_i \geq \theta_e - \sum_{j=0}^n \beta_j g(X_{ij})) \\
= F(\theta_c - \sum_{j=0}^n \beta_j g(X_{ij})) - F(\theta_e - \sum_{j=0}^n \beta_j g(X_{ij}))
\] (5)

**Dominant Control**

\[
\text{prob}(C_i^* = 1) = \text{prob}(C_i \geq \theta_e | \theta_e' = 1) \\
= \text{prob}(u_i \geq \theta_e - \sum_{j=0}^n \beta_j g(X_{ij})) \\
= 1 - F(\theta_e - \sum_{j=0}^n \beta_j g(X_{ij}))
\] (6)

\(F(.)\) is the cumulative distribution function (CDF) for \(u_i\). Equations 4, 5, and 6 are solved by evaluating \(f(.)\), the probability density function (PDF) for \(u_i\), over the relevant range for the probability being evaluated. To assess the probability of an insignificant influence relationship, the PDF is evaluated from minus infinity up to the cut-off \(\theta_s\) for \(C_i\). That is:

\[
\text{prob}(C_i^* = -1) = \int_{-\infty}^{\theta_s} f(u_i) \, du_i
\] (7)

For the probability that the relationship is one of significant influence, the PDF is evaluated from the cut-off \(\theta_s\) up to the boundary \(\theta_c\) for \(C_i\). That is:

\[
\text{prob}(C_i^* = 0) = \int_{\theta_s}^{\theta_c} f(u_i) \, du_i
\] (8)

For the probability that the relationship is one of dominant control, the PDF is evaluated from the cut-off \(\theta_c\) through to plus infinity, the maximum for \(C_i\). That is:

\[
\text{prob}(C_i^* = 1) = \int_{\theta_c}^{\infty} f(u_i) \, du_i
\] (9)

Evaluating these PDFs requires some knowledge or assumption about the generating process for \(u_i\). This generating process in turn will influence the choice of
statistical methods to employ in estimating the model (see Maddala, 1983; Hensher and Johnson, 1981).²

The general model captures all levels of control. However it is the dominant control boundary \( \theta_c \) which is of greater research interest for two reasons. First from a regulatory perspective the boundary for significant influence \( \theta_s \) is widely accepted, whereas the dominant control boundary \( \theta_c \) is yet to be universally adopted. Second, misclassifying inter-firm relationships at the dominant control boundary \( \theta_c \) is likely to have a greater impact on loan and valuation decisions than misclassifying investments at the significant influence boundary \( \theta_s \). Numerous studies have shown that non-consolidation of controlled entities masks the true debt levels of the group, thus lowering reported leverage, and increasing return on assets and interest coverage ratios (e.g. Francis, 1986; Livnat and Sondhi, 1986; Copeland and McKinnon, 1987; Mohr, 1988; Heian and Thies, 1989). The remainder of this paper, therefore, focuses exclusively on modelling dominant control and the boundary \( \theta_c \), which is in a state of regulatory flux and is economically more significant than the boundary \( \theta_s \).

3. Four Attributes of Dominant Control

A review of the literature in accounting, law, finance, economics, and management suggests four key attributes determine the level of dominant control: (1) the total ownership level; (2) the level of direct versus indirect ownership; (3) the dispersion of non-owned equity; and (4) the level of representation on the Board of Directors. This gives the following four attribute linear model of dominant control:

\[
C_i = \sum_{j=0}^{d} \beta_j X_{ij} + u_i
\]

Where:

\( C_i \) = Degree of control over related entity \( i \);
\( X_{i0} \) = Unit vector to capture fixed effect over all \( i \) entity relationships;
\( X_{i1} \) = Total level of ownership in entity \( i \);
\( X_{i2} \) = Direct versus indirect ownership in entity \( i \);
\( X_{i3} \) = Dispersion of ownership of other stock in entity \( i \);
\( X_{i4} \) = Representation on entity \( i \)'s Board of Directors; and
\( u_i \) = Non-systematic attributes of relationship \( i \).

² For example, a logistic error distribution requires a logit estimation procedure, and normal errors demand a probit (normit) or linear probability model (dichotomous regression). Ordered versions of these statistical procedures are more appropriate for estimating the general model outlined above as the dependent variable \( C_i \) represents a set of ordered categories.
3.1. Total Level of Ownership

Historically both practice and regulation have used the total percentage of shares owned to determine if a company does or does not control related entity \( i \). However other attributes may contribute to the strength of the control relationship. Empirical evidence suggests that majority ownership is not necessary, and in some cases may not be sufficient, for dominant control (Shaw, 1976; Leo, 1987; Markovic, 1992; Ashton, 1986; Blue, 1990). However, majority ownership is a sufficient criterion for control in the markets for corporate control. The proposition arising out of this evidence is that there is a direct proportional relationship between the total level of ownership, \( X_{ij}, j = 1 \), and the degree of control over related entity \( i \).

3.2. Level of Direct versus Indirect Ownership

Corporate legislation and accounting standards recognise that the directness of an ownership link is a key attribute in assessing the degree of control associated with that ownership. Corporate regulations use the term beneficial interest to mean all interests, direct or indirect, from which one entity can obtain benefit. Further, the accounting standards define an 'ownership interest' to be capital held either directly, or indirectly through another entity.

Case evidence, such as the collapse of the Adelaide Steamship 'group' in Australia (Shvets, 1990; Gottliebson, 1991), demonstrates that control assessments are more problematic where ownership is indirect through intervening structures. Directors, accountants, and auditors must consider whether the complexity of the indirect links lessens the capacity to control. Therefore the second proposition states there is a direct proportional relationship between the level of direct versus indirect ownership, \( X_{ij}, j = 2 \), and the degree of control over related entity \( i \).

3.3. Dispersion of Ownership of Other Stock

Dispersion refers to the level of concentration in ownership held by parties other than by the potentially dominant entity. In a de facto control framework a broad view of dispersion would define entity \( i \) as widely held if there is a low probability that other stockholders will act in concert against the dominant entity. This includes actions at

---

3 See Copeland and Weston (1988) for a review of the research on the role of ownership in takeovers and anti-takeover counter measures.

4 See, for example, the Australian Corporations Act 1989, the UK Companies Act 1989, and the New Zealand Companies Act 1981.

5 Specifically, IAS 27, SSAP 8 (NZ), SSAP 14 (UK), and AASB 1024 (Australia).
annual general meetings, directors' meetings, or in the courts. Alternatively, entity $i$ is **closely held** where a third party holds a significant block of $i$'s stock, thus making it more likely that the dominant entity has to consider the third party's wishes.

Research on proxy contests (Dodd and Warner, 1983; Kesner, Victor and Lamont, 1986; Jones, 1986; Kesner and Johnson, 1990), and on the role of dispersion in equity markets (Fama and Jensen, 1983; Williamson, 1983; Dann and DeAngelo, 1983), as well as case evidence (Tricker, 1984), suggests ownership dispersion is an important attribute in assessing control relationships. Dispersion indicates the possibility of other interests competing for control, which at the extreme could make dominant control impossible. Therefore the third proposition states there is a direct proportional relationship between the level of dispersion of ownership of other stock, $X_{ij}, j=3$, and the degree of control over related entity $i$.

### 3.4. Representation on Board of Directors

Dominant control over decision making hinges upon the level of board representation as the decision making power in the modern corporation lies with the Board of Directors (Tricker, 1984). The degree of common control of two corporate boards is defined in the organisational literature to be proportional to the number of common or interlocking directorships (Mariolis and Jones, 1982). The creation of common directorships may, however, be to achieve a range of organisational goals, including establishing dominant control, where control through majority ownership is impossible or undesirable (Pfeffer, 1972; Dooley, 1969; Burt, 1980; Palmer, 1983; Stearns and Mizruchi, 1986; Mizruchi and Stearns, 1988).

Research has found that common directorships, in conjunction with other boundary spanning devices, such as ownership, allow an entity to achieve dominant control over the decisions of other entities (Burt, 1980; Palmer, 1983; Zajac, 1988). Further, case evidence suggests that dominant control will rest with the party that controls the board (Shvets, 1990; Gottliebson, 1991). That is, where the majority of the board are under the influence of a single entity, and that entity has sufficient ownership interest to establish and maintain that majority position. Level of board representation therefore includes both common board members and board members under the influence of the dominant party. The fourth proposition follows that there is

---

6 A distinction is often drawn between managerial and owner controlled firms in terms of the proportion of inside (executive) directors to outside (non-executive) directors (Williamson, 1983; Jensen and Meckling, 1976; Fama and Jensen, 1983; Weisbach, 1988; Pfeffer, 1972; Tricker, 1984; Dalton and Kesner, 1987; Kesner and Johnson, 1990). This distinction is not relevant to the dominant control model as it is the commonality of board membership between the dominant entity and dominated entity that is important, not the composition of the board *per se* (Tricker, 1984).
a direct proportional relationship between the level of board representation, $X_{ij}, j = 4,$ and the degree of control over related entity $i$.

4. Research Methodology

A conjoint experiment was designed to estimate the parameters of the four attribute model of dominant control (equation 10). Conjoint methods allow the researcher to decompose total-object evaluations of multi-attribute alternatives to reveal the decision importance of the underlying attributes. The technique addresses two related problems in judgement research. First the decomposition approach overcomes the lack of an independent measure for the weights decision makers assign to the underlying dimensions of their decisions (Luce and Tukey, 1964; Krantz and Tversky, 1971). Second the technique avoids the problem of decision makers either not being able to assign explicit weights, or assigning inaccurate weights, to the underlying attributes of their decisions (Shepard, 1964).

4.1. Dependent Variable - Degree of Control

The subjective control evaluations of decision makers are captured in a conjoint experiment which presents subjects with cases containing different combinations of the four control attributes, while holding constant all other extraneous variables. A mixture of measures, similar to Rosenberg's (1956) category assignment and rating task, is used to capture the decisions of the subjects. First, the subjects make a dichotomous judgement $C_i \geq \theta_C$ (i.e. controlled) or $C_i < \theta_C$ (i.e. not controlled), based on the researcher manipulated multi-attribute case situations. Second the subjects rate the degree of confidence they have in their decisions, measured on a 5-point Likert-type scale with anchor points at "Not Too Confident" and "Extremely Confident".

An 'index' of the degree of dominant control is constructed by multiplying a dummy variable for the control evaluation (ie. -1 if case $i$ is evaluated as "Not Controlled", and 1 if it is evaluated as "Controlled"), by the subject's confidence level, measured on a 5 point Likert-type rating scale. This coding scheme gives the ten point integer range from -5 to +5 which excludes zero. For analysis purposes this index is re-scaled to lie on a ten point equidistant scale from -4.5 to +4.5. Finally, the re-scaled index is standardised so that parameter estimates for individual models can legitimately

\footnote{The actual control decisions of companies cannot be used as the dependent variable as in practice this decision is confounded by the reporting objectives of management.}

\footnote{To enable testing of convergent validity subjects were also required to provide self-explicated ratings of the importance of each control attribute.}
be compared across respondents. This control 'index' simultaneously reflects the practitioner's dichotomous operationalisation of the concept and approximates the continuous control concept depicted in Figure 1.

4.2. Independent Variables - Levels of Control Attributes

The independent variables in equation 10 are manipulated through a series of cases. Each case contains varying levels of the four control attributes identified in section 2. The manipulation levels for each attribute are summarised in Table 1. The choice of levels for each attribute was influenced by:

1. the legislation and standards regulating reporting practices;
2. case evidence of the attributes influencing control;
3. research evidence on the number and spacing of attribute levels; and
4. practical issues of subject fatigue and interest in the case.

4.3. Conjoint Instrument Development

An orthogonal array (ie. a highly fractional factorial design) was used to identify a parsimonious set of attribute combinations for the treatment cases (Addelman, 1962; Bose and Bush, 1952; Raghavarao, 1971; Dey, 1985). The array was randomly selected from one of many possible balanced designs using the SPSS-PC: Conjoint Module. This array provided the factorial design for the 32 treatment cases. A further 6 holdout cases were added to the initial set of 32, giving a total of 38 treatment cases altogether. The holdout cases provide a small data set against which to evaluate the within subject predictive ability of the model estimated using the 32 treatment cases.

---

9 See Duncan (1993) Chapter I and Appendix A for a discussion of the legal and regulatory framework surrounding consolidated reporting.
12 The number of cases for evaluation, and hence the number of attributes and attribute levels, is limited by the time the research task requires. Green and Srinivasan (1978) suggest it is difficult to maintain respondent interest much beyond 30-40 cases which limits the number of attributes and attribute levels to a maximum of 5 or 6.
13 The orthogonal array overcomes the fatigue problems of a full design and the fact that a full design creates a multicollinear independent variable set that leads to inflated standard errors when estimating the regression parameters. In contrast, an orthogonal array, which typically consists of 30-40 cases, gives mathematically valid (ie. uncorrelated) estimated attribute parameters (Green, 1974).
Table 2 presents the matrix of attribute level combinations in which each cell represents one of the 384 treatments in a full factorial design. The twenty-four rows in the table represent the six levels of total ownership each subdivided by the four levels of direct and indirect ownership. The sixteen columns comprise the four levels of board representation, further subdivided by the four levels of dispersion. The cell labels "1" to "38" correspond to the 38 attribute combinations in the 38 cases (i.e., 32 estimation cases and 6 holdout cases) in the treatment instrument.

4.4. Test Booklet and Pre-Testing

The test booklet presented subjects with instructions for the experiment, definitions of the variables, 38 four-line case descriptions, and a response sheet. The ordering of the stimuli cases in the experiment, however, was randomised to control for potential testing and/or halo confounding effects.

The test instrument and instructions were circulated amongst the accounting faculty at the University of Southern California, Los Angeles, and Bond University, Gold Coast, Australia, and the marketing faculty at Murdoch University, Perth, Australia. The revised instrument was then pre-tested on seven subjects whose occupational credentials included experience as directors, financial executives, security analysts, and accountants. The pre-test resulted in minor modifications to the test instrument.

4.5. Subjects

Directors, financial executives, accountants, and credit/security analysts were chosen as the population of subjects as they deal with the issue of 'control' frequently and thus are appropriate judges of whether one company controls another. A random sample of 1000 directors, financial executives, public accountants, and credit/security analysts was selected from the US and Australian populations of potential subjects. The reporting environment for the Australian subjects differs from that for the US subjects where control is defined in terms of ownership (i.e., SFAS 94). Australia has recently adopted (for income years ending on or after 31 December 1991) a broader de facto control test consistent with IAS 27. Thus collecting judgements of US and Australian subjects facilitates testing of a fifth proposition, implicit in the international standard, that the concept of control is cross-culturally stable.

4.6. Data Collection Procedures

The test instrument was mailed to the potential subjects with a personally addressed cover letter, signed by the researcher, introducing the study and inviting the
addressee's participation. The mailed test instrument defined each of the attributes in turn and included the following instructions for the subjects on how to evaluate the case cards and self score their responses:

1. Detach along the perforations each of the 38 cases to form a series of "cards".

2. Sort all 38 "cards" into two piles -- one pile for those cases you consider company X controls company Z and one pile for those where company X does not control company Z. Some respondents may wish to use a third 'doubtful' pile, which is then re-evaluated and split as appropriate between the control and not control piles.

3. Examine the contents of your final two piles, making sure that you agree with your evaluation, swapping some "cards" over to the other pile if you like.

4. Taking each pile in turn, record your responses on the response form over the page. Make sure that you circle YES if you consider company X does control company Z and NO for each case you consider company X does not control company Z. Also indicate how confident you are about your evaluation on the 5-point scale.

5. Complete the additional questions concerning your evaluations and background. Seal the response booklet in the reply-paid envelope and place in the post.

The card sort approach was chosen for three reasons. First, card sorting (also referred to as Q sorts) is a proven research method for capturing individual opinions, preferences and decisions (Stephenson, 1953; Rosenberg, 1956; Kerlinger, 1986) and is often used in marketing conjoint studies (Green and Srinivasan, 1978; Wittink and Cattin, 1989). Second, the method allows subjects to freely compare and sort the case cards, a freedom that conventional 'rate-the-list' formats do not afford. This means subjects can separate straightforward cases from a 'doubtful' pile that can be returned to for more careful consideration. If the card format makes it easier for the subjects to assess the cases then judgement quality is likely to be higher. Third, the 'game-like' quality of the task generates subject interest. Such a positive disposition on the part of subjects improves the probability of obtaining quality responses. Figure 2 reproduces the example case and response form provided as a guide for the subjects.

**INSERT FIGURE 2 HERE**

4.7. Response Rate, Non-Response Bias, and Reliability Analysis

A high proportion of the mailed surveys were returned marked indicating participation "Declined" or "Return to Sender" (i.e. respondent not prepared to participate or undeliverable due to database decay factors such as location or personal changes). From the remaining 611 surveys mailed but not returned unopened, a total of
246 (110 for the US and 136 for Australia) useable responses were received (ie. 40.3 per cent of the possible responses). Techniques to enhance response rates, such as follow up mailing procedures, were not possible due to the anonymous response format and the restricted access to databases.

Non-response bias was examined by comparing the responses of early and late respondents on the basis that non-respondents are often similar to late respondents (Oppenheim, 1966, p. 34). The analysis showed little evidence of any systematic difference in the mean and variance of the early responses (ie. first two thirds received) to the responses for the late respondents (ie. the last one third received).

A modified version of Beesley and Hensher's (1987) paired-choice-dominance technique was used to test reliability as the anonymous survey did not permit a second mail out to collect test-retest or alternative form data for consistency analysis (Green and Srinivasan, 1978; Carmines and Zeller, 1979; Segal, 1982). The analysis supports the conclusion that respondents were internally consistent in their case ratings.

4.8. Analysis Methods and Hypotheses

To disaggregate the 32 estimation control evaluations to reveal the weights for each attribute, the following regression equation was estimated for each subject.

\[ DC_{i,m} = \beta_0 + \beta_1 \cdot Own_i + \beta_2 \cdot Dir/Ind_i + \beta_3 \cdot Disp_i + \beta_4 \cdot Board_i + \xi_{i,m} \]  

Where:

- \( DC_{i,m} \) = subject \( m \)'s (\( m = 1, \ldots, M \); \( M = 246 \)) 'index' score for the degree of control for case \( i \) (\( i = 1, \ldots, T; T = 32 \)).
- \( Own_i \) = ownership level (ie. \( X_{1i} \)) is either 15, 30, 45, 49, 51, or 65%.
- \( Dir/Ind_i \) = level of direct vs indirect holding (ie. \( X_{2i} \)) is either 100, 60, 40 or 0%.
- \( Disp_i \) = dispersion (ie. \( X_{3i} \)) is either 0, if "widely held", or 10, 20 or 30%.
- \( Board_i \) = level of board membership (ie. \( X_{4i} \)) is either 20, 40, 60 or 80%.

---

14 Beesley and Hensher's (1987) test requires the researcher to 'plant' a series of logically dominant choices in the set of paired comparisons. The hypothesis is that consistent respondents will correctly identify the dominant cases. In the current study, case 16 represents a logically dominant stimulus case (ie. 65 per cent owned, all direct, remaining share widely held, and 8 of 10 Board members). All respondents judged this case to be a control situation with a confidence rating of 3 or greater, indicating some degree of logic in respondent judgement. The design did not allow for further logically dominant cases. However consistency in response to similar and dissimilar cases was tested. A Fisher z-test (Klugh, 1974, p. 237) for differences in correlation found that only one correlation between responses to similar cases was significantly less than the defined 'test' value (\( \rho = 0.5 \)). The remaining correlations were either statistically the same, or significantly greater than, the test level of 0.5. Finally, there was no significant correlation between dissimilar pairs of cases.
As discussed above, the dependent variable is constructed by multiplying the dummy variable for the control evaluation (i.e. -1 if case \( i \) is evaluated as "Not Controlled", and 1 if it is evaluated as "Controlled"), by the subject's confidence level, measured on a 5 point Likert-type rating scale. This index was re-scaled and standardised prior to estimating the control model. The independent variables, the four attributes, are coded as continuous variables reflecting the levels presented in Table 1.

**Hypotheses One to Four:**

The theoretical model presented in section 2 proposed a direct proportional relationship between the total level of ownership \( (X_{i1}) \), the level of direct versus indirect ownership \( (X_{i2}) \), the dispersion of the other equity \( (X_{i3}) \), the level of board membership \( (X_{i4}) \), and the degree of dominant control over related entity \( i \). Thus the first four null hypotheses are that each of the parameters for the attributes in equation 11 will be zero.

**Hypothesis Five:**

A fifth related null hypothesis is that dominant control is determined by an equally weighted combination of the four attributes.

**Hypothesis Six:**

The estimated regression model for each individual and the aggregate model are used to 'predict' each subject's decision for the 32 estimation cases and for the 6 holdout cases. The null hypothesis is that there is no correlation between the predicted decisions and actual evaluations for the estimation and holdout cases.

**Hypothesis Seven:**

The fifth proposition related to the stability of the model across countries. Australian subjects, regulated by a broader concept of control, should place less weight on ownership and more emphasis on other attributes of control, than US subjects. Stated in null form the hypothesis is that the parameters for the US and Australian subjects are equal.

To test these hypotheses the model in equation 11 was estimated separately for each of the \( M = 246 \) individual respondents. An average model was calculated from the mean estimated attribute coefficients for the \( M \) individual models as follows:

\[
\beta_{j,m} = \frac{1}{M} \sum_{m=1}^{M} \beta_{j,m}
\]  

(12)
Where \( \bar{\theta} \) signifies that the parameter is for the average model. The average model represents the mean 'consensus' weighting for the attributes and henceforth it is referred to as the aggregate model.

5. Individual and Aggregate Control Models

A summary of the parameter estimates for the \( M \) individual models and the aggregate model is presented in Table 3. The F-statistics for each of the \( M \) individual models are significant (\( p < 0.01 \)) suggesting each model has significant in-sample explanatory power. The residuals for the individual OLS equations were pooled to construct a F-statistic which is equivalent to testing a seemingly unrelated regression (SUR) estimation of the entire set of equations (Zellner, 1962; Dwivedi and Srivastava, 1978; Hirschey, 1981; Judge et al., 1985, 1988; Dielman, 1989).\(^{15}\) The F-Value based on the pooled residuals is 17.39 (\( df = 984, 6642, p < 0.001 \)). This confirms the \( M \) individual F-tests and implies that the \( M \) individual models as a group have significant explanatory power. Finally, an Omnibus F-test, constructed to test the aggregate model, is significant (\( F = 9.39; df = 989, 6637; p < 0.001 \))\(^{16}\) suggesting that the aggregate model also has significant explanatory power.

**INSERT TABLE 3 HERE**

The hypotheses concerning the structure of the control model are tested at both the individual and aggregate levels. The individual level results are reported in Panel A of Table 3. The table reports the percentage of significant (\( p < 0.10 \)) individual-model t-tests for each attribute. Over eighty-nine per cent of the estimated parameters for the constant, ownership, and board membership, are significant. Thirty per cent of the estimated parameters for directness of ownership, and forty-four per cent of the

---

\(^{15}\) This procedure is appropriate provided the residuals for the \( M-246 \) models do not violate the homogeneous variance assumption implicit in the F-test.

\(^{16}\) The F-statistic for the aggregate model is defined in terms of the coefficient of determination (\( R^2 \)), adjusted for degrees of freedom (which allow for the \( M \times k \) individual model parameter estimates from which the \( k \) parameters for the aggregate model are estimated), which in turn is the square of the multiple correlation coefficient (\( R \)) for the aggregate model. The F-statistic based on the average parameters from \( M \) individual \( k \)-variable regressions each with \( T \)-observations is defined as:

\[
F = \frac{R^2/(M(k-1)+k)}{(1-R^2)/(M(T-k)-k)}
\]

Where: \( M = 246, k = 5, \) and \( T = 32. \)
Attributes of Dominant Control: Theoretical Model and Empirical Tests

estimated parameters for dispersion, are significant. For the majority of individuals this
evidence rejects the null for hypotheses one and four that the betas for ownership and
board membership (ie. \( \beta_1 \) and \( \beta_4 \)) are equal to zero. For some individuals the evidence
also rejects the null for hypotheses two and three that the betas for the directness of
ownership and dispersion attributes (ie. \( \beta_2 \) and \( \beta_3 \)) equal zero.

At the aggregate level a t-test (based on the sampling distribution for the betas)
is used to test whether the mean parameter for the \( j \)th attribute (ie. \( \hat{\beta}_{j,m} \)) is different
from zero. The results presented in Panel B of Table 3 reject the null to hypotheses one
to four that the betas for the four attributes (ie. \( \beta_1, \beta_2, \beta_3, \) and \( \beta_4 \)) are equal to zero.

The average parameters for Own and Board (ie. \( \hat{\beta}_1 \)and \( \hat{\beta}_4 \)) have a significant
positive (\( p < 0.001 \)) bearing on the degree of control one entity has over another. The
large positive coefficient for the ownership attribute supports the ownership definition
of control, the mainstay of regulation and practice until recently. The significant
positive weighting on board membership suggests, however, that regulation and
practice based solely on ownership defined control will only partially capture the true
control relationships of companies.

The ratio of direct to indirect ownership (ie. \( \hat{\beta}_2 \)) has a significant positive impact
on control (\( p < 0.001 \)), suggesting that control is enhanced if ownership is direct. The
average coefficient is small indicating this attribute has a marginal impact on the control
relationship. The individual model parameter estimates for Dir/Ind range from
negative to positive values suggesting that not all respondents interpreted this variable
as having a positive impact on control.

The average estimated parameter for dispersion (ie. \( \hat{\beta}_3 \)) is negative and
significant (\( p < 0.001 \)), although there is a wide range of estimated values for the \( M \)
individual models. The negative average Disp parameter suggests that respondents
place a negative weight on the control effects of other blocks of equity. The more
closely held the firm, the greater the level of the other attributes required to establish
the capacity to control. Nevertheless, dispersion has a small effect on the degree of
control relative to the ownership and board membership attributes.

The individual and aggregate level evidence on the structure of the control
model rejects the null hypotheses. The conclusion is that dispersion has a negative
direct effect on the degree of control while ownership, directness of ownership, and
board membership have a positive direct effect on the degree of control. The individual
level evidence is, however, less conclusive for the dispersion and directness of
ownership attributes.
Hypothesis five stated in null form that the parameters for the four attributes would be equal. The hypothesised equal weighting of the attributes suggests that equation 11 can be reformulated as follows:

$$DC_{i,m} = \beta_0,m + \beta_{Rest,Restricted,m} (Own_{i} + Dir/Ind_{i} + Disp_{i} + Board_{i}) + \xi_{i,m}$$

(13)

The explanatory power of the restricted model in equation 13 can be compared to the unrestricted model at both the individual and aggregate levels. The F-statistic, constructed from the pooled residuals for the $M$ restricted and unrestricted individual models, was significant ($F = 16.39$, $df = 738, 6642; p < 0.001$). This evidence rejects the null for hypothesis five at the individual level.

An F-test based on the coefficient of determination ($R^2$) was used to assess the explanatory power of the aggregate level unrestricted and restricted models (Gujarati, 1988, p. 231). The respective coefficients of determination ($R^2$) for the unrestricted and restricted models are 0.5832 and 0.2114. The F-statistic for the difference between these two $R^2$ parameters was significant ($F = 8.02; df = 738, 6637; p < 0.001$). This evidence for the aggregate model rejects the null hypothesis that the parameters for the model are equal (ie. $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4$) at the aggregate level.

To test the alternative to hypothesis five, that all parameters are different, each of the $M$ individual models were re-estimated with different pairs of parameters restricted to be equal to each other. Panel A of Table 4 reports the F-Values (based on the pooled disturbances for each restricted estimation), and the number of individual models for which this F-ratio was significant. The results indicate that the parameters for all four attributes are different for the pooled tests. Further these differences exist for eleven per cent or more of the individual respondents, supporting the alternative to hypothesis five.

**INSERT TABLE 4 HERE**

---

17 This statistic is equivalent to a SUR estimation of the $M$ individual models with the restriction that all the parameters for the $mth$ individual are equal (ie. $\beta_{im} = \beta_{Restricted,m}, j = 1, 2, 3, 4$), although the estimates for $\beta_{Restricted,m}$ may vary across individuals.

18 See footnote 16 for a discussion of the relationship between the coefficient of determination ($R^2$) and the multiple correlation coefficient ($R$) for the aggregate model. The F-statistic for the unrestricted aggregate model ($k$ average parameters estimated from $M$ equations each with $k$-variables and $T$-observations) and the restricted aggregate model (estimated from $M$ equations each with $j$ independent linear restrictions) is defined as follows:

$$F = \frac{(R^2_{Unrestricted} - R^2_{Restricted})/Mj}{(1-R^2_{Unrestricted})/M(T-k) - k}$$
Panel B of Table 4 reports corresponding aggregate level analysis. Pairwise t-tests were constructed based on the sampling distribution of the beta values for the base $M$ individual models. The results for the aggregate level t-tests are consistent with the individual level F-tests. In sum this evidence supports the alternative to hypothesis five and implies that the weights for the four attributes are all significantly different.

6. Predictive Ability Analysis

Predictive ability is evidenced by the correlation between the input values for the control evaluations (the dependent variable) and the estimated control values from the control model (Green and Srinivasan, 1978). Pearson's correlations between the predicted values for each of the $M$ individual models and the respondent judgements for the 32 estimation cases ranged between 0.63 and 0.95. Table 5 provides a summary frequency distribution for the individual correlations, all of which were significant at the 0.001 level or better. The $M$ individual models therefore have a high level of estimation sample predictive ability.

Table 5 also reports the distribution of correlations between the respondents’ control evaluations and the aggregate model's predicted level of control. The correlations for the aggregate model tend to be slightly lower than the correlations for the predictions from the $M$ individual models. The significant $X^2$ statistic, based on collapsed categories, rejects the null hypothesis that the frequency distributions are the same. On the whole the aggregate model does not perform as well as the $M$ individual models. Nevertheless, the correlation between the pooled estimation sample predictions for the aggregate model and the pooled individual evaluations was 0.7636, and significant ($p < 0.001$).

The predictive ability of the estimated models was tested against the holdout sample evaluations (Acito and Jain, 1978). Predicted values for the six holdout cases were computed using the estimated parameters for each $M$ individual models. The Pearson's correlations between the $M$ individual model predictions and the actual evaluations ranged between 0.07 and 0.99, with an average Pearson's correlation of

---

19 Calculation of the $X^2$ statistic requires that no more than one expected frequency (i.e. the distribution for the individual models) is less than five, but none can be less than one. Only by collapsing adjacent categories (at the upper and lower ends of the range) do all categories for the expected distribution meet this test (see Siegel and Castellan, 1988). This procedure is applied for all $X^2$ tests of equivalence of frequency distributions in this paper.
0.85 (median of 0.89). Ninety-three percent of the $M$ individual model holdout correlations were significant at the 0.05 level or better.

Table 6 reports the frequency distribution of correlations between each respondent's holdout control evaluations and (1) control predicted by their respective $m$th individual model, and (2) control predicted by the aggregate model. The pooled cross-sectional correlation for the holdout sample predictions by the aggregate model is 0.8173, and highly significant ($p < 0.001$). This evidence suggests that both the $M$ individual models and the aggregate model have holdout sample predictive ability.

**INSERT TABLE 6 HERE**

The $\chi^2$ statistic for frequency distribution equivalence is not significant, suggesting that the aggregate and $M$ individual models predict the holdout evaluations equally well. The mean and median Pearson correlations support this conclusion. Further a comparison of the first columns in Tables 5 and 6 suggests that the prediction rates for the holdout sample are on average higher than for the estimation sample.

An F-statistic was constructed for each respondent to test whether their model's holdout prediction rate was significantly different to its estimation sample prediction rate. Under the null of no significant difference in prediction, the critical value for $F_{0.01, 6, 27}$ is 3.56. Figure 3 depicts the expected and actual frequencies for the F-Values. One of the $M$ F-Values is significantly greater than the critical value (two further F-Values are significant at the 0.05 level, $F_{0.05, 6, 27} = 2.46$), indicating that the predictive performance of the vast majority of $M$ individual models was not significantly less for the holdout responses than for the estimation sample responses.²¹

**INSERT FIGURE 3 HERE**

Finally, the performance of the $M$ individual models as a whole, based on the pooled distribution of residuals, was not significantly different between the holdout and estimation samples ($F = 0.837, p > 0.40$). Similarly, the residuals for the aggregate model were not significantly different between the holdout and estimation samples ($F = 0.649, p > 0.70$). The finding that most $M$ individual models and the aggregate model evidenced holdout predictive ability leads to the rejection of the null hypothesis. We

---

²⁰ The test statistic is based on the assumption that the prediction errors for each sample are normally distributed. Given this assumption the ratio of the two sums of squared errors, adjusted for the number of profiles in each set, is distributed $F$ with (in this case) 6, 27 degrees of freedom.

²¹ A chi-squared statistic, based on 13 collapsed categories, was calculated to test the equality of the two frequency distributions in Figure 3. The statistic was significant ($\chi^2 = 46.73; df = 12; p < 0.001$) supporting the conclusion that the observed frequency of F-Values is significantly different from the expected distribution (i.e. lies to the left of, and is more kurtose).
can accept hypothesis six that the holdout correlations are significantly positive, and the individual and aggregate models have predictive ability.\(^{22}\)

### 7. Cross-Cultural Stability of the Model

The null hypothesis seven stated that the parameters for the US and Australian respondents would be equal (i.e., \(\beta_{j,US} = \beta_{j,Aus}, j=1,2,3,4\)). To test this hypothesis, a homoskedastic and cross-sectionally uncorrelated SUR model was estimated for both the US and Australian sub-samples (i.e., pooling the responses for each country sub-sample). Table 7 reports the estimated beta vectors and model statistics for the two country sub-samples. The SUR estimation is significant (p < 0.001) and all the individual coefficients are significant. The structure of the model is similar to the aggregate model in Table 3 for the entire sample of respondents.

**INSERT TABLE 7 HERE**

An F-statistic and Wald \(\chi^2\) statistic were computed to test if the coefficients for the US model were equal to the corresponding coefficients for the Australian model (i.e., \(H_{0b}: \beta_{j,US} = \beta_{j,Aus}, j=1,2,3,4\)). Both these statistics were significant (p < 0.001) thus the null for hypothesis seven is rejected. To explore which of the individual parameters were different between the models, five additional F-statistics were computed. The F-statistics, reported in the last column of Table 7, test the hypothesis that the \(j\)th coefficient of the US model is equal to the \(j\)th coefficient for the Australian model (i.e., \(H_{0a}\)). The results show that the estimated parameters for ownership and board membership are significantly different (p < 0.001) between the models for the two country sub-samples. All other parameters are not significantly different except for dispersion which is significant at the 0.05 level. The null for hypothesis seven (i.e., that \(\beta_{j,US} = \beta_{j,Aus}\)) is therefore rejected for \(j = 1, 3, 4\).

These cross-cultural differences are consistent with the bias that current reporting regulations would produce. For the Australian sub-sample one would expect a multi-attribute control model, reflective of the broad concept of control in that country. The results are consistent with this. The ownership defined control in the US was expected to produce an ownership dominated control model. The US model has a

---

\(^{22}\) Additional analysis reported in Duncan (1993, Chapter 4 and Appendices M and N) found that the estimated individual control models outperformed a self-explicated model and two naive specifications. Thus providing evidence as to the face validity of the estimated control model.
definite bias towards ownership, but the other attributes are also significant. Even the
US respondents perceive that control is determined by more than just ownership.

Within cultural differences were analysed to gain an insight into the between
cultural differences. The \( M \) individual model parameters for each sub-sample were
cluster analysed to test if the cluster structures for the country sub-samples accounted
for the significantly different conjoint model coefficients (Green and DeSarbo, 1978;
Huber and Moore, 1979; Louviere, 1988). A k-means cluster analysis was performed
using the SAS FASTCLUS procedure to identify distinct groups of respondents that
exhibited similar implicit parameters for their individual control models. \(^{23}\)

Figure 4 plots the unexplained variance (1-\( R^2 \)) for the 1 to 15-means cluster
solutions for the US and Australian sub-samples as an indicator of the number of
'significant' clusters (SAS, 1988; Aldenderfer and Blashfield, 1984). This is akin to the
scree test for identifying factors in factor analysis. The flattening of the rate of
improvement in explanatory power in the plot at four clusters suggests that there are
four clusters in the data.

\[\text{INSERT FIGURE 4 HERE}\]

The clusters for the two countries were not exactly the same. Cluster one for
the US has no comparable cluster for the Australian respondents. Similarly, cluster
three for the Australian sub-sample has no corresponding cluster in the US sub-sample.
There are, however, some cross-cultural similarities between the within culture clusters.
Cluster two for the US, that weights ownership and dispersion more heavily,
corresponds with cluster four in the Australian sub-sample. The 'ownership-board'
type respondents are in cluster three for the US sub-sample and cluster one for the
Australian respondents. Finally, clusters four and two represent the 'ownership' only
respondents respectively in the US and Australian sub-samples. Similar proportions of
the two sub-samples fall into the corresponding clusters which suggests that between
country differences are to some extent an artefact of the within sub-sample differences.
This hypothesis is tested by comparing the SUR estimated coefficients for each of the
'corresponding' clusters in a restricted and unrestricted F-statistic. Table 8 reports the
results for this estimation and testing.

\[\text{INSERT TABLE 8 HERE}\]

\(^{23}\) This is a non-hierarchical method (ie. clusters do not form a tree structure) which identifies
clusters based on Euclidean distances computed from the \( M \) individual model parameter estimates
(Aldenderfer and Blashfield, 1984; Kaufman and Rousseeuw, 1990). The k-means method is
particularly appropriate for large data sets where there are over 100 observations, such as in the current
All the parameters for the 'ownership' clusters are insignificantly different between the two sub-samples. Approximately one third of respondents place the most weight on the ownership attribute. The parameters for ownership and dispersion are insignificantly different (at the 0.01 level) between the US and Australian 'ownership-dispersion' clusters. Board membership is, however, weighted differently between the models for these matched clusters. For the 'ownership-board' clusters, both ownership and board membership parameters are significantly different between the US and Australian models. In both cases ownership and board membership are the highest weighted attributes, but the US model places more weight on ownership than board membership. The reverse is the case for the Australian model. This probably reflects the regulatory bias of each country. The 'other' cluster represents the remaining clusters for the US and Australian sub-samples for which there was no 'corresponding' cluster. All except the parameters for the constant and direct versus indirect ownership attribute are significantly different which is not surprising given the differences in cluster profiles.

8. Discussion and Conclusions

The estimated aggregate model rejected the null hypotheses one to four that the attributes have no direct effect on degree of control. The individual level analysis was less conclusive and suggested that the directness of ownership and dispersion attributes are significant for control assessments for only some subjects. All four attribute coefficients were, however, found to be different to each other at both the individual and aggregate levels, rejecting the null for hypothesis five.

The estimated parameters for the model indicated that ownership and board membership are perceived to be the most important attributes in dominant control relations. However, the implicit weights for indirect ownership links, and low levels of dispersion of non-owned equity, suggests these attributes are perceived to mitigate the level of dominant control achieved through ownership and board membership.

The predictive ability analysis supported hypothesis six, that the model has predictive ability, for both the estimation and holdout samples. The aggregate model, however, did not perform as well as the $M$ individual models in predicting the estimation sample judgements, although it did provide better predictions for the holdout sample. The overall conclusion is that the estimated conjoint models support the theoretical model developed in section 2.

The stability of the model across cultural boundaries was also tested. The null to hypothesis seven was rejected as the US and Australian control models were found to be significantly different. Within cultural differences indicated that there were at
least four different groups of respondents for each of the sub-samples. Three of the clusters for the US respondents corresponded with clusters for the Australian sub-sample. The 'ownership' groups were not significantly different. While some similarities were observed for the other two pairs of corresponding clusters. The fourth cluster for each sub-sample was, however, unique to the respective sub-sample. In sum the evidence suggests that the cross-cultural differences are to some extent an artefact of the within culture clustering of professional opinion as to the attributes of corporate control.

The research provides a model, based on consensus professional judgement, that predicts whether one entity controls another. This model can be used by auditors, corporate accountants and regulators to assess control relationships. Further, researchers can use the model to test reporting problems that relate to the level of control. Finally the study represents an exposition on the conjoint methodology as a research tool for investigating multi-attribute decision making in accounting and auditing.
References


ma, r., parker, r.h., and whittred, g., (1991), *consolidation accounting*. melbourne, longman cheshire limited.


mian, s.l., and smith, c.w., (1990a), "incentives for unconsolidated financial reporting", *journal of accounting and economics*, vol. 12, pp. 141-171.

mian, s.l., and smith, c.w., (1990b), "incentives associated with changes in consolidated reporting requirements", *journal of accounting and economics*, vol. 13, pp. 249-266.


mohr, r.m., (1988), "unconsolidated finance subsidiaries: characteristics and debt/equity effects". *accounting horizons*, vol. 2, no. 1, pp. 27-34.


organisation for economic co-operation and development, (oe cd), (1988), *accounting standards harmonization no. 5: consolidated financial statements*. paris, organisation for economic co-operation and development.

oppenheim, a.n., (1966), *questionnaire design and attitude measurement*. new york, basic books inc.


Figure 1: Categories on the Control Continuum and Accounting Technology

**Cut-off Boundaries**

<table>
<thead>
<tr>
<th>No Control</th>
<th>Insufficient Influence</th>
<th>Significant Influence</th>
<th>Control</th>
<th>Dominant Control</th>
<th>Absolute Control</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Lower of Cost or Market</th>
<th>Equity Method</th>
<th>Consolidation</th>
</tr>
</thead>
</table>

*Accounting Technology*

Figure 2: Example Case Presentation and Response Form

**Example Case Presentation:**

X's Total Level of Ownership of Z's Stock: 65%
X's Level of Direct Versus Indirect Ownership in Z: All direct
Dispersion of Ownership of Other Stock in Z: Widely Held
Company X's Representation on Z's Board of Directors: 8 of 10

If you judge that company X does control company Z then place this case in the control pile and record your evaluation by circling YES on the response form. If you feel **EXTREMELY CONFIDENT** about your classification then circle a number close to 5, as below.

<table>
<thead>
<tr>
<th>Case No.</th>
<th>Does Co. X Control Co. Z?</th>
<th>Not too Confident</th>
<th>Extremely Confident</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1 2 3 4 5</td>
<td></td>
</tr>
</tbody>
</table>

*Eg. YES NO 1 2 3 4 5*  

If, however, you are NOT TOO CONFIDENT about your classification of the case then circle a number closer to 1, as appropriate. Be sure to use the full range of the scale to indicate the degree of confidence you have in your evaluations and remember there are no right answers to this task. We are interested in **YOUR PERCEPTIONS** of the control relationship.
Table 1: Independent Variables - Levels for Control Attributes

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Levels for Control Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Percentage Ownership ($X_{i1}$)</td>
<td>15%, 30%, 45%, 49%, 51%, and 65%</td>
</tr>
<tr>
<td>Fraction of Ownership Direct ($X_{i2}$)</td>
<td>0%, 40%, 60%, and 100% a</td>
</tr>
<tr>
<td>Dispersion of Other Ownership ($X_{i3}$)</td>
<td>&quot;Widely Held&quot;, 10%, 20%, and 30%</td>
</tr>
<tr>
<td>Level of Membership on 10 Member Board ($X_{i4}$)</td>
<td>2, 4, 6, and 8 members</td>
</tr>
</tbody>
</table>

a The % Indirect = 100% - % Direct

Table 2: Matrix of Attribute Levels and Orthogonal Array of 38 Treatment Cases for Control Instrument

<table>
<thead>
<tr>
<th>Ownership, Total Direct, and Indirect %</th>
<th>Board Membership 2 of 10</th>
<th>Board Membership 4 of 10</th>
<th>Board Membership 6 of 10</th>
<th>Board Membership 8 of 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Direct, Indirect %</td>
<td>10% 20% 30%</td>
<td>10% 20% 30%</td>
<td>10% 20% 30%</td>
<td>10% 20% 30%</td>
</tr>
<tr>
<td>15%</td>
<td>6% 9% 12%</td>
<td>6% 9% 12%</td>
<td>6% 9% 12%</td>
<td>6% 9% 12%</td>
</tr>
<tr>
<td>15%</td>
<td>9% 12% 15%</td>
<td>9% 12% 15%</td>
<td>9% 12% 15%</td>
<td>9% 12% 15%</td>
</tr>
<tr>
<td>15%</td>
<td>12% 15% 18%</td>
<td>12% 15% 18%</td>
<td>12% 15% 18%</td>
<td>12% 15% 18%</td>
</tr>
<tr>
<td>15%</td>
<td>18% 21% 24%</td>
<td>18% 21% 24%</td>
<td>18% 21% 24%</td>
<td>18% 21% 24%</td>
</tr>
<tr>
<td>15%</td>
<td>24% 27% 30%</td>
<td>24% 27% 30%</td>
<td>24% 27% 30%</td>
<td>24% 27% 30%</td>
</tr>
<tr>
<td>15%</td>
<td>30% 33% 36%</td>
<td>30% 33% 36%</td>
<td>30% 33% 36%</td>
<td>30% 33% 36%</td>
</tr>
<tr>
<td>15%</td>
<td>36% 39% 42%</td>
<td>36% 39% 42%</td>
<td>36% 39% 42%</td>
<td>36% 39% 42%</td>
</tr>
<tr>
<td>15%</td>
<td>42% 45% 48%</td>
<td>42% 45% 48%</td>
<td>42% 45% 48%</td>
<td>42% 45% 48%</td>
</tr>
<tr>
<td>15%</td>
<td>48% 51% 54%</td>
<td>48% 51% 54%</td>
<td>48% 51% 54%</td>
<td>48% 51% 54%</td>
</tr>
<tr>
<td>15%</td>
<td>54% 57% 60%</td>
<td>54% 57% 60%</td>
<td>54% 57% 60%</td>
<td>54% 57% 60%</td>
</tr>
<tr>
<td>15%</td>
<td>60% 63% 66%</td>
<td>60% 63% 66%</td>
<td>60% 63% 66%</td>
<td>60% 63% 66%</td>
</tr>
<tr>
<td>15%</td>
<td>66% 69% 72%</td>
<td>66% 69% 72%</td>
<td>66% 69% 72%</td>
<td>66% 69% 72%</td>
</tr>
</tbody>
</table>
Table 3: Parameter Estimates for the $M$ Individual Models and the Aggregate Model

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Panel A: M Individual Models</th>
<th>Panel B: Aggregate Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st Quartile</td>
<td>Median</td>
</tr>
<tr>
<td>Constant ($\hat{\beta}_0$)</td>
<td>-2.671</td>
<td>-2.402</td>
</tr>
<tr>
<td>Own ($\hat{\beta}_1$)</td>
<td>3.039</td>
<td>3.850</td>
</tr>
<tr>
<td>Dir/Ind ($\hat{\beta}_2$)</td>
<td>-0.071</td>
<td>0.099</td>
</tr>
<tr>
<td>Disp ($\hat{\beta}_3$)</td>
<td>-1.815</td>
<td>-0.622</td>
</tr>
<tr>
<td>Board ($\hat{\beta}_4$)</td>
<td>1.174</td>
<td>1.906</td>
</tr>
</tbody>
</table>

a Mean $\hat{\beta}_j$ for the $M = 246$ individual models is signified by the $\hat{\beta}_{jm}$ subscript.
b Aggregate model $R^2 = 0.5832$, and Adjusted $R^2 = 0.5830$.
c t-test for $H_0: \beta_{jm} = 0$, df = 32-5 = 27.

Table 4: Analysis of Equality of Model Parameters

<table>
<thead>
<tr>
<th>Variables</th>
<th>Panel A: M Individual Models</th>
<th>Panel B: Aggregate Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F-Value b  p-Value</td>
<td>% Sig c</td>
</tr>
<tr>
<td>Own v Dir/Ind</td>
<td>$\hat{\beta}<em>{1,m} = \hat{\beta}</em>{2,m}$</td>
<td>30.68</td>
</tr>
<tr>
<td>Own v Disp</td>
<td>$\hat{\beta}<em>{1,m} = \hat{\beta}</em>{3,m}$</td>
<td>9.19</td>
</tr>
<tr>
<td>Own v Board</td>
<td>$\hat{\beta}<em>{1,m} = \hat{\beta}</em>{4,m}$</td>
<td>12.63</td>
</tr>
<tr>
<td>Dir/Ind v Disp</td>
<td>$\hat{\beta}<em>{2,m} = \hat{\beta}</em>{3,m}$</td>
<td>2.64</td>
</tr>
<tr>
<td>Dir/Ind v Board</td>
<td>$\hat{\beta}<em>{2,m} = \hat{\beta}</em>{4,m}$</td>
<td>15.18</td>
</tr>
<tr>
<td>Disp v Board</td>
<td>$\hat{\beta}<em>{3,m} = \hat{\beta}</em>{4,m}$</td>
<td>5.49</td>
</tr>
</tbody>
</table>

a Linear restriction placed on the $M$ individual models.
b F-Value (df = 246, 6642) for the pooled residuals.
c Percentage of $M$ individual level F-Value significant at the 0.01 level.
d Aggregate model parameter comparison for t-test, two-tailed p-Values.
Table 5: Distribution of Correlations Between Estimation Control Evaluations and Control Predicted by the $M$ Individual Models and the Aggregate Model

<table>
<thead>
<tr>
<th>Range for Pearson's $r$</th>
<th>Frequency of $r$ for:</th>
<th>$M$ Individual Models</th>
<th>Aggregate Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0.50</td>
<td>0</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>0.51-0.55</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0.56-0.60</td>
<td>0</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>0.61-0.65</td>
<td>1</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>0.66-0.70</td>
<td>3</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>0.71-0.75</td>
<td>16</td>
<td>37</td>
<td></td>
</tr>
<tr>
<td>0.76-0.80</td>
<td>29</td>
<td>59</td>
<td></td>
</tr>
<tr>
<td>0.81-0.85</td>
<td>67</td>
<td>58</td>
<td></td>
</tr>
<tr>
<td>0.86-0.90</td>
<td>80</td>
<td>33</td>
<td></td>
</tr>
<tr>
<td>0.91-0.95</td>
<td>47</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>0.96-1.00</td>
<td>3</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Total $n = 246$  
Mean $r = 0.8466$  
Median $r = 0.8560$

$r$ for Aggregate Model $b = 0.7636$  
$\chi^2 (df = 5) = 779.99$  
$p < 0.001$

---

*a* See $\chi^2$ statistic for equivalence of frequencies, based on 6 collapsed categories.

*b* Correlation between pooled aggregate model predictions and pooled evaluations.
Table 6: Distribution of Correlations Between Holdout Control Evaluations and Control Predicted by the $M$ Individual Models and Aggregate Model

<table>
<thead>
<tr>
<th>Range for Pearson's $r$</th>
<th>Frequency of $r$ for $M$ Individual Models</th>
<th>Frequency of $r$ for Aggregate Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$&lt;0.50$</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>0.51-0.55</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.56-0.60</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>0.61-0.65</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>0.66-0.70</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>0.71-0.75</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>0.76-0.80</td>
<td>23</td>
<td>17</td>
</tr>
<tr>
<td>0.81-0.85</td>
<td>34</td>
<td>30</td>
</tr>
<tr>
<td>0.86-0.90</td>
<td>53</td>
<td>66</td>
</tr>
<tr>
<td>0.91-0.95</td>
<td>79</td>
<td>79</td>
</tr>
<tr>
<td>0.96-1.00</td>
<td>35</td>
<td>35</td>
</tr>
</tbody>
</table>

Total $n = 246$ 246
Mean $r = 0.8639$ 0.8707
Median $r = 0.8935$ 0.8969

$r$ for Aggregate Model $^b = 0.8173$

$\chi^2_{(df=7)} = 6.47$ $p = 0.486$

$^a$ See $\chi^2$ statistic for equivalence of frequencies, based on 8 collapsed categories.

$^b$ Correlation between pooled aggregate model predictions and pooled evaluations.

Figure 3: Observed and Expected Frequency for F-Values for Change in Explanatory Power
### Table 7: US and Australian Culture Specific Models and Tests for Cross-Cultural Parameter Stability

<table>
<thead>
<tr>
<th>Variable</th>
<th>US</th>
<th>Australia</th>
<th>H₀: ( \beta^{j}<em>{US} = \beta^{j}</em>{Aust} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \hat{\beta}^{j}_{1} ) a</td>
<td>t-Value</td>
<td>( \hat{\beta}^{j}_{1} ) t-Value</td>
</tr>
<tr>
<td>Constant ( \hat{\beta}^{0}_{0} )</td>
<td>-2.375</td>
<td>-61.0</td>
<td>-2.431</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td></td>
<td>(0.036)</td>
</tr>
<tr>
<td>Own ( \hat{\beta}^{1}_{1} )</td>
<td>4.064</td>
<td>67.2</td>
<td>3.655</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td></td>
<td>(0.056)</td>
</tr>
<tr>
<td>Dir/Ind ( \hat{\beta}^{2}_{2} )</td>
<td>0.186</td>
<td>6.6</td>
<td>0.173</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td></td>
<td>(0.026)</td>
</tr>
<tr>
<td>Disp ( \hat{\beta}^{3}_{3} )</td>
<td>-0.891</td>
<td>-9.8</td>
<td>-0.643</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td></td>
<td>(0.084)</td>
</tr>
<tr>
<td>Board ( \hat{\beta}^{4}_{4} )</td>
<td>1.783</td>
<td>39.3</td>
<td>2.140</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td></td>
<td>(0.042)</td>
</tr>
</tbody>
</table>

Pearson's \( r \) 0.7908
R² b 0.6253
F-Value 1311.9
p < 0.001

H₀: \( \beta^{j}_{US} = \beta^{j}_{Aust} \)
F = 12.4 \( \chi^2 = 61.92 \)
F < 0.001 \( \chi^2 < 0.001 \)

\( ^a \) Standard Error for \( \hat{\beta}^{j}_{1} \)
\( ^b \) Buse R² (Judge et al, 1985, pp. 477-478)

### Figure 4: Plot of Unexplained Variance Against Number of Clusters for US and Australian Sub-Samples
<table>
<thead>
<tr>
<th>Coefficient</th>
<th>'Own/Disp'</th>
<th>'Own/Board'</th>
<th>'Own'</th>
<th>'Other'</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>US Two</td>
<td>Aust Four</td>
<td>US Three</td>
<td>Aust One</td>
</tr>
<tr>
<td>Constant ($\beta_0$)</td>
<td>-1.62</td>
<td>-2.06*</td>
<td>-2.68</td>
<td>-2.61</td>
</tr>
<tr>
<td>F-value</td>
<td>6.46</td>
<td>56.08</td>
<td>1.04</td>
<td>24.80</td>
</tr>
<tr>
<td>Sig.</td>
<td>p &lt; 0.001</td>
<td>p &lt; 0.001</td>
<td>p = 0.394</td>
<td>p &lt; 0.001</td>
</tr>
<tr>
<td>Frequency</td>
<td>21</td>
<td>32</td>
<td>39</td>
<td>52</td>
</tr>
<tr>
<td>Total Percent</td>
<td>21.5%</td>
<td>37.0%</td>
<td>34.1%</td>
<td>7.3%</td>
</tr>
</tbody>
</table>

* SUR estimated coefficients: (F-statistic, significance) tests for the $j$th parameter the hypothesis $H_{0j}: \beta_{jUS} = \beta_{jAust,j} = 0$, $1, 2, 3, 4$.

* F-statistic tests the hypothesis that all $j$ parameters are equal for the two sub-sample models $H_{0j}: \beta_{jUS} = \beta_{jAust,j} = 0, 1, 2, 3, 4$. 

* F-statistic tests the hypothesis that all $j$ parameters are equal for the two sub-sample models $H_{0j}: \beta_{jUS} = \beta_{jAust,j} = 0, 1, 2, 3, 4$. 

<table>
<thead>
<tr>
<th>Cluster Number and Title</th>
<th>'Own/Disp'</th>
<th>'Own/Board'</th>
<th>'Own'</th>
<th>'Other'</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>US Two</td>
<td>Aust Four</td>
<td>US Three</td>
<td>Aust One</td>
</tr>
<tr>
<td>Dir/Ind ($\beta_2$)</td>
<td>0.29</td>
<td>0.29</td>
<td>0.11</td>
<td>0.17</td>
</tr>
<tr>
<td>(0.0001, p = 0.994)</td>
<td></td>
<td></td>
<td>(1.13, p = 0.289)</td>
<td></td>
</tr>
<tr>
<td>Disp ($\beta_3$)</td>
<td>-3.17</td>
<td>-2.50</td>
<td>-0.09</td>
<td>0.13</td>
</tr>
<tr>
<td>(6.06, p = 0.014)</td>
<td></td>
<td></td>
<td>(1.39, p = 0.237)</td>
<td></td>
</tr>
<tr>
<td>Board ($\beta_4$)</td>
<td>0.98</td>
<td>1.68</td>
<td>2.39</td>
<td>3.33</td>
</tr>
<tr>
<td>(26.23, p &lt; 0.001)</td>
<td></td>
<td></td>
<td>(104.30, p &lt; 0.001)</td>
<td></td>
</tr>
</tbody>
</table>