CHAPTER 4

RESEARCH FRAMEWORK AND METHODOLOGY

4.0 INTRODUCTION

The last two chapters, which reviewed the literature on intellectual capital (IC), its disclosure, and potential determinants, shape the research focus and design of this study. This chapter describes the research method and design for the study, the hypotheses proposed, and the tools for data analysis. It revisits the research objectives and type of study in Section 4.1, followed by the research method employed in Section 4.2. Section 4.3 identifies the main variables and introduces the research instrument, the method of data capture, including coding units, coding scheme, and the measurements of IC disclosure. Section 4.4 explains the sampling procedure. Section 4.5 discusses the research design and introduces the hypotheses for investigation. More detailed development of hypotheses is allocated to the relevant empirical findings chapters (Chapters 6, 8 and 9). Section 4.6 outlines the methods of data analysis with Section 4.7 summarising the chapter.

4.1 TYPE OF STUDY

Chapter 1 introduced the aims of this study as 1) to extend our understanding of IC disclosure activity in UK firms; 2) to investigate the possible determinants of IC disclosure practice in the annual report across firms from three perspectives of corporate governance structure, company characteristics, and market factors, using a large database; 3) to explore and compare a variety of ways of measuring IC disclosure; and 4) to explain variations in IC disclosure practices with theoretical underpinnings. The findings of this study have practical implications for both regulatory bodies and business enterprises in relation to IC disclosure and corporate governance issues, as well as for the information users.

This study is essentially a cross-sectional, country specific study of firms in a developed country with an active stock market. The review of the IC disclosure literature identified that intangibles are very important to UK industry,[1] and that relatively few studies have been conducted among UK firms. It was decided to limit the study to London Stock Exchange (LSE) main board listed UK firms, as they offer greater investor protection and provide a rich source of the information required for this study.

4.2 RESEARCH METHOD

The research approach employed in addressing any research question has a direct bearing on the validity and reliability of the final results generated by the research process (e.g. Bryman, 2004). This section describes the research method chosen, and why it is preferred to alternative methods.

There are many different ways of defining and classifying research, for instance: normative/positive (e.g. Ryan et al., 1992; Cohen et al., 2000), deductive/inductive (e.g. Nachmias and Nachmias, 1996; Schutt, 1996; Cohen et al., 2000; Walliman, 2005), and exploratory/explanatory (e.g. McNeill, 1990; Schutt, 1996). The most common classification is qualitative or quantitative (e.g. Creswell, 1994; Neuman, 2003; Bryman, 2004; Blaxter et al., 2006; Hair et al., 2007). They differ not only in the nature of the data sought and the subsequent methods of data analysis, but also in their philosophical rationales (Walliman, 2005). Creswell (1998: 15) describes qualitative research as

> *'an inquiry process of understanding based on distinct methodological traditions of inquiry that explore a social or human problem. The researcher builds a complex, holistic picture, analyzes words, reports detailed views of informants, and conducts the study in a natural setting'.*

Blaxter et al. (2006) view qualitative research as concerned with collecting and analysing information in as many forms as possible, and exploring it in as much detail as possible, in a small number of instances. It aims to achieve 'depth' rather than 'breadth'

[1] The Global Intangible Study 2006 documents that UK ranked fourth in relation to the importance of intangibles (IPA, 2006: 7).

(p.64). According to Saunders et al. (1997: 339) 'qualitative data are associated with highly ambiguous and elastic concepts. Thus, they are not easy to quantify in a meaningful way'. Therefore, such data are better analysed qualitatively.

In comparison, quantitative research is an inquiry 'based on testing a theory composed of variables, measured with numbers, and analyzed with statistical procedures, in order to determine whether the predictive generalizations of the theory hold true' (Creswell, 1994: 1-2). If the data have been collected quantitatively, such as via a questionnaire survey or content analysis, logically the analysis method is quantitative (Saunders et al., 1997; Easterby-Smith et al., 2002; Bryman, 2004).

Qualitative research differs from quantitative research not only in the usage of language and style, but also in the generation of ideas. Qualitative research is 'situational' or contextual, often based on specific case studies and particular circumstances rather than replication or generalisation. The aim of qualitative social research is to discover meanings and involves both interpretation and a critical approach to the social world. A few attributes of qualitative research have been summarised by Neuman (2003). Research questions are posed, rather than hypotheses, and theory is often grounded in data. Concepts come in the form of themes, motifs, generalisations and taxonomies rather than causal relationships. Data are often in the form of words and images from observations, documents, interviews and participations. A variety of forms of data collection are used, which include ethnography, unstructured interviewing, participant observation and field notes.

Quantitative and qualitative methodologies are not mutually exclusive. The two approaches differ in overall form and the emphasis and objectives of the study (Ghauri and Grønhaug, 2005: 109). To be successful, a quantitative researcher must integrate some qualitative knowledge into the survey's design and interpretation, and/or understand the respondent's frame of reference (May, 1993: 114). Indeed, in order to quantify IC disclosure in the annual report, development of the research instrument (checklist) requires understanding of the concept.

According to Ryan et al. (1992), the normative approach is the conventional approach in accounting research. It is concerned with prescribing 'what ought to happen'. It aims to meet the needs of managerial users. Positive accounting theory, being grounded in empirical data, offers researchers the possibility to provide further evidence of value judgements and theoretical speculation of the normative approach. Watts and Zimmerman (1986: 1) state that 'the objective of accounting theory is to explain and predict accounting practice'.

Qualitative data from interviews are extended and detailed. The method generates an informed and well-illustrated account of the subject matter, giving valid and reliable data (Saunders et al., 1997; Easterby-Smith et al., 2002). Others regard qualitative data and results as limited, unreliable and lacking solidity (Walliman, 2005: 246-247). McNeill (1990: 47) argues that there is no guarantee that what people say in interviews is a true account of what they actually do. Furthermore, this method has disadvantages, such as being more complicated, slower, more expensive, more intuitive, and limited to small samples, resulting in a study being difficult to generalise. It is also difficult to compare and measure. In contrast, quantitative research strategies involve the collection of evidence that is more standardised, measurable, and comparable (Smith, 1998). With this type of method, the researcher should aim to gather data from many investigation units, thus ensuring that results are statistically viable. Other claimed advantages of this method are that it is cheap, straightforward, relatively quick, and its results are easier to generalise. However, there are several disadvantages to this method, including the need for a higher level of interpretation skills, greater probability of bias, lack of details on explanation, and dependence on statistical accuracy, in comparison to a qualitative approach (Saunders et al., 1997; Easterby-Smith et al., 2002).

In this study, one of the main aims is to investigate the possible determinants of IC disclosure practice on a more generalisable scale via testing proposed hypotheses. A quantitative approach is therefore deemed to be more appropriate. The study is considered primarily deductive in that it results in a logical conclusion from given premises and theories. At the same time, it also has some inductive elements as the concept of IC is still relatively new and needs further development. Thus the study may be viewed as primarily exploratory, descriptive and positive.

Bryman (2004) distinguished research designs from research methods. Research designs, referring to the whole structure and orientation of a study, are classified into five groups: experimental research, survey research, qualitative research, case study and action research. The author also identified seven methods[2] of data collection: self-administered questionnaires, structured interviews, participation observation, unstructured interviews, structured observation, simulation, and archival information. No method of data collection is exclusively associated with a given topic area in the social sciences, although some will be more practical than others for various reasons, such as constraints of time, personal space or funding. Some research designs use a combination of data collection techniques, often referred to as 'triangulation' (Nachmias and Nachmias, 1996). For the present study, it is in principle possible to employ all seven techniques summarised in Bryman (2004), but three would be exceptionally difficult, i.e. simulation, participant observation and structured observation techniques.

The survey is a popular method for data collection in business and management research. It is characterised by a structured or systematic set of data that seeks an understanding of

[2] 'Method' refers to the techniques or tools used to gather data, and can include both qualitative and quantitative data collection techniques.

what causes some phenomenon by looking at variation in variables across cases (De Vaus, 1996). In terms of the questionnaire survey, questionnaires can be sent to chief accounting officers of a sample of firms asking, for instance, for their perception of the importance of IC in their firm and the availability of measurement and reporting capacity for such assets (e.g. Bontis, 1998; Bontis et al., 2000; De Pablos, 2003; Gallego and Rodríguez, 2005). It is also possible to achieve the same goal using structured, unstructured, or semi-structured interviews (e.g. Holland and Stoner, 1996; Holland, 2004; 2006 a, b; Chaminade and Roberts, 2003; Habersam and Piper, 2003; Roslender and Fincham, 2004). Use of archival data, especially the annual report, is another way of accomplishing the same task, which has been the approach most popularly applied in both general disclosure and IC disclosure studies (e.g. Guthrie and Petty, 2000; Brennan, 2001; Beattie and Thomson, 2007).

The use of interviews is not considered feasible for this large sample study on the grounds of cost and effectiveness. It would require extensive research resources to interview the accounting officers of a large sample of LSE-listed UK firms to ascertain their perceptions and discretionary choices toward IC and its disclosure. Questionnaires, though more cost effective than interview techniques, were avoided for the following two reasons. First, they have not gone through the independent authentication procedure of external auditing which the annual report has gone through. Second, asking officers of firms to give opinions on actions they initiated can often be difficult, and may lead to low response rates and even unreliable answers.

Given the nature of the problem being investigated, in contrast to the other methods discussed above, the archival technique of data collection recommends itself readily as the most cost effective, reliable and sensible method of collecting the data for the study. The advantage of using archival data is that the materials are non-reactive, with possible biases that are often recognised as deriving from interviews and questionnaires removed (Bryman, 2004). In addition, the materials are readily accessible for research purposes and in a permanent form which can be subject to reanalysis allowing reliability[3] checks and replication.

4.2.1 ANNUAL REPORT

Within the domain of the archival method, there are several alternative approaches: 1) data can be gathered from periodical reports (e.g. annual reports, interim reports, corporate social responsibility reports, and environmental reports) of firms; 2) a general survey of corporate websites can be used as a data source; and 3) other corporate communication vehicles to external information users can be used as data sources, such as IPO prospectuses, presentations to analysts, webcasts, and analyst reports.

Annual reports have been widely used in IC disclosure studies as audit objects because they are major public documents that have a significant influence on the way financial markets and the general public perceive and react to a firm. The inclusion of voluntary information in the annual report can be, and is, used by managers to send specific signals and messages to the public (Brown and Deegan, 1998; Bozzolan et al., 2003; Guthrie et al., 2007). Additionally: annual reports are used by a number of stakeholders as the sole source of certain information (Deegan and Rankin, 1997); have greater potential to influence due to widespread distribution (Parker, 1982; Adams and Harte, 1998); offer a snapshot of management's mindset in a particular period (Neimark, 1992); and are also more accessible for research purposes (Woodward, 1998). It has also been emphasised that the annual report a) is the major medium for a firm to promote itself[4] and the inclusion of other information with the financial information may indicate

[3] Reliability refers to the extent to which findings can be replicated, or reproduced, by another inquirer (McNeill, 1990).

[4] Beattie et al. (2008) argue that the annual report has been transformed into a 'marketing and public relations document' (p.181). Lee (1994) argues that firms are increasingly using the annual report as a means of establishing corporate identity. Neu et al. (1998) share the same view that the annual report is being used to construct the organisation's image for relevant stakeholders.

its relative importance (Gray et al., 1995a); b) is used to persuade readers to accept management's view of society (Amernic, 1992); and c) is both reflective and constitutive of a wider set of societal values (Dyball, 1998). Moreover, annual reports are perceived as a very suitable research object to apply the IC framework, as they are a good proxy measure for the comparative positions and trends of IC between firms, industries and even countries, are argued to represent the concerns of individual corporations in a comprehensive and compact manner (Abeysekera and Guthrie, 2005), and are regularly and consistently produced documents in permanent forms, given their mandatory nature, thus affording opportunities for comparative analyses of management attitudes and policies across reporting periods and across firms, which enhances their credibility (Gray et al., 1995a; Neu et al., 1998; Tilt, 2001).

A review of the relevant IC disclosure studies in these regards was provided in Chapter 2. All forms of data reaching the public domain can be considered part of the accountability-discharge activity of an organisation (Gray et al., 1995a). Ideally, all communications by an organisation should be monitored if one is to capture all external corporate IC communication. However, the problem there is that it is impossible to be certain that all communications have been identified (Gray et al., 1995a). Although the use of annual reports as the sole source of content analysis data has its limitations (e.g. Unerman, 2000; Adams and Frost, 2004; Striukova et al., 2008), it offers, through narratives, information beyond financial statements that explains accounting figures, sketches and presents perspectives (Beattie et al., 2002). Moreover, the majority of previous studies have taken the view that the annual report offers a relevant and useful proxy for the level of IC disclosure provided by a firm along all disclosure avenues (Lang and Lundholm, 1993; Guthrie et al., 2007).[5] In addition, the corporate annual

[5] Lang and Lundholm (1993) found a positive correlation between disclosures in annual reports and disclosures provided via other means. Guthrie et al. (2007) observed similar information content contained on the Internet and in the annual reports.

report goes through an independent authentication procedure of external auditing, unlike the other documents or communication channels. Annual reports can therefore be argued to be a sufficiently trustworthy channel for IC communication.

In view of the above discussion, and given that there are few stand-alone IC reports, especially in the context of UK firms (Guthrie et al., 2007), it was considered in this study that the annual report is the most reliable and representative source of data for the evaluation of IC disclosure practice. Therefore, this study focuses on investigating IC disclosure practice in annual reports, whilst acknowledging that this is one of the limitations of the study and an area that requires future investigation.

4.2.2 LOCATIONS OF IC DISCLOSURE

The impact of reporting content in different sections of the annual report is noted in several areas of the voluntary reporting literature, such as environmental reporting (e.g. Gibson and Guthrie, 1995; Hughes et al., 2001). Different views on the importance of disclosing information in different sections within annual reports are discussed in Chapter 5 (Section 5.4). Gray et al. (1995a) argue that there is no single choice for why any particular disclosure location in the annual report should be preferred. Beattie and Thomson (2007) suggest that the locations of IC disclosure in annual reports may be informative in terms of, for example, the importance attached to the information, reader attention and auditor confirmation. However, few prior studies have taken the location of IC information captured into consideration in analysing firms' IC disclosure practices, while some studies restrict their analyses to certain sections of the annual report.[6]

This thesis develops the sections identified in the existing literature (e.g. Choon et al., 2000; Hughes et al., 2001; Abeysekera, 2003) and segregates the annual report into nine

[6] Olsson's (2001) study excluded various sections of the annual report such as information about firms' stock, and pictures and information about the board (see review in Chapter 2, Section 2.3.3). Cerbioni and Parbonetti (2007) investigated only the Operating and Financial Review section of the annual report.

sections: Chairman's Statement; Chief Executive Review; Operational and Financial Review; Board of Directors; Corporate Governance; Corporate Social Responsibility; Directors' Report; Auditor's Report, Accounting Standards, Financial Statements and Notes to Accounts section; and the rest of the report as a section (Others).[7] This enables the coding of IC information captured under individual sections of the annual report.

4.2.3 CONTENT ANALYSIS

Beattie et al. (2004b) summarise the methods for analysing annual report narratives and these include subjective analyst ratings, disclosure indices, content analyses, readability studies and linguistic analyses. Content analysis has been selected for this study as it is a means of categorising items of text and can be used where a large amount of qualitative data needs analysing (Holsti, 1969). Content analysis is defined as a technique for gathering data that consists of codifying qualitative and quantitative information, in anecdotal and literary form, into categories in order to derive quantitative scales of varying levels of complexity (Abbott and Monsen, 1979: 504). Content analysis has become a widely used method of analysis in financial accounting research (Beattie, 2005), where it has been applied to corporate social, ethical and environmental reporting, and increasingly to IC disclosure studies (e.g. Gray et al., 1995b; Hackston and Milne, 1996; Milne and Adler, 1999; Guthrie and Petty, 2000; Unerman, 2000; Wilmshurst and Frost, 2000; Brennan, 2001), demonstrating that it is a rigorously tested research approach for such studies.

As a technique for gathering data, content analysis involves reading the annual report, and codifying qualitative and quantified information (words, phrases and sentences) into predefined categories in order to derive patterns in the presentation and reporting of information. A spreadsheet is constructed on the basis of the information reported on the

[7] IC disclosure in the whole annual report was examined for each sample firm. Where sections could not be explicitly identified by the nine sections listed for a given firm in the sample, they were carefully classified into the closest section. Business reviews were classified under the Operating and Financial Review section.

coding sheets. This method seeks to determine the manifest content of written or other published communications by 'systematic', 'objective' and 'reliable' analysis (Krippendorff, 1980; Guthrie and Parker, 1990).

4.2.3.1 LIMITATIONS OF CONTENT ANALYSIS

The content analysis method is practical and useful; however, the major limitation is the subjectivity involved in coding (Wilmshurst and Frost, 2000; Linsley and Shrives, 2006). Since raw data in annual reports are not in a state that can be used for research purposes, the raw data need to be coded into the coding sheet in terms of IC items in the context of this study, which involves the application of judgment. The process can give rise to two errors, 1) IC items in the annual report may not reflect all of the issues of interest actually embedded in the annual report, and 2) raw data can be inaccurately coded into the coding sheet while categorising them into IC items. Both of these potential errors in the coding of raw data can affect the validity and reliability of the research results (Abbott and Monsen, 1979).[8]

Weber (1990) and Milne and Adler (1999) discuss the approach taken by Krippendorff (1980) where three different types of reliability are identified: stability, reproducibility (or inter-coder reliability), and accuracy. Stability refers to a coder being able to code the data consistently over time and can be tested by coding the data more than once by the same coder. The problem of reproducibility arises when more than one coder is introduced, and accuracy is concerned with how well the coding compares to a preset standard. Reproducibility measures the consistency of shared understanding held by two or more coders (Weber, 1990; Milne and Adler, 1999), i.e. the extent to which different coders produce the same results when coding the same content.

[8] McKinnon (1988: 36) defined validity and reliability in a broader context that 'validity is concerned with the question of whether the researcher is studying the phenomenon she/he purports to be studying' and 'reliability is concerned with the question of whether the researcher is obtaining data on which she/he can rely'.

For valid inferences to be drawn, it is also important that the classification procedure is valid (Abbott and Monsen, 1979; Nachmias and Nachmias, 1996). Given the threats of reliability and validity of content analysis, the next section outlines the steps taken to minimise the threats outlined.

4.2.3.2 OVERCOMING THE LIMITATIONS OF CONTENT ANALYSIS

For this thesis, three approaches to increase the objectivity in recording and analysing data were devised. These three methods involve pre-defining the coding instrument, re-coding a sample of the annual reports by another two researchers to confirm reproducibility (i.e. inter-coder reliability), and re-examining a sample of the annual reports at a later point in time to confirm coding consistency (i.e. stability).

To aid consistency of scoring, the research instrument was mainly completed by one researcher interacting with the document. The researcher's frame of reference could then affect the ascertaining of content in the annual reports. Therefore, each IC item in the checklist was defined by the researcher and agreed by another two researchers before analysing the content in annual reports.

Further, if only one researcher was involved in the coding process, then the method used would only reflect that person's conception of reality (Gray et al., 1995a), rather than any potential objective reality that exists in relation to the IC concept (Beattie and Thomson, 2007). Therefore, three coders independently coded the same four annual reports and Krippendorff's (1980) alpha[9] was used to test for reliability as it can account for chance agreement among multiple coders. Krippendorff's *alpha* was computed for both IC disclosure index and word count measures (see Table 4.1). The independent scores were all above the minimum 80% threshold for content analysis to be considered

[9] The conventional reliability test requires a measure of consensus between different coders which is interpreted by a consensus coefficient. The most popular coefficients in business and the social and behavioural sciences are percentage agreement, such as Krippendorff's *alpha*, Cohen's *kappa*, Scott's *pi*, Spearman *rho*, and Pearson *r* (Neuendorf, 2002).

reliable (Neuendorf, 2002; Riffe et al., 2005), and this was achieved after a second round of independent coding of another four annual reports. Explanations of how Krippendorff's *alpha* was computed are provided in Appendix 4-A.

Table 4.1 Reliability Test: Krippendorff's Alpha

		Coders 1&2	Coders 1&3	Coders2&3	3 Coders
1st round - 4 annual reports	ICWC	0.946	0.849	0.958	0.907
	ICDI	0.86	0.936	0.947	0.912
2nd round - 4 annual reports	ICWC	0.972	0.936	0.91	0.932
	ICDI	0.97	0.982	0.972	0.972
Both rounds - 8 annual reports	ICWC	0.972	0.933	0.954	0.95
	ICDI	0.963	0.987	0.972	0.97

The researcher for this study then completed the coding for the remaining ninety-two annual reports. To confirm consistent identification of content in the annual reports by the single researcher, rescoring was done on a random selection of ten firms three months after initial analysis, which confirmed over ninety per cent consistency of identification of content in the annual reports in all ten cases.[10] This process enabled the researcher to examine her own background assumptions in analysing the content, and subsequently increased the quality and reliability of the data produced by the analysis (Carney, 1972).

This research captures IC information disclosed in annual reports based on a pre-determined list of IC items. The statistics of both reproducibility and stability suggest the measurements of IC disclosure of the study to be reliable.

4.3 DEPENDENT VARIABLE: IC DISCLOSURE

4.3.1 DEVELOPMENT OF THE RESEARCH INSTRUMENT

One of the essential elements of content analysis is the selection and development of categories into which content units can be classified (Haniffa and Cooke, 2005). There are no widely accepted theoretical guidelines for selecting items. Therefore, the

[10] This is based on consistent identification of information in the annual reports as IC disclosure (i.e. word count) and consistent categorisation of content in the annual reports into IC items.

successful use of the disclosure index method depends on critical and cautious selection of items (Marston and Shrives, 1991). This list of items is the basis for constructing different disclosure indices in order to give a measure of the extent and specificity of the IC information revealed.

As previously stated, various authors (e.g. Edvinsson and Sullivan, 1996; Sveiby, 1997; Meritum, 2002) suggest that IC can be grouped into three subcategories: (1) *Human Capital*, for example staff education, training, experience, knowledge and skills, (2) *Structural Capital*, covering internal structures such as R&D, patents, management processes, and (3) *Relational Capital*, covering external relationships such as customer relations, brands and reputation. These forms of IC can be leveraged to create competitive advantage and value for stakeholders. While these categories are generally recognised, Beattie and Thomson (2007) observe that there is no consensus or precise definition of the constituents of such categories, giving rise to difficulties for information preparers and researchers seeking to quantify IC disclosure.

The categories and items in the designed research instrument were drawn from previous literature on IC definition, classification and disclosure (e.g. Brooking, 1996; Edvinsson and Malone, 1997; Lynn, 1998; Roos et al., 1997; Sveiby, 1997; Guthrie and Petty, 2000; Bukh et al., 2001; Mouritsen et al., 2001; Mouritsen et al., 2003; Beattie and Thomson, 2004; Guthrie et al., 2004). The majority of previous IC disclosure studies have adopted or adapted Sveiby's (1997) framework, which typically contains 22-25 items (Beattie and Thomson, 2007). The problem with too few coding categories is that it potentially increases the likelihood of random agreement in coding decisions and subsequently results in an overestimation of reliability (Milne and Adler, 1999). Similarly, higher numbers of items in the instrument increase the complexity (Beattie and Thomson, 2007) and may potentially increase coding errors (Milne and Adler, 1999). However, in order to achieve greater variation and better understanding of IC disclosure, a more detailed checklist covering items relating to three themes: *human capital (HIC), structural capital (SIC) and relational capital (RIC)* was developed, capturing information in the forms of text, number and graph/picture. While Guthrie and Petty (2000) highlight the difficulty in seeking to quantify the qualitative aspects of IC, evidence from Habersam and Piper (2003) questions this view.[11] All items in the designed research instrument were considered equally capable of disclosure across all sample firms in all three formats.

The development of the research instrument started with a list of 150 items. This initial draft of the research instrument was pilot tested by one researcher,[12] using a sample of annual reports (not included in the final sample). As argued by Gray et al. (1995a), the use of content analysis demands that the categories of analysis are derived by reference to shared meanings. Hence, the preliminary list of items was evaluated by another two researchers. Based on feedbacks from the pilot test and discussions with two other researchers, the instrument was modified to ensure that it captured the necessary and desired information for which it was designed. The research instrument was reduced to 61 IC items, which comprised 22 human capital items, 18 structural capital items and 21 relational capital items, in three presentational formats.[13] The extraction of data from the

[11] Informants of Habersam and Piper (2003) claim all IC can be quantified. For example, an informant says 'everything (can be quantified), even the quality of the relations in an indirect way, e.g. by how often one will be (repeatedly) asked for consultancy…'.
[12] Test coding on sample of text reveals ambiguities in the rules, and often leads to insights suggesting revision of the classification scheme (Weber, 1990: 23).
[13] First, items that were never disclosed based on the results of the pilot test (e.g. staff breakdown by age, staff breakdown by level of education, and training effectiveness) were identified. These items were then integrated with each other or other items with close meanings in the list, and replaced with broader items such as *'employee age'*, *'employee education'* and *'employee training'*. If in any case the items were disclosed, such disclosures will be captured by the word count measure. Second, items that were not considered to be mutually exclusive by three researchers were then integrated and presented as one item, such as employee satisfaction and loyalty were combined as *'employee relationship'*; customer satisfaction, loyalty, and recommendation were all included under *'customer relationship'*; leading market share and leading market position were merged as *'market leadership'*. Third, closely related sub-items of a broader category were merged. Examples include, names of customers, type of customers, customer reputation, customer base, customer purchasing histories and knowledge of markets/ customers were included under *'customer'*; quality management policy and objectives, quality management program and control activity, and quality performance were included under *'quality management and improvement'*; employee training policies, programmes, investment, and time spent were included under *'employee training'*. Such procedures reduced the initial 150 items to 61 items, which reduced the ambiguousness of the coding process, and hence reduced the possibility for coding errors. Compared to the IC instruments used in

annual reports was facilitated by the use of this list of IC items specially designed for the purposes of this study. The operational definitions of each IC item and coding rules were defined by the researcher and checked and agreed by another two researchers before analysing the content of the sampled annual reports to ensure that the data collected were objective and reliable (Milne and Adler, 1999). Appendix 4-B outlines the 61 IC items included in the research instrument and their operational definitions. Appendix 4-C provides some example extracts from annual reports. These help increase the transparency of the research method applied and enable future replication.

One of the limitations of this study is that the intellectual liabilities of firms (Abeysekera, 2006; Abeysekera and Guthrie, 2005) are not captured (see Section 2.1.1 of Chapter 2 for a brief discussion). The justification for this could be firms' potentially low level of disclosure of such information (Beattie and Thomson, 2007). In addition, the question of the value of regulated versus unregulated information remains (Parker, 2007: 43). Unlike other studies focusing on purely voluntary IC information, this study does not distinguish if the information is mandatory or voluntary for three main reasons: 1) voluntary and mandatory information regarding to IC is very hard to define, there is no checklist providing a comparison between voluntary and mandatory disclosures formed in the literature; 2) for firms with multiple listings, certain information may be mandatorily required in one country while voluntary in the other, such distinctions can be vague and complex given the multiple listing status of many of the sampled firms; and 3) the purpose of the study is to examine the level of IC disclosure as a whole. Although voluntary and mandatory IC disclosures are not distinguished in this study, it was considered that the majority of IC information captured was voluntary.

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prior studies, the present 61-item instrument is much more detailed. In addition, disclosures made toward any of the eliminated items were still covered by broader item and captured by the word count measure.

4.3.2 FORMAT OF IC DISCLOSURE

The knowledge economy facilitates propagating thoughts, value, and power by ultimately packaging and selling them in language (Graham, 1999), which includes presenting information using a multitude of qualitative and quantitative reporting units, such as narrative, pictures, graphs and numbers. Annual report data can be analysed by their qualitative and quantitative aspects. The qualitative aspects studied in this thesis include text and graphs/pictures, while the quantitative aspect examined refers to numerical (both fiscal and non-fiscal) disclosures. These three formats of information

disclosure found in annual reports are of great importance in the reporting process.

The text provides the bulk and the backbone of the reported message, which is an important means not only of clarifying and validating the quantitative measures contained in financial statements (Chungh and Meador, 1984), but also of offering useful insights into value-generation drivers (Lev and Zarowin, 1999; Robb et al., 2001; Holland, 2006a). The graphs/pictures provide wholeness, and the numbers through quantification provide an element of seriousness, accuracy and reality to the text and graphs/pictures (Botosan, 1997; Mouritsen et al., 2001; Toms, 2002).[14]

As pointed out by several authors (e.g. Guthrie and Petty, 2000; Brennan, 2001; April et al., 2003; Holland, 2001, 2006a; Guthrie et al., 2007; and Sujan and Abeysekera, 2007), text is the predominant unit used in IC communication to stakeholders. Some authors argue that people learn best from stories (Brown and Duguid, 2000) and the core of storytelling is the sequencing of the events, which is the key factor in creating a substantive text (Weick, 1995). Some argue that text can influence and change people's perception and decision-making (Hough and White, 2001), and is thus a powerful tool to promote and project a positive image of a firm (Neimark, 1992; Abeysekera, 2003).

[14] As noted in Botosan (1997), numerical disclosures are proxies of the quality of information, since numbers demonstrate reliability and function almost as a guarantee of facts. Toms (2002) shares the same view.

Some concur that encoding knowledge in stories enables a firm to leverage the value of their IC (Davenport and Prusak, 1998). Others argue that text disclosures of IC are free of measurement problems (Collier, 2001) and provide a mechanism by which IC can be understood and reported (Mouritsen et al., 2001; Mouritsen et al., 2003).

Words and pictures manifest themselves in different ways. The use of sentences along with words and characters is argued to be partial in that it will only capture narrative disclosures (Unerman, 2000). Several authors call for attention to the use of other visual forms of communication, such as graphs and pictures, which have been typically neglected (Beattie, 2005), and have been evidenced to provide an immediate and effective means of disclosure in annual reports (e.g. Beattie and Jones, 1992; Graves et al., 1996; cited in Beattie and Thomson, 2007). Pictures are deemed to be self-evident and simple, and do not require special training in order to read them. Graves et al. (1996) suggest that television-based formats, such as pictures and photographs, allow firms to assert their truth claims unobtrusively to the stakeholders. Certain sorts of diagrams improve both the speed and accuracy of deductive performance and help the reasoning of an individual (Johnson-Laird, 1996: 122). Beattie et al. (2008) posit that people's capacity to remember visual patterns is vastly superior to their memory for text or numbers. In addition, the communicative advantages of graphs are argued to be their capacity to attract readers' attention, reliance on spatial rather than linguistic intelligence, enabling data to be readily retrieved and seen in a direct and immediate way which facilitates the perception of comparisons, and the identification of patterns, trends and anomalies (Beattie and Jones, 2002). Previous research suggests that corporate performance displayed in charts is viewed most favourably by readers (Beattie and Jones, 2002). Financial graphs appear in many corporate annual reports in prominent positions intended to create an impression on the reader (Roberts et al., 2005). Davison and Skerratt (2007) examined the use of words and pictures in the communication of intangibles in corporate annual reports of FTSE 100 firms. They argue that ‘while … pictures, have traditionally been regarded by accountants as lightweight elements of the annual report package, it may be argued that they are, on the contrary, heavyweight ingredients, both in the richness and variety of their messages, and in their potency’. The authors give recognition to the communicative power of graphical representations. The study found that discretionary words, pictures and graphs occupied 59% of the sampled annual reports and reviews. Furthermore, the ASB (2000), as cited in Beattie et al. (2008), identifies graphs as a powerful medium of communication and makes recommendations about the use of graphs in annual reports in a discussion paper that examines ways of improving communication with private shareholders. Therefore, graphs and pictures are potentially powerful and highly effective methods for IC communication.

According to Ambler et al. (2001), quantitative measures should be supplemented by a commentary, although text alone has little value. Thus, they advocate the use of a proper mix of qualitative and quantitative data by combining text, numbers and figures, in much the same way as transparency is proposed in the Danish guideline for IC statements (Mouritsen et al., 2003).

In summary, text is a very powerful communicative reporting medium for constructed IC messages to be disclosed in annual reports. Graphs/pictures assist and support the text and provide wholeness to the document. These two presentational formats have been evidenced to be important for the communication of non-financial information in Beattie et al. (2008). Quantification enables firms to communicate some elements of the text and graphs concerning IC more effectively and add accuracy and credibility to the information communicated. Combining the three reporting units in annual reports enables a firm to construct their reported message about IC more meaningfully as a story about the past and the future.

IC information relating to the 61 IC items in the designed instrument[15] was recorded under the three formats, i.e. text, number and graph/picture.[16] Therefore, the coding sheet is comprised of a total of 183 format items (i.e. 61 IC items in three formats).

4.3.3 MEASUREMENTS OF IC DISCLOSURE

As summarised in Beattie et al. (2004b), to date, two principal ways of measuring disclosure have been employed: 1) subjective analyst disclosure quality rankings; and 2) researcher-constructed disclosure indices where the amount of disclosure is used as a proxy for disclosure quality. Both approaches are subject to limitations and weaknesses (see Beattie et al., 2004b). Authors call for research effort to be devoted to developing new ways of documenting disclosure practices and exploring possible measurement proxies (Beattie et al., 2004b) to measure the extent (Healy and Palepu, 2001) and quality (Core, 2001) of disclosure. Beattie and Thomson (2007) argue that many of the content analysis research methods adopted in prior studies for IC disclosure measurement lack transparency, specificity, uniformity and rigour, and that these deficiencies may give rise to misleading evidence.

The present study has two methodological contributions. First, it brings to the IC literature a method for generating a richer descriptive profile of a firm's IC disclosure. The basis of this profile is based on the coding of IC items and format of disclosure. The development of a comprehensive IC disclosure profile serves as a practical tool, permitting the benchmarking of current and future practices. It allows inter-firm, inter-industry and inter-country comparisons to be made in the future, and also allows changes over time to be monitored. Second, the dependent variable, IC disclosure, is

[15] See section 4.3.1 for the development of the research instrument and Appendix 4-B for a list of 61 IC items.
[16] It is common that, in the annual reports, the three disclosure formats overlap with each other as numbers are often embedded in text and/or graphs and pictures are often accompanied by text. A 'piece' of IC information receives a score of 2 if numbers are embedded in text (i.e. 1 score is given for the text disclosure and 1 score is given to the numbers); and a 'piece' of information scores 3 points if numbers are embedded in graphs, which is then accompanied by text description.

measured using three different metrics: disclosure index (ICDI) to indicate the *variety*; word count (ICWC) to represent the *volume*; and word count as a percentage of annual report total word count (ICWC%) to indicate *focus* in the annual report. Although the amount of disclosure might not be an exact indicator of disclosure quality (Beattie et al., 2004b), by expressing such quantities from three dimensions, this study provides a more holistic view of firms' IC disclosure practices and permits much more powerful testing of the research questions.

4.3.3.1 DISCLOSURE INDEX (DI) - VARIETY

One of the measures of IC disclosure is disclosure index, a technique first used by Buzby (1975) and Stanga (1976) and formalised by Cooke (1989a, b), then widely used in a variety of disclosure studies (e.g. Ahmed and Nicholls, 1994; Hossain et al., 1994; Wallace et al., 1994; Gray et al., 1995b; Botosan, 1997; Jaggi and Low, 2000; Richardson and Welker, 2001; Haniffa and Cooke, 2002, 2005; Chavent et al., 2006). It is a ratio comparing the actual level of disclosure and the possible maximum level.

There are two methods for determining the level of corporate disclosure: weighted and unweighted (Cooke, 1989a).[17] The equal weighting system is commonly viewed as superior to the differential weighting system[18], and 'has become the norm in annual report studies' because it reduces subjectivity (Ahmed and Courtis, 1999: 36). Earlier studies suggested that the weighted and unweighted scores tend to give the same results (e.g. Choi, 1973; Firth, 1980; Chow and Wong-Boren, 1987; Zarzeski, 1996; Inchausti,

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[17] It is argued that the weighted scoring approach allows distinctions to be made for the relative importance of information items to users (Inchausti, 1997). The advocates of this approach are of the opinion that all items of information are not equally important and, therefore, different weights are assigned to different items to reflect on their relative importance determined either subjectively by the researcher (e.g. Cerf, 1961; Singhvi and Desai, 1971) or taken from previous studies (e.g. Barrett, 1977) or weighed based on user groups' attitude surveys (e.g. Buzby, 1975; Stanga, 1976; Firth, 1979; McNally et al., 1982). A weighted scoring approach is often accused of being too subjective and the extra sophistication to be unnecessary (Roberts et al., 2005). The unweighted approach assumes that each item of disclosure is equally important. Firth (1979) posits that if the index of items is sufficiently comprehensive, every firm is ranked equally whether the items are weighted or not because an extensive list of items implies gradual equalization. Cooke (1989a: 115) argues that 'one class of user will attach different weights to an item … than another class' and that 'the subjective weights of user groups will average each other out'. This is supported by Wallace (1988) who contends that all disclosure items are equally important to the average users.

[18] For example, Cooke (1989a, b), (1991), (1992), (1993), Ahmed and Nicholls (1994), Hossain et al. (1994), Hossain et al. (1995), Wallace et al. (1994), Wallace and Naser (1995), Inchausti (1997), Owusu-Ansah (1998), Chen and Jaggi (2000), Haniffa and Cooke (2002), Archambault and Archambault (2003).

1997; Prencipe, 2004). Hence, the unweighted scoring approach was chosen for this study, because of the potential scoring bias and scaling problems associated with the weighting approach, i.e. all 61 IC items in the checklist carry equal weight.

In addition, as reviewed in Chapter 2, scoring approaches applied in prior IC disclosure studies are often either a binary coding scheme (a nominal score, which is called a dichotomous coding scheme in this study) to indicate the presence/absence of an item (e.g. Guthrie and Petty, 2000; Brennan, 2001), or an ordinal level score to capture the 'importance' of the specific disclosure format (an extension of the weighting system) (e.g. Bozzolan, et al., 2003; Sujan and Abeysekera, 2007; Cerbioni and Parbonetti, 2007),[19] typically in relation to 22-25 categories of IC information. Similar to the weighted scoring approach, an ordinal scoring approach involves subjective judgements while assigning different weight to the format of IC disclosure. Hence, a dichotomous coding scheme was considered to be more appropriate for this study, bearing in mind that dichotomous and ordinal coding schemes may produce similar results (see Chapter 10 for a comparison of results).

Therefore, one of the three IC disclosure measures applied in this study is a disclosure index, which is the number of IC items disclosed expressed as an index. It captures the *variety* of IC information disclosed. Each disclosure item in any of the three formats (text, number, graph/picture) identified has an equal weight for the analysis. Disclosure of an item in any format receives a score of 1,[20] while non-disclosure receives a score of 0. The scores for each format item were added to derive a final score for each firm. The IC disclosure index (ICDI) was then calculated as a percentage of the total disclosure score divided by the total maximum score of 183 (i.e. 61 IC items in three formats). A

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[19] Nominal measurement is to divide the data into separate categories that can then be compared with each other (Walliman, 2005: 101). An ordinal scale consists of a set of categories that are rank ordered on some continuum (Neuendorf, 2002: 120).

[20] For example, a firm scores 1 for disclosure of any number of pictures/graphs under each IC item, hence capturing merely the variety of disclosure rather than the volume.

high scoring firm is therefore likely to reinforce its IC message by using qualitative text data, more objective numerical data and more visual graphical/pictorial data. The IC disclosure index $ICDI_j$ for each firm is computed based on the disclosure index formula used in for example Haniffa and Cooke (2005), shown as follows:

$$ICDI_j = \frac{\sum_{i=1}^{n_j} X_{ij}}{n_j}$$

where n_j = number of format items for j^{th} firm, $n_j = 183$,

$X_{ij} = 1$ if i^{th} format item disclosed, 0 if i^{th} format item not disclosed,

so that $0 \leq ICDI_j \leq 1$.

4.3.3.2 WORD COUNT (WC) - VOLUME

The use of a dichotomous procedure in scoring the instrument for the disclosure index can be criticised because it treats disclosure of one item (regardless of its format or content) as being equal, and does not indicate how much emphasis is given to a particular content category. To capture the volume of IC content and to partly overcome the problem of using a disclosure index, this study introduces another form of measure, namely IC disclosure word count (ICWC), expressed by number of words. Zéghal and Ahmed (1990) indicate that words are the smallest unit of measurement for analysis and can thus be expected to provide maximum robustness to this study in assessing the quantity of disclosure; this is supported by Deegan and Gordon (1996), and Wilmshurst and Frost (2000). Using the same research instrument, and taking ‘phrases’, or what Beattie and Thomson (2007) term ‘pieces of information’, as the basis of coding,[21] the

[21] Weber (1990: 22) argues that long, complex sentences may need to be broken down into shorter thematic units or segments. The author suggests that large portions of text (e.g. paragraphs and complete texts) are usually more difficult to code as a unit than smaller portions, such as words and phrases, as large units typically contain more information and a greater diversity of topics which are more likely to present coders with conflicting cues and reduce reliability. Beattie et al. (2004b) and Beattie and Thomson (2007) found it necessary to split sentences into text units with each group of words containing a ‘single piece of information that was meaningful in its own right’. Similarly, using ‘phrases’ as the unit of analysis, each piece of information in a sentence is coded based on the context of that sentence. The unit of measurement used to value such disclosures is word count. This form of coding is labour-intensive, but leads to much more detailed and sophisticated results (Weber, 1990).

number of words relating to each IC item in the checklist was counted and added together to arrive at an ICWC for each firm. Graphical and pictorial messages were excluded from the word count measure.[22] This is one of the reasons for adopting both disclosure index and word count measures.

Coding under ‘phrases’ and measuring by word count avoids the problem of coding sentences in terms of decisions over dominant themes; the ‘phrases’ remain meaningful in their own right, while enabling the measuring of the amount of information provided.[23] Coding annual reports into ‘phrases’ is a three-stage process involving 1) selection of sentences containing IC information; 2) splitting such sentences into ‘phrases’ and selecting only those relating to IC; and 3) coding ‘phrases’ under each relevant item(s) in the research instrument. The process adds greater robustness to the analysis. Where a ‘phrase’ relates to more than one item in the checklist and cannot be split, it is then coded under all related items and the word count is evenly distributed across all the items coded. An example is shown here:

‘The trust and confidence of all our stakeholders, together with our reputation, are among our most valuable assets.’ (AstraZeneca plc 2004 Annual report).

The sentence was split into three ‘phrases’: (1) The trust and confidence of all our stakeholders, (2) together with our reputation, (3) are among our most valuable assets. Phrase 1 was coded under ‘relationship with stakeholders’, phrase 2 was coded under ‘company reputation’ and phrase 3 was coded under both items. All words in each ‘phrase’ were counted and the word count for phrase 3 was equally distributed between the two items.

Beattie and Thomson (2007) identify problems with word count (such as print size,

[22]Although IC disclosures in graphs/pictures are captured in the disclosure index using a dichotomous coding scheme, it only shows the presence/absence of such disclosure. It is not the aim of this study to measure the volume of disclosures in graph/picture form. Multiple disclosures were only recorded once. The size of each graph/picture and the total space of the annual report devoted to those disclosures were not measured. This is an interesting issue that requires further investigation in future studies.

[23] Milne and Adler (1999) discredit the coding of single words on reliability grounds as they have no meaning to provide a sound basis for coding without a sentence or sentences for context.

colour, font variations and disclosures in graphs/pictures format), and propose word count as a measure addressing the differentiation in length and number of sentences used in expressing similar meanings encountered by coding sentences.[24] Word count as a measure of level of disclosure has nevertheless been employed in a number of previous studies.[25] Moreover, Weber (1990: 39) suggests that the reliability at all levels of measurement (e.g. sentences and paragraphs) was substantially less than the reliabilities for specific words or phrases.

4.3.3.3 WORD COUNT PERCENTAGE (WC%) – FOCUS

As far as quantity of communication is concerned, two aspects have to be balanced (Beretta and Bozzolan, 2004), which are 1) the quantity, i.e. the absolute number of pieces of information disclosed which is a proxy for the amount of disclosure provided; and 2) the density, i.e. the relevance assumed by IC information depends on the weight it has inside the overall communication. Krippendorff (1980) notes that words are a preferred measure when it is intended to measure the amount of total space devoted to a topic and to ascertain the importance of that topic. Although word count is not assumed to be representative of the quality of disclosure,[26] it is assumed to be indicative of the overall responsiveness by corporate management.[27] For these reasons it can be contended that an absolute index (e.g. number of words) is not adequate to appreciate

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[24] Other commonly used measurement methods include sentence count (e.g. Entwistle, 1999; Milne and Adler, 1999), summed page proportions (e.g. Guthrie and Parker, 1990; Gray et al., 1995b; Campbell, 2000; Striukova et al., 2008), frequency of disclosure (e.g. Cowen et al., 1987; Ness and Mirza, 1991) and 'high/low' disclosure (e.g. Patten, 1991). Sentence as the unit of analysis is argued to be more reliable than any other unit of analysis (Milne and Adler, 1999). However, sentences vary in length and grammatical differences might result in the same context being expressed using a different number of sentences (Unerman, 2000). It was proposed by Beattie and Thomson (2007) that counting the number of words in each sentence could solve this problem.

[25] For example, Deegan and Gordon (1996), Subbarao and Zéghal (1997), Wilmshurst and Frost (2000), Campbell (2004), Haniffa and Cooke (2005), and Campbell et al. (2006).

[26] Given the difficulty of assessing disclosure quality directly, a key assumption in many content analysis studies is that the volume of disclosure signifies the relative importance of the information disclosed (Botosan, 1997; Weber, 1990).

[27] This assumption is based on the belief that management has editorial control of content when a large number of demands for inclusion of information are likely to exist. Annual reports are time consuming and costly to produce, and management must rationalise the competing demands for space. As a result, space must be allocated on the basis of some perception of the importance of information to report users. It is found in Gibbins et al. (1990) that the structure of a firm's reporting model also refers to the content, i.e. the number of words disclosed. Managing this content may go beyond accounting calculations or policy choices, into arranging business affairs so as to produce the desired disclosure content. It is supported by Weber's (1990) argument that text producers will typically allocate their efforts to a range of issues and themes given resources available for text production are finite (p.73).

the relative quantity of disclosure made by any firm. Therefore, in addition to the word count of IC disclosure, the density dimension was also considered, in other words the *focus* on such disclosure.

It is evident that the style of writing strongly influences the effectiveness of narrative reporting. It is contended in this study that the relevance of IC information disclosed in narrative reporting is influenced by how much it is diluted into the mass of the other pieces of information disclosed. From the reader's perspective, finding a low number of IC related words of information among hundreds of pages of narrative reporting makes it difficult to appreciate the system of IC affecting a firm's prospects. On the other hand, from the firm's perspective, diluting a limited amount of IC information in as thick a document as the annual report may reveal a strategy of 'hiding the needle in a haystack' as described in Beretta and Bozzolan (2004), which makes relevant information disclosed hard to find.

It can be deduced from the above argument that the greater the number of words related to IC being disclosed in relation to the total number of words in the annual report, the greater the emphasis (i.e. focus) given by management to such information. Hence, a third measure of IC disclosure is introduced, ICWC%, which is the proportion of IC disclosure word count to the total word count of the whole annual report. This measure captures the IC focus in the annual report. As a consequence, the value assumed by the *focus* measure is between 0 and 1, which assumes higher value when the importance of IC information in the annual report is greater. For example, a firm with a short annual report may have a low IC disclosure index (ICDI) and word count (ICWC) but a high word count percentage (ICWC%), conveying to the reader the importance placed by management on IC information. The formula for the computation of *focus* on IC disclosure in annual reports, $ICWC\%_j$, for each firm is shown as follows:

$$ICWC\%_j = \frac{\sum_{i=1}^{n_j} X_{ij}}{k_j}$$

where k_j = total word count of annual report for j^{th} firm,

n_j = the number of IC items for j^{th} firm, $n_j = 61$,

X_{ij} = total word count of i^{th} IC item disclosed,

so that $0 \leq ICWC\%_j \leq 1$.

4.4 POPULATION AND SAMPLE

As mentioned in an earlier section, this study investigates IC disclosure practices in the annual report of LSE-listed UK firms.[28] Annual reports that were studied cover financial year ends between March 2004 and February 2005.[29] There were 3,091 firms fully listed on LSE at the time of data collection (30 December 2005).[30] Overseas firms and Alternative Investment Market (AIM) listed firms were excluded, leaving 1,358 LSE main board listed UK firms as at 30 December 2005.

The LSE classification of industries was consolidated and seven IC-intensive categories were selected.[31] IC-intensive firms include computer firms and other high-technology firms, software firms, and manufacturers of new or differentiated products; and in the services industry include law firms, consulting firms, financial services firms, and media firms (Edvinsson and Malone, 1997). Striukova et al. (2008) argue that firms in information technology and biotechnology and pharmaceutical sectors are highly IC

[28] A large number of the LSE listed UK companies produce two documents as their corporate annual reports, i.e. the annual report and accounts and a separate annual review. The majority of the annual reviews of companies are a shortened version of the annual report and accounts. Only a small number of companies provide the account and directors' report separately from the narrative reports, which are instead included in the separate annual review. For example, in 2004, Hammerson plc and Tomkins plc both provided a separate annual review and a report containing directors' report and accounts. In these cases, both reports will be examined. On the other hand, for companies with the annual review being merely a shortened version of the annual report and account, only the latter will be examined. All the 100 sampled firms in this study provided a full annual report and account and, hence, annual reviews were not examined in the study.

[29] The reason for selecting financial year ends between March 2004 and February 2005 is that the Operating and Financial Review (OFR) reporting regulation was going to become effective for firms with a financial year end on or after April 2005, although this was subsequently withdrawn. As the OFR required a considerable amount of information on IC, it was considered that the regulatory requirement would significantly affect firms' IC disclosure behaviour. It was expected that as firms anticipate changes in reporting requirements, the changes in disclosure behaviour would be earlier than the new OFR requirement and one year's lag time was given to reduce such an effect.

[30] LSE, URL: http://www.londonstockexchange.com/en-gb/pricesnews/statistics/listcompanies/ (accessed on 10/01/06).

[31] Waterlow Stock Exchange Yearbook 2005.

reliant. White et al. (2007) and Cerbioni and Parbonetti (2007) examined IC disclosure of biotechnology firms in particular. Beattie and Thomson (2005) document that the average market-to-book ratios for pharmaceutical and media firms in their sample were 5.6 and 4.4 respectively and the two sectors were argued to be knowledge-intensive. This is supported by the results of The Global Intangible Study 2006 (IPA, 2006: 6) that sectors containing the highest proportion of intangible assets are Media and Pharmaceuticals, followed by Food, Retail, Telecom, Banking, and Insurance. Despite the recognition of financial services firms as high IC firms in Edvinsson and Malone (1997), prior IC disclosure literature has often excluded financial services firms from their studies, arguing they have different regulatory reporting requirements. Financial services firms can be expected to place a high value on the customer relationship and employee knowledge, which is evidenced by the fact that branch managers of banks are increasingly called ‘relationship managers’. Although it is argued that banks are highly regulated business entities with their financial reports influenced by a specific regulatory framework (Tadesse, 2006), practices of disclosure of information required by the regulations still vary a great deal from firm to firm. In addition, IC information disclosure has been largely considered as voluntary, and therefore it was decided to include banks and insurance firms in the sample.

The seven reclassified industry sectors selected are: Biotechnology & Pharmaceutical (BPH), Information Technology (IT), Media & Publishing (M&P), Business Services Providers (BSP), Telecommunication Services (Telecom), Banks & Insurance (B&I), and Food Production & Beverage (F&Bev).[32] This results in a population size of 346

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[32] Firms in the health industry were also included in the biotechnology & pharmaceuticals sector. The IT sector includes computer hardware, semiconductors, software, computer services and Internet firms. The media & publishing sector includes TV, radio and filmed entertainment, subscription entertainment networks, media agencies, photography and publishing, and printing firms. Business services providers are always perceived to have higher IC value than manufacturing firms, which are mainly human and relational capital centred, and include business support services, delivery services, education, business training & employment agencies, environmental control, transaction and payroll services and security & alarm services. The telecommunication services sector includes both wireless and fixed-line services.

firms. However, in total 27 firms were listed after the financial year end chosen for the study,[33] and hence were excluded from the sample. Therefore, the final population size is 319 firms. The next step was to determine the sample size suitable for the study.

Although general rules are hard to make without knowledge of the specific population, 30 cases has been argued to be the minimum sample size for studies in which statistical data analysis is required (Bailey, 1978), while some researchers regard 100 cases as the minimum. Moser and Kalton (1996) and Easterby-Smith et al. (2002) suggest a formula for sample size calculation, which is,

$$n = \pi(1-\pi)/[S.E.(p)]^2$$

where n = required sample size

π = proportion of the particular attribute in the population (estimated at 50/50)

S.E. (p) = the standard error that is allowed for the study (set at 5%)

If the variability in the population (proportion with particular attribute in the population) is estimated at 50%[34] with standard error of 5%, the sample size is 100. Therefore, a sample size of 100 firms for a population size of 319 firms was selected (31%).

A systematic stratified sampling procedure was applied in this study.[35] The number of firms in each industry group is not the same (see Table 4.2). Simple random sampling will not be able to ensure the representativeness of sample firms in each industry sector. Proportionate stratified sampling was then applied (Moser and Kalton, 1996). The number of samples required to be selected from each of the seven industry sectors was computed and shown in Table 4.2. A list of the 100 sampled firms is provided in

[33] For instance, a firm's financial year end was July 2004 and started its listing on LSE from January 2005.
[34] This value is always assumed to be the maximum variance.
[35] Systematic sampling procedure involves the selection of unit in a series according to a predetermined system (Walliman, 2005: 277). Based on stratified sampling, the population is divided into two or more relevant and significant strata based on one or a number of attributes (Saunders et.al., 1997). A sample is then selected from each stratum separately, producing s stratified sample. The two main reasons for stratified sampling design are 1) to ensure that particular groups within a population are adequately represented in the sample, and 2) to improve efficiency by gaining greater control on the composition of the sample and greater precision can be achieved. The sample size is usually proportionate to the relative size of the strata.

Appendix 1.

Table 4.2 Distribution of Firms According to Industry Sectors

	Industry Category	No. Firms	100 Samples	Proportion
1	Biotechnology & Pharmaceutical (BPH)	40	13	32%
2	Information Technology (IT)	60	19	32%
3	Telecommunication Services (Telecom)	18	6	33%
4	Business Services Providers (BSP)	83	26	31%
5	Media & Publishing (M&P)	45	14	31%
6	Banks & Insurance (B&I)	51	15	29%
7	Food Production & Beverage (F&Bev)	22	7	32%
Total		**319**	**100**	**31%**

In addition, previous IC disclosure studies have concentrated on large firms (e.g. April et al., 2003; Williams, 2001) in the country studied. It is pertinent to question the extent to which these studies can claim to represent the actual IC disclosure practices in a particular country. Large firms by their multinational character and complexity might tend to disclose more IC information with the international marketplace in mind. A more balanced approach would be to include a sample of both large and small firms with both high and low market capitalisation. Therefore, this study covers both large and small LSE-listed UK firms in the seven selected industry sectors with market values ranging from £98,258m to £8.24m.[36] For this purpose, the average market capitalisation of the firms in each of the seven industry groups was computed and firms were ranked by market capitalisation in descending order. Firms were then stratified into two groups in their relative industry sectors, i.e. those with market capitalisation higher than average (HMV) and those with market capitalisation lower than average (LMV). Half of the sample was selected from the HMV group and the other half selected from LMV.[37] Then the samples were systematically selected from HMV and LMV firms, e.g. one firm from every three firms, depending on the number of firms the sample was to be chosen from.

[36] The market capitalisation is the financial year end value of each firm.
[37] If firms from one group (HMV or LMV) are less than the number of samples to be selected, all firms in the group were selected with the rest of the samples to be selected from the other group systematically.

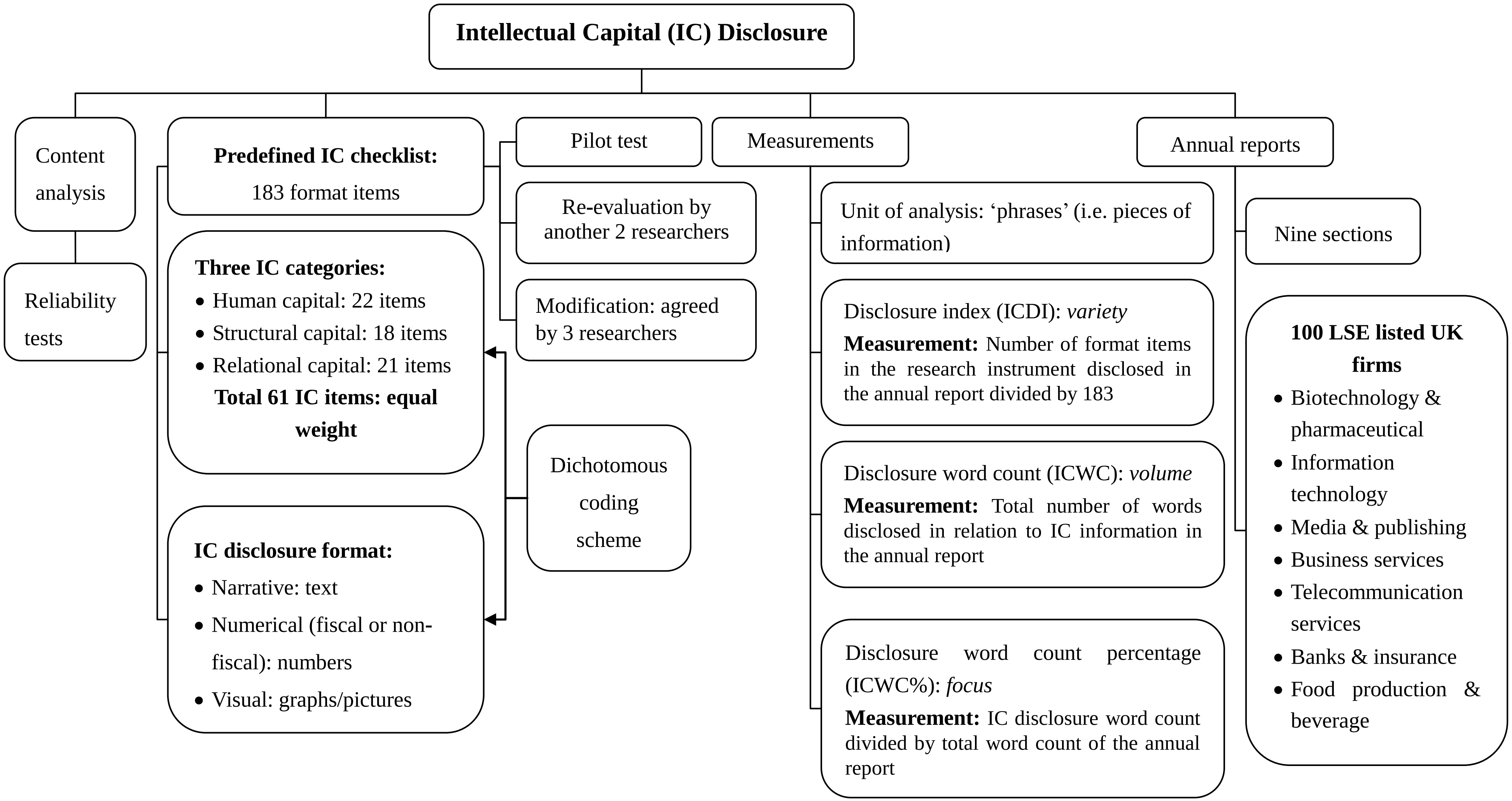
It is important to note that this study is biased towards IC-intensive industry sectors, and it is not the objective of this study to provide a comparison of IC disclosure practices across all industries or to attempt to offer findings representative of the whole stock market. The sample cannot claim to represent the IC disclosure practices of all LSE-listed UK firms. Given that the study employs a variety of formats to observe IC disclosure, it was decided to focus on those sectors expected to include a good proportion of IC-intensive firms, while retaining considerable variation in intensity between firms. There is a possibility that industry differences in the level of IC disclosure are quite small, given the IC-intensive bias in industry selection. However, disclosure may vary considerably at the subcategory level. For example, the biotechnology & pharmaceutical sector may invest heavily in R&D (structural); the financial services, business services providers and media sectors may have greater investment in relational and human capital; the food production & beverage sector may rely heavily on brand names, product images and high levels of marketing activity (relational); while the telecommunication services and IT sectors may have greater emphasis on infrastructure and technology (structural). The focus on IC-intensive sectors is therefore viewed as both a design strength and limitation; as a strength, it enables greater focus on IC disclosure in IC-intensive sectors, as a limitation, it prevents wider generalisation to the whole LSE population.

So far, the discussion has described the research method applied in the study (see Figure 4.1 for a summary). The following sections focus on the research design and data analysis methods.

4.5 RESEARCH DESIGN AND PROPOSED HYPOTHESES

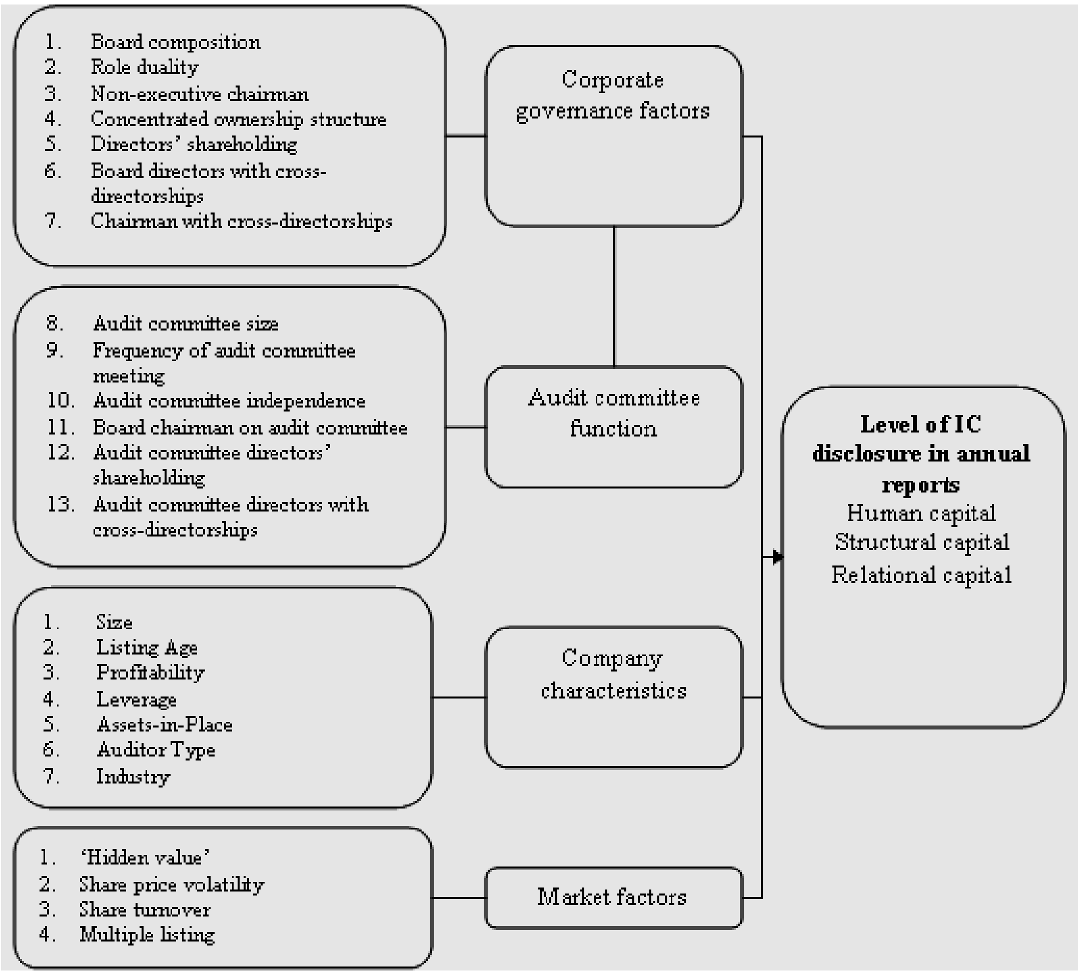
This section provides a brief review of the research design, the main variables of interest in this study (i.e. determinants of IC disclosure) and the research propositions

Figure 4.1 Summary of Research Method



developed. The research design of the study is shown in Figure 4.2, highlighting the focus of the study on examining the determinants of firms' IC disclosure practices in the annual report.

Figure 4.2 Research Design and Independent Variables Examined



Such determinants of IC disclosure correspond to the internal and external stimuli of the corporate disclosure process proposed by Gibbins et al. (1990) (see Chapter 3 for a discussion). Internal stimuli examined in this study include corporate governance factors and company characteristics, together with market factors as external stimuli.

4.5.1 INDEPENDENT VARIABLES AND PROPOSED HYPOTHESES

The independent variables examined in this study under the three groups include thirteen corporate governance factors (including six audit committee characteristics), seven company characteristics and four market factors (see Figure 4.2). These explanatory variables selected are based on prior studies and theories built up in the voluntary and IC disclosure literature.

4.5.1.1 CORPORATE GOVERNANCE FACTORS

Although there has been an increase in the literature on corporate governance issues, its impact on IC disclosure practice has not been extensively explored. The corporate governance factors (board composition, role duality, non-executive chairman, share ownership structure, directors' shareholding, board directors with cross-directorships, and chairman with cross-directorships), including audit committee characteristics (size, frequency of meeting, independence, board chairman on the committee, committee directors' shareholding, and committee directors with cross-directorships), were selected based on earlier studies investigating board of director issues in relation to firms' performance and corporate disclosure practice. These are justified further in Chapters 3, 6 and 8 beyond the brief discussion provided in this section.

Non-executive directors are argued to act as guardians of shareholders' interests and help reduce agency problems (Rosenstein and Wyatt, 1990), and will encourage management to take a more proactive disclosure position (see Gibbins et al., 1990), such as IC disclosure. In addition, Cotter and Silvester (2003) argue that the independence of non-executive directors allows them to provide objective assessments of firm actions and to ensure adequate 'checks and balances' on managerial behaviour. Hence, board composition (INED), defined as the proportion of independent non-executive directors to the total number of directors, is seen as an important indicator of board independence and is considered to be an important determinant of the extent of IC disclosure.

Role duality (RDUAL) is a board leadership structure in which the same person undertakes both the roles of CEO and chairman. There is widespread acknowledgement that a dominant personality commanding a firm results in ineffective monitoring of managerial opportunistic behaviour (Haniffa and Cooke, 2002), poor and reduced disclosure (Forker, 1992; Gul and Leung, 2004). A non-executive chairman (NEC) can also be expected to play an independent role in influencing executive directors to disclose information, being in a better position than other independent non-executive directors to provide important checks on the board's behaviour.

Agency theory argues that firms with greater ownership diffusion are more likely to experience pressure from shareholders for greater disclosure to reduce agency costs and information asymmetries (Fama and Jensen, 1983a). In contrast, firms with closely-held ownership are expected to have less information asymmetry between management and dominant shareholders who typically have access to the information they need (Bushee et al., 2003; Cormier et al., 2005). This is particularly relevant to IC disclosure because fund managers have access to such information via private communication channels (Holland, 2006b). Hence, share ownership concentration (SCON) is considered to have an impact on IC disclosure practice.

Managerial ownership (DISH) is considered as an effective mechanism to realign the executive directors' decision-making and disclosure attitudes based on agency theory (Jensen and Meckling, 1976; Nam et al., 2006). Therefore, increased director ownership is likely to see executive directors support the disclosure of more information. However, O'Sullivan (2000) argues that when there is significant managerial ownership, less disclosure can be expected, due to managerial entrenchment effect.

Directors sitting on more than one board may provide more transparency (Dahya et al., 1996) because of knowledge of other organisations and greater access to information in more than one firm (Haniffa and Cooke, 2002, 2005). Hence, a positive association between the extent of disclosure and the proportion of board directors with cross-directorships as well as chairperson with cross-directorships can be expected.

With regard to audit committee characteristics, effective audit committees can be expected to act as a powerful monitoring device for improving value-relevant IC disclosure. In order to perform their role effectively, including overseeing IC disclosure practice, audit committees should have adequate resources and authority (SAC), as well as sufficient meeting time (MAC) to discharge their increasing responsibilities (Mangena and Pike, 2005; Yang and Krishnan, 2005; Raghunandan and Rama, 2007).

The importance of the independence of the audit committee (INED_AC) has been addressed by many (e.g. Cadbury Committee, 1992; BRC, 1999; Smith Report, 2003). It is expected that independent audit committee directors would ensure better financial reporting (e.g. Yang and Krishnan, 2005; Ashbaugh-Skaife, et al., 2006) and IC disclosure to reduce agency costs and information asymmetries. Another way to examine the independence of an audit committee is the presence of the board chairman on the committee (CHAC). It is recommended by the Smith Report (2003) that 'the chairman of the company should not be an audit committee member' (para. 3.2).

The arguments on the effect of stock ownership by audit committee directors (ADISH) are twofold. Beasley (1996) and Yang and Krishnan (2005) argue that share ownership provides incentives for outside directors to monitor management. However, Wright (1996) argues that share ownership by audit committee directors may weaken the independence of directors.

The proportion of audit committee directors with cross-directorships (XDIR_AC) reflects the resource of the committee being available for carrying out their functions effectively. Outside directors, who are usually directors of other firms, have incentives to develop reputations as monitoring experts of well-run firms, thus signalling their competence to the market (Fama and Jensen, 1983a). Hence, audit committee directors with cross-directorships can be expected to provide greater transparency and monitoring.

4.5.1.2 COMPANY CHARACTERISTICS

Previous empirical studies on corporate disclosure in annual reports, including IC disclosure, tried to examine the relationship between the extent of disclosure and some company characteristics.[38] A brief review on these studies is provided in Chapter 3 Section 3.2.1.1. Company characteristics examined in this study include firm size, listing age, profitability, leverage, assets-in-place, auditor type and industry type.

Large firms are more visible and are likely to disclose more information to meet investors' demand for information, reduce political costs and raise capital (e.g. Firth,

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[38] Company characteristics can be classified into three non-mutually exclusive categories, i.e. performance, structure and market related variables (see Wallace et al., 1994; Haniffa, 1999). Haniffa (1999) provides a review on a number of company characteristics commonly examined in previous disclosure studies and their proxies used.

1979; Watts and Zimmerman, 1986; McKinnon and Dalimunthe, 1993). Hence, firm size (SA) is considered an important determinant of the extent of disclosure. Based on signalling theory, the length of time a company has been listed on a capital market, i.e. listing age (AGE), may also be relevant in explaining the variation of disclosures. Younger listed companies without an established shareholder base are expected to be more reliant on external fund raising than more mature companies (Barnes and Walker, 2006) and have greater need to reduce scepticism and boost investor confidence (Haniffa and Cooke, 2002). Profitability (ROA) may be the result of continuous investment in IC and firms may engage in higher disclosure of such information to signal the significance of their decision in investing in it for long-term growth in the value of the firm. Leverage (LEV) has been found to be an important explanatory variable (e.g. Leftwich et al., 1981; Wallace et al., 1994; Ferguson et al., 2002). As IC is recognised as an important asset for firms to gain competitive advantage, highly leveraged firms may disclose more IC information as an assurance to their creditors and other stakeholders (Myers, 1977; Schipper, 1981; Cooke, 1996). Debreceny and Rahman (2005) suggest assets-in-place (AIP) to be one of the major variables that could generate agency costs. It is expected that firms with a high level of assets-in-place have less agency problems and are less reliant on IC, and hence are less likely to provide such disclosure. Size of audit firm (AUD) has been related to the extent of disclosure (Haniffa and Cooke, 2002). Top audit firms are said to be more likely to influence firms to disclose additional information (Wallace et al., 1994), and can be considered to be more knowledgeable in relation to IC reporting with regard to what and how much to disclose. Industry characteristics (IND) may also influence a firm's disclosure decisions (Verrecchia, 1983; Botosan, 1997; Nagar et al., 2003; Roberts et al., 2005). More detailed literature review on each of the company characteristics and the development of hypotheses are provided in Chapter 6.

4.5.1.3 MARKET FACTORS

The market factors were selected based on the IC literature and previous studies investigating market-related issues in relation to voluntary disclosure practice (see Chapters 3 and 9). The reason voluntary disclosure literature was considered in this study is that the majority of IC disclosures in corporate annual reports can be considered to be voluntary disclosures and the theories that are behind IC disclosures tie in with the voluntary disclosure literature.

Studies have observed that improved corporate disclosure reduces information asymmetry (Welker, 1995; Leuz and Verrecchia, 2000). The inability of conventional financial statements to reflect adequately human, structural and relational capital means that IC-intensive firms are likely to exhibit a greater gap between market and book values (Petty and Guthrie, 1999; Guthrie, et al., 2006), i.e. 'hidden value'. Therefore, arguments drawn from information asymmetry suggest that firms with higher 'hidden value' (M2B) will provide greater IC disclosure.

It is argued that the higher a firm's share price volatility, the more difficult it is for investors to assess the firm's value, and the more likely they are to incur information costs (Foster, 1986). In addition, IC-intensive firms are more sensitive to market events than less IC-intensive firms and, as such, their share prices are expected to be more volatile (Lev and Sougiannis, 1999). Therefore, it is expected that investors in high price volatility (SPV) firms reduce their information costs by demanding greater IC disclosure.

Bushee et al. (2003) argued that firms whose shares are actively traded are more likely to face pressures from shareholders to disclose information. Hence, a positive association between the level of IC disclosure and share turnover (STO) can be expected.

Prior research (e.g. Meek and Gray, 1989; Emenyonu, 1993) suggests some associations between listing status and the disclosure practices of firms, with multi-listed firms usually expected to achieve proportionately higher rates of disclosure than domestic listed firms. Despite the number of previous studies exploring the association between multiple listing status and corporate disclosure, little research has been done to establish the association between multiple listing status and the level of IC disclosure. This study suits this purpose.

4.5.1.4 OPERATIONALISATION OF INDEPENDENT VARIABLES AND PROPOSED HYPOTHESES

The previous sections provide a brief overview on the independent variables that are examined in the thesis. The operationalisation of the independent variables (also listed in Figure 4.2) is summarised in Table 4.3.

Table 4.3 Measurement of Independent Variables[39]

No.	Variable	Proxy	Measurement
Company Characteristics			
1	Firm size	Sales (SA)	Sales revenue of the financial year of study (e.g. Cooke, 1989a, b; Raffournier, 1995).
2	Length of listing on LSE	Listing age (AGE)	Number of days listed scaled by 365 days a year till the financial year end of study.
3	Performance: profitability	Return on assets (ROA)	Return/total assets for the financial year of study (e.g. Haniffa, 1999).
4	Leverage	Leverage (LEV)	Debt/equity (e.g. Wallace et al., 1994; Hossain et al., 1994; Wallace and Naser, 1995; Haniffa and Cooke, 2002, 2005).
5	Assets-in-place	Assets-in-place (AIP)	Tangible fixed asset over total assets (e.g. Haniffa and Cooke, 2002; Xiao et al., 2004).
6	Auditor	Type of auditor (AUD)	Dummy variable with a value of 1 if the firm is audited by a big-4 auditor, otherwise a value of 0 is given (e.g. Hossain et al., 1994; Raffournier, 1995; Haniffa and Cooke, 2002).[40]
7	Industry	Type of industry (IND)	Dummy variables for the seven industry sectors selected (e.g. Cooke, 1989b, 1992; Haniffa and Cooke, 2002).
Corporate governance factors			
1	Board composition	Independent non-executive directors (INED)	Number of independent non-executive directors on board (specified in the annual report) divided by the total number of directors on board.
2	Role duality	Combined role of chairman and CEO (RDUAL)	Dummy variable with a value of 1 if the roles of chairman and CEO are held by the same person, otherwise a value of 0 is given.
3	Position of chairman	Non-executive chairman (NEC)	Dummy variable with a value of 1 if the chairman is a non-executive director, otherwise a value of 0 is given.
4	Ownership structure	Share concentration (SCON)	Cumulative shareholdings by individuals or organisations classified as substantial shareholders (currently a 3% stake required by the Companies Act 1985), with the exception of significant directors' shareholdings, to the total number of outstanding common shares (e.g. Cormier et al., 2005; Brammer and Pavelin, 2006).
5	Directors' shareholding	Board directors' shareholding (DISH)	Number of shares held by board directors to the total number of outstanding common shares.
6	Cross-directorships	Board directors with cross-directorships (XDIR)	Number of directors on board holding cross-directorships (sitting on the board of one or more of other firms) divided by the total number of directors on board.
7	Chairman cross-directorships	Chairman with cross-directorships (CXDIR)	Dummy variable with a value of 1 if chairman holds cross-directorships, otherwise a value of 0 is given.
8	Audit committee characteristics	Audit committee size (SAC)	Number of board directors on audit committee.
9	Audit committee characteristics	Frequency of audit committee meeting (MAC)	Number of audit committee meetings held within the financial year of study.
10	Audit committee characteristics	Audit committee composition (independence)	Number of independent non-executive directors on audit committee (specified in the annual report) divided by the

[39] For nominal variables, dummy variables are created for each of these variables to be included in the regression model. The number of dummy variables included in the regression model is one less than the number of classifications of each nominal variable, so as to avoid the dummy variable trap. Gujarati (2003) suggests that 1/0 assignment to variables with two categories is arbitrary but it is best that 0 is assigned to the category used as a benchmark for comparison as the group will be left out of the equation. For instance, for the industry classification comprising seven groups, only six dummy variables will be included in the regression routines with any one sector omitted as benchmark. The relationships among the coefficients are the same, although different numbers will be obtained depending on the group left out (Haniffa, 1999).

[40] Studies that examined type of auditors used to refer the variable to the big-6 and the non-big 6. Due to consolidations, the big-6 now is big-4, which includes Ernst & Young, Deloitte & Touche, PricewaterhouseCoopers and KPMG.

		(INED_AC)	total number of directors on audit committee.
11	Audit committee characteristics	Board chairman on audit committee (CHAC)	Dummy variable with a value of 1 if board chairman sits on audit committee, otherwise a value of 0 is given.
12	Audit committee characteristics	Audit committee directors' shareholding (ADISH)	Number of shares held by audit committee directors to the total number of outstanding common shares.
13	Audit committee characteristics	Audit committee directors with cross-directorships (XDIR_AC)	Number of audit committee directors holding cross-directorships divided by the total number of directors on audit committee.
Market factors			
1	Hidden value (IC value)	Market-to-book ratio (M2B)	Stock market price over stockholders' equity (e.g. Miller and Whiting, 2005). The ratio of the financial year end studied.
2	Share price volatility	High/Low price difference (SPV)	Difference between the highest and lowest share price during the study period, scaled by the lowest share price (e.g.Frankel et al., 1999; Bushee et al., 2003).
3	Share turnover	Percentage of shares traded (STO) (Ratio)	Total number of shares traded during the period of study divided by the total number of outstanding common shares (e.g. Cormier et al., 2005).
4	Listing status	Multiple listing (ML)	Dummy variables with a value of 1 if the firm is listed on one or more international stock exchange(s) apart from its national listing status (LSE), otherwise a value of 0 is given (e.g. Cooke, 1989a,b, 1992; Hossain et al., 1994; Haniffa and Cooke, 2002, 2005).

As mentioned previously, the detailed literature review on the three groups of independent variables and the development of hypotheses are provided in the results chapters (Chapters 6, 8 and 9). The hypotheses proposed in this study were based upon previous research findings and various theories applied in disclosure studies. It is considered necessary to list the proposed hypotheses to be tested in the study at this juncture although the development of hypotheses will be explained in detail in the respective empirical findings chapters. This thesis examines three main hypotheses, which are:

H01: The level of IC disclosure is associated with a number of corporate governance factors, ceteris paribus.

H01a: There is a positive relationship between the level of IC disclosure and representation of independent non-executive directors on board, ceteris paribus.

H01b_1): There is a negative relationship between the level of IC disclosure and role duality, ceteris paribus.

H01b_2): There is a positive relationship between the level of IC disclosure and the position of chairman as a non-executive director, ceteris paribus.

H01c: There is a negative relationship between the level of IC disclosure and concentrated share ownerships, ceteris paribus.

H01d: There is a negative relationship between the level of IC disclosure and the level of directors' shareholding, ceteris paribus.

H01e_1): There is a positive relationship between the level of IC disclosure and the proportion of board directors with cross-directorships, ceteris paribus

H01e_2): There is a positive relationship between the level of IC disclosure and chairman with cross-directorships, ceteris paribus.

H01f_1): There is a positive relationship between the level of IC disclosure and audit committee size, ceteris paribus.

H01f_2): There is a positive relationship between the level of IC disclosure and frequency of audit committee meeting, ceteris paribus.

H01f_3): There is a positive relationship between the level of IC disclosure and the independence of audit committees, ceteris paribus.

H01f_4): There is a negative relationship between the level of IC disclosure and the presence of board chairman on audit committee, ceteris paribus.

H01f_5): There is a negative relationship between the level of IC disclosure and the level of audit committee directors' shareholding, ceteris paribus.

H01f_6): There is a positive relationship between the level of IC disclosure and the proportion of audit committee directors with cross-directorships, ceteris paribus.

H02: The level of IC disclosure is associated with a number of company characteristics, ceteris paribus.

H02a: There is a positive relationship between the level of IC disclosure and firm size, ceteris paribus.

H02b: There is a negative relationship between the level of IC disclosure and firms' listing age, ceteris paribus.

H02c: There is a positive relationship between the level of IC disclosure and firms' profitability, ceteris paribus.

H02d: There is a positive relationship between the level of IC disclosure and *firms' leverage, ceteris paribus.*

H02e: There is a negative relationship between the level of IC disclosure and firms' assets-in-place, ceteris paribus.

H02f: There is a positive relationship between the level of IC disclosure and firms' auditor type (big-4), ceteris paribus.

H02g: Level of IC disclosure is associated with type of industry, ceteris paribus.

H03: The level of IC disclosure is associated with a number of market factors, ceteris paribus.

H03a: There is a positive relationship between the level of IC disclosure and firms' 'hidden value', i.e. market-to-book ratio, ceteris paribus.

H03b: There is a positive relationship between the level of IC disclosure and share price volatility, ceteris paribus.

H03c: There is a positive relationship between the level of IC disclosure and firms' share turnover, ceteris paribus

H03d: There is a positive relationship between the level of IC disclosure and firms with multiple listing(s), ceteris paribus.

The empirical models have been constructed to examine the proposed hypotheses and the specifications of these models are presented in the respective findings chapters.

4.5.2 DATA COLLECTION APPROACH

Secondary data are drawn from two resources: 1) hard-copy references, and 2) electronic databases. The hard-copy reference for data collection is the annual report. Annual reports were downloaded from sample firms' corporate websites. Scoring of IC information was performed manually covering the whole annual report. Studies such as Bontis (2003) applied a keyword search approach of content analysis. Words have been argued to have the advantages of being more direct and reliable in their coding, more easily categorised and can be used for large databases (Gray et al., 1995a). However, such an approach has problems with words with multiple meanings (potentially resulting in hits that are completely irrelevant), synonyms, and/or versions of words (e.g.

pronouns and nouns) for stylistic reasons (may lead to the underestimation of actual use of words), when using frequency keyword counts (Weber, 1990). It is also problematic with company-specific terms (Beattie and Thomson, 2007), such as names of customers, suppliers and competitors, and brand names. Milne and Adler (1999) and Neuendorf (2002) question electronic keyword search methods on the grounds that individual words are unlikely to convey the meaning that could be achieved by consideration of whole sentences. This is supported by Stewart and Shamdasani's (1998) argument that the procedure of simply counting and sorting words loses the contexts in which the words occur, because the meaning of words are frequently context dependent. Although conducting content analysis manually is a time-consuming process, it allows qualitative judgements in the coding, potentially reduces the problem of under or over counting of keywords; it allows the coding of items in the checklist to be put in the context of sentences; and it allows company-specific information to be captured. Moreover, similar to the problem with using words as the unit of analysis, keyword search is limited to text only (Neuendorf, 2002), while manual coding allows consideration beyond the text, such as graphs/pictures.

Data was then collected manually from annual reports for information on corporate governance structure such as board composition, share ownership concentration, directors' shareholding and audit committee characteristics.[41] Other information was collected from databases and websites. Sales and all other market related data (except for listing age) was collected from Thomson Research. Information such as industry type and listing age was collected from the LSE website.

[41] Directors' cross-directorship holdings were collected from both annual reports and Thomson Research.

4.6 METHODS OF DATA ANALYSIS

The previous sections discussed the study design and data sources. This section discusses the process for data analysis. The results are analysed both at aggregated and subcategory levels. Analysing IC disclosure at subcategory level highlights reporting differences that may not otherwise be apparent at aggregated level, thus enhancing the researcher's ability to comprehend differences in such disclosures among the sampled firms. The qualitative information regarding each IC item disclosed in the annual report was measured and analysed quantitatively to test the proposed hypotheses listed in Section 4.5. Quantitative data were analysed using SPSS (version 14) software.

4.6.1 DESCRIPTIVE ANALYSIS

The analysis in this study involves both descriptive and inferential data analyses. The first part of the analysis consists of descriptive statistics, in terms of the mean, minimum, maximum and standard deviation for both the level of IC disclosure and the identified independent variables. Descriptive statistics also extend to the IC subcategories of human capital, structural capital and relational capital in three formats. One major limitation of linear regression lies in its application to the total disclosure index (addition of items) rather than to the pattern (profile) of items. This means the regression method cannot reflect the structure of disclosure, because the items are combined for incorporation into the disclosure index. In other words, the often highly time-consuming work done by the researcher to determine the disclosure index is 'thrown away' at the regression stage (Chavent et al., 2006). This usually results in information loss and can be mitigated by examining the quality and type of data communicated (Gray et al., 1995a). Detailed descriptive analysis partially mitigates the problem of 'information loss', which is provided in Chapter 5 of the thesis. Descriptive statistics also provide information for normality tests, one of the assumptions for multiple regression analysis (see Section 4.6.3), which are discussed in each relevant empirical findings chapter.

4.6.2 UNIVARIATE ANALYSIS

The second part consists of univariate analysis, which in this study serves primarily as a precursor to multivariate analysis, indicating the relationship between the dependent and each of the independent variables. Statistical methods for univariate analysis are of two types, parametric and non-parametric (Cohen and Holiday, 1996; Field, 2005). In order to test the proposed hypotheses, both parametric (Pearson correlation, two-sample independent t-test and analysis of variance) and non-parametric tests (Mann Whitney U test and Kruskal-Wallis test) were conducted in this study on the dependent and independent variables, which combine both methods' strengths and reduce the probability of incorrectly rejecting the proposed hypotheses (Haniffa, 1999).[42]

Correlation analysis was employed prior to the multiple linear regression analysis to provide preliminary evidence of the relationship between IC disclosure and the independent variables. Two-tailed Pearson correlation coefficients were considered appropriate. Correlation coefficient, 'r', indicates the strength of the association between the variables. Correlation coefficient is scale-free and will always lie between ±1 (Pindyck and Rubinfeld, 1998; Bryman and Cramer, 2002).[43] However, correlations only demonstrate relationships between variables, they do not necessarily indicate any causality in the relationship (Easterby-Smith et al., 2002: 141).

The choice of level of significance is usually one or five per cent (Black and Champion,

[42] Non-parametric tests do not use population parameters such as mean and standard deviation; however, non-parametric tests are not as powerful as their parametric counterparts when distributions are approximately normal and homoscedastic (Bradley, 1968; Conover, 1980). See Maxwell (1970) for comprehensive treatments on parametric and non-parametric statistics respectively.

[43] A positive correlation indicates that the variables move in the same direction, while a negative correlation implies that they move in the opposite direction, and the closer the absolute value of r is to 1, the stronger the correlation between the two variables (Bryman and Cramer, 2002; Field, 2005; Hair et al., 2007).

1976; Pindyck and Rubinfeld, 1998).[44] To examine the correlations between IC disclosure and the independent variables after netting out firm size effect, partial correlation analysis was used to determine the relative importance of each variable (Pindyck and Rubinfeld, 1998: 101), helping to determine the final regression models.

For the associations between the dependent variables (measures of IC disclosure) and the nominal independent variables (e.g. auditor type, role duality, see Table 4.3), the two-sample independent t-test and Mann-Whitney U test were conducted, and for nominal independent variables that comprised more than two groups (i.e. industry type), the analysis of variance (ANOVA)[45] and Kruskal-Wallis were undertaken. F-probability value in ANOVA indicates that the more significant the F ratio is, the stronger the evidence against the null hypothesis. A limitation of ANOVA is that the F statistic does not indicate which of the groups are significantly different from each other. Therefore, the post-hoc Bonferroni test is needed to find which of the groups are significantly different from each other. The Mann-Whitney U test and Kruskal-Wallis test provide the average rank for each group of data and a rank of one is assigned to the smallest value, with the significance values indicating whether the null hypothesis may be rejected.

4.6.3 MULTIPLE REGRESSION ANALYSIS

The third part consists of multivariate analysis, i.e. multiple linear regression analysis,[46] which is used to test the proposed propositions on the impact of corporate governance

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[44] The test of any hypothesis with a statistical technique involves establishing a significance level. The level of significance selected serves as an objective standard and assists the researcher in making a decision about the significance of what s/he has found. The level of significance defines the probability of making a type of error or rejecting a hypothesis when, in fact, it should not be rejected. Supporting or failing to support a given hypothesis, in terms of probability, depends on the level of significance chosen. The significance level should be rigorous enough that error is minimised. (see Black and Champion, 1976, p.161)

[45] The t-test produces two versions of t-value, one is equal variance which assumes that the variances in the two populations are equal, and the other is unequal variance, which does not. Thus, the Levene test (a test for homogeneity of variance) is used as a benchmark in deciding which t-value to consider in rejecting the null hypothesis. If the F-value in the Levene test is not significant (p>0.05), it means that the equal variance assumption is approximately met, and hence the equal variance t-value is used to test the significance of association between the dependent and the nominal independent variable (see Haniffa, 1999).

[46] This analysis is a statistical technique that can be used to analyse the relationship between a single dependent variable and several independent variables (e.g. Norusis, 1995; Easterby-Smith et al., 2002). It has been used extensively to link the disclosure level to the financial and non-financial variables (Chavent et al., 2006).

factors, company characteristics and market factors on IC disclosure. Regression results produce beta coefficients that range between ±1.00, which indicate the strength of the relationship between dependent and independent variables (Hair et al., 2007) within a model, not between models. A significant R^2 (ranges from 0 to +1) measures the strength of the overall relationship between dependent and independent variables. It represents the amount of variation in the dependent variable explained by the independent variables combined (Hair et al., 2007), i.e. the larger the R^2, the better the regression model explains the variations in the level of IC disclosure across the sample firms. The problem with R^2 is that it is sensitive to the number of independent variables included in the model. The addition of more independent variables to the regression equation can never lower R^2 and is likely to raise it (Pindyck and Rubinfeld, 1998), this is because some independent variables' chance variations 'explain' small parts of the variance of the dependent variable. Therefore, the adjusted R^2 is a more desirable goodness-of-fit measure than R^2;[47] the higher the adjusted R^2, the stronger the explanatory power.

The analysis of variance (ANOVA) was used to examine the significance of the overall regression models, i.e. to test the proposition that there is a relationship between the dependent and independent variables. The statistic used to test this proposition is the F test. A high F statistic is a rationale for rejecting the null hypothesis that there is no relationship between the dependent and independent variables (Pindyck and Rubinfeld, 1998: 91). The more significant the F statistic,[48] the greater the power of the model to reject the null hypothesis and the more supportive it is for the regression model results. However, lower levels of significance such as <0.10 (Field, 2005; Hair et al., 2007) are

[47] Some authors conceive of adjusted R^2 as the percentage of variance 'explained in a replication, after subtracting out the contribution of chance' (Graeme and Sofroniou, 1999: 76).
[48] The normal social science 'rule of thumb' value for significance is <0.01 and <0.05 levels.

also acceptable in business, but are considered as weakly significant.

As suggested by Field (2005) and Hair et al. (2007), before the conduct of regression analysis, it is important to examine the assumptions of normality, multicollinearity, homoscedasticity and linearity.[49] There are both graphical and numerical methods for tests of normality. Graphical methods display the distributions of random variables or differences between an empirical and a theoretical distribution, which are intuitive and easy to interpret. However, numerical methods provide more objective ways of examining normality. Therefore, both graphical and numerical methods were applied in this study, i.e. visual inspections of histograms, normal Q-Q plots of standardised residuals, detrended Q-Q plots of residuals,[50] and numerical normality tests based on skewness, kurtosis,[51] and the non-parametric Kolmogorov-Smirnov test (i.e. K-S Lilliefors). The rule of thumb is that skewness of ±1.96 and kurtosis of ±2 indicate normality (Haniffa, 1999). A significant K-S Lilliefors value indicates that the normality assumption is questionable (Haniffa and Cooke, 2002).

One of the assumptions of the multiple regression model is that there is no exact linear relationship between any of the independent variables in the model (Pindyck and Rubinfeld, 1998: 95). Multicollinearity arises when two or more variables (or

[49] Homoscedasticity is the assumption of constant variance, the lack of which indicates a nonlinear relation of the two variables in question, and/or that the variables are not normally distributed (Graeme and Sofroniou, 1999: 28). Analysis of residuals, which are measures of goodness of fit (i.e. the difference between the observed value of the dependent variable and the value predicted by the regression line) (Norusis, 1995; Pindyck and Rubinfeld, 1998), needs to be conducted with regard to this assumption. Visual inspection of scatterplots of standardised residuals against predicted values can be used to examine violations of the assumption (Haniffa, 1999). A homoscedastic model will display a cloud of dots, whereas lack of homoscedasticity will be characterised by a pattern such as a funnel shape, indicating greater error as the dependent variable increases. The importance of fulfilling this assumption is because heteroscedasticity may result in loss of efficiency and invalid standard errors (Berry, 1993). However, Fox (2005: 516) argues that moderate violations of homoscedasticity have only a minor impact on regression estimates. The linearity assumption can be checked by plotting the studentised residuals against the predicted values (Ostrom Jr., 1990). The linearity assumption is violated if a bowed pattern is observed

[50] Q-Q plot is used to see how well a theoretical distribution models the empirical data. Detrended normal Q-Q plots depict the actual deviations of data points from the straight horizontal line at zero. If the points in a detrended Q-Q plot fall randomly in a band around zero and show no specific pattern, normality assumption of the variable is said to be met.

[51] Skewness and kurtosis show how the distribution of a variable deviates from a normal distribution based on empirical data. Skewness is a statistic that provides useful information about the symmetry of a probability distribution (Pindyck and Rubinfeld, 1998). If skewness is greater than zero, the distribution is skewed to the right. Kurtosis provides a measure of the 'thinness' of the tails or 'peakedness' of a probability distribution. However, the actual values of skewness and kurtosis are not informative (Field, 2005: 72). The values need to be converted into standardised values, i.e. z-scores. Z-score skewness and kurtosis are converted as follows:

$Z_{skewness} = S\text{-}0/SE_{skewness}$, S= value of skewness, $SE_{skewness}$ = standard error of the skewness

$Z_{kurtosis} = K\text{-}0/SE_{kurtosis}$, K= value of kurtosis, $SE_{kurtosis}$ = standard error of the kurtosis combination of variables) are highly correlated with each other, and thus does not allow the examination of the individual effects of variables. To identify potential multicollinearity problems, the correlations between independent variables were reviewed, the variance inflation factors (VIF) were computed, and the condition indices and variance decomposition proportions associated with the regressions were examined. The ‘rule of thumb’ for checking problems of multicollinearity using a correlation matrix is when the correlation is >0.80 (Bryman and Cramer, 2002; Gujarati, 2003). VIF measures the degree to which each explanatory variable is explained by the other explanatory variables (Patton and Zelenka, 1997; Owusu-Ansah, 1998; Ho and Wong, 2001). Therefore, when VIF is high there is high multicollinearity.[52] A range of values between 5.0 and 10.0 is normally used as a cut-off point for an indication of severe multicollinearity (Judge et al., 1988; Haniffa and Cooke, 2002, 2005). In order to investigate the possibility of harmful collinearity further, the diagnostic procedures suggested by Belsley et al (2005) were also applied, which involves the following double condition, i.e. a singular value judged to have a high condition index, and which is associated with high variance-decomposition proportions for two or more estimated regression coefficient variances. As a rule of thumb, a large condition index is one greater than 30, and a high variance decomposition proportion is a value higher than 0.5. A problematic variable is the one that has the highest condition index and high decomposition proportion. It is the joint condition of high variance-decomposition proportions for two or more coefficients associated with a high condition index that signals the presence of degrading collinearity (Belsley et al., 2005: 128). Using condition indices and the variance decomposition proportions, it is possible to determine

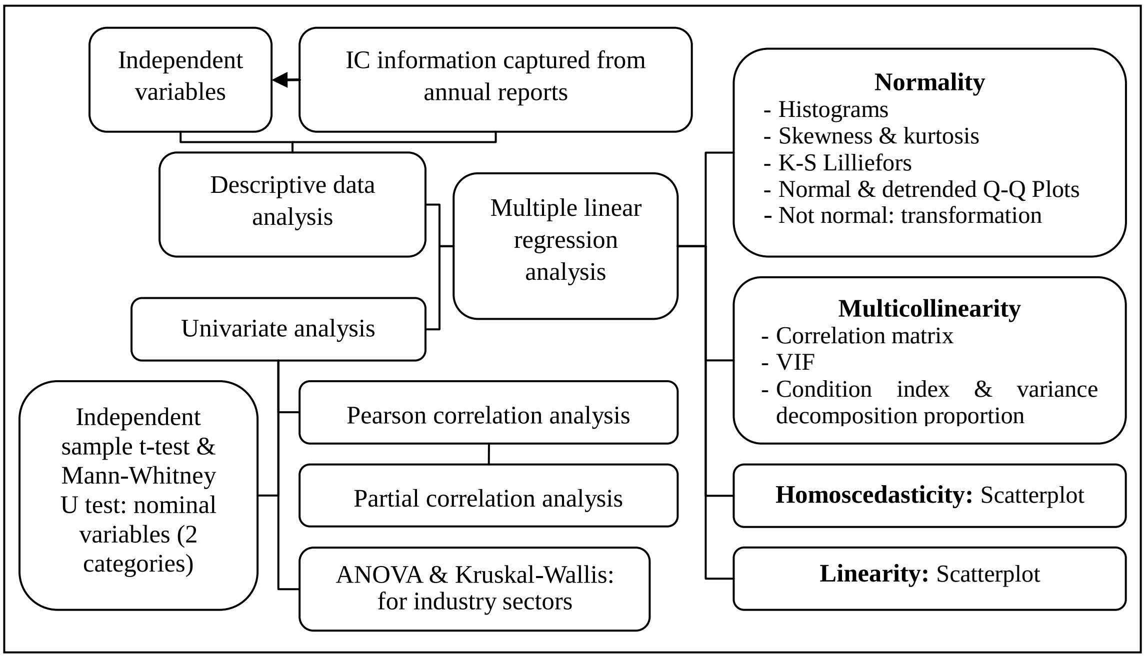
[52] An alternative approach is to calculate the tolerance statistic, the reciprocal of VIF. The tolerance statistic for a variable is 1 minus R^2 for the regression of that variable on all the other independents, ignoring the dependent. If there is absolutely no collinearity, the tolerance factor will approach 1; if there is a high degree of collinearity, the tolerance factor will approach zero. Tolerance values <0.1 indicate collinearity problem (Norusis, 1995).

the number of collinear relationships and the identity of the variables involved (Board et al., 1992: 448). One of the resolutions for multicollinearity problems is to run different regression models, each model using only one of the independent variables identified as generating a multicollinearity problem (see Cooke, 1989a, b, 1991; Ahmed and Nicholls, 1994; Chavent et al., 2006).

One possible solution to problems related to the violation of assumptions of normality, homoscedasticity and linearity is to transform the data, which by so doing, would not distort the true picture, because transformation only changes the scale on which a variable is measured (Norusis, 1995; Cohen et al., 2003; Field, 2005). Many poorly shaped distributions can be improved through simple transformation. There are a few options available for transforming the data, one of which is logarithmic transformation, i.e. to take the logarithm of the data. The logarithm transformation used in this study is natural logarithms, noted *ln*, with a base (noted *e*) of $e = 2.7178$ (approx.).[53] Another data transformation is square root transformation which mainly deals with positive skewness. A data transformation technique is desirable if the variable is to be included in analyses that assume normality because the transformed variable will produce more accurate results. The distribution of the transformed variable should always be inspected to ensure that it accomplishes the intended task, inducing normality. Hence, continuous variables with normality problems were transformed using either logarithmic or square root transformations. An analysis of residuals and plots of the studentised residuals against predicted values as well as the normal and detrended Q-Q plots were also conducted to test for homoscedasticity, linearity and normality assumptions. Figure 4.3 presents an overview of the data analysis process.

[53] However, zero or negative numbers cannot get a log value (Mosteller and Tukey, 1977). Therefore, for variables with non-positive data, which need to be transformed by logarithmic transformation, a very small constant needs to be added to all the scores in the distribution before the transformation.

Figure 4.3 Process of Data Analysis



One of the difficulties in data analysis of this study relates to the need for sufficient observations in relation to the number of independent variables. Petrie et al. (2002) noted the importance of not over-fitting the model by including too many explanatory variables. It is suggested in Ramanathan (1998) that adding variables means a loss of degrees of freedom, which makes the power of a test weak. Some argue that there should be at least ten samples for each independent variables included in the multiple regression model (Halinski and Feldt, 1970; Miller and Kunce, 1973; Petrie et al., 2002). Therefore, the sample size of 100 in the present study limits the number of independent variables to be included in the regression model, i.e. a maximum of 10 variables. However, this study aims to explore the impact of a total of twenty-four variables (if industry sectors are considered as one variable) on IC disclosure practice. Thus, not every variable can be included in one regression model.

Deciding which variables to include/exclude from a model is a common dilemma for researchers (Ramanathan, 1998; Murray, 2006). As is argued in Ramanathan (1998), we face a trade-off in deciding what to include and exclude from a regression model, comparing the theoretical consequences of adding irrelevant variables with those of omitting potentially important variables. The inclusion of variables having no relevance to the actual process of generating the dependent variable in the sample and are irrelevant to the other independent variables (i.e. irrelevant variables) leads to unbiased estimates of the regression coefficients for the other independent variables, but the variance of the estimated coefficients increases (i.e. unbiased but inefficient estimators) (Ramanathan, 1998; Maddala, 2001; Cohen et al., 2003; Murray, 2006).[54] On the other hand, when a theory or prior research states that a set of independent variables should be included in the regression model, omission of any of the independent variables leads to *potential* bias in the estimates of the remaining regression coefficients and their standard errors (Cohen et al., 2003; Murray, 2006). The error introduced into an analysis by the omission of a relevant variable is called 'omitted variables error', which is one of a class of potential sources of 'misspecification errors' (Mauro, 1990: 315).[55] An investigator who puts more emphasis on unbiasedness, consistency, and reliability of tests would rather keep an irrelevant variable than face the consequences of omitting a crucial variable. However, if a researcher cannot tolerate inefficient estimators, deleting the offending variable(s) would be preferable. Theoretical framework and an understanding

[54] If the included irrelevant variable is correlated with any of the other independent variables in the equation then an unnecessary element of multicollinearity will have been introduced into the estimation process. This will lead to larger standard errors on the coefficients.

[55] General discussions on omitted variables error can be found in e.g. Leamer (1978), Mariano and Ramage (1983), Ramsey (1974), Dougherty (1992), Maddala (2001), Montgomery et al. (2006) and Thomas (1997). A statistical model is said to be misspecified when the variables included in the model or the specified relations between the variables differ from those of the 'true' model (Mauro, 1990: 315). Model misspecification could come from omission of relevant variables, or inclusion of irrelevant variables, and the misspecification of the functional form of the model.

of the underlying behaviour can often help in selecting the regressors to be used in the model (Ramanathan, 1998; Montgomery, et al., 2006).

One of the most accepted approaches in building a regression model is the ‘general-to-specific’ approach, which involves the gradual elimination of apparently unimportant variables and thus a testing down to an empirically determined suitable model (Thomas, 1997: 355). However, the problem is that such an approach is limited by the sample size. If the sample size is limited and the initial specification contains a large number of potential explanatory variables, multicollinearity may cause most or even all of them to have insignificant coefficients. In an extreme case, the number of variables may exceed the number of observations, and the model would not be fittable at all. Where the model is fittable, the lack of significance of many of the coefficients may appear to give the investigator considerable freedom to choose which variables to drop. The final version of the model may be highly sensitive to this initial arbitrary decision. A variable that has an insignificant coefficient initially and is dropped might have had a significant coefficient in a cut-down version of the model had it been retained. The conscientious application of the general-to-simple principle, if applied systematically, might require the exploration of an unmanageable number of possible model-reduction paths (Thomas, 1997). In the case of this study, it is impractical to include all twenty-four variables (if industry sectors are considered as one variable) in one regression model with the number of observations available, i.e. 100 samples.

Hence, this study applied two approaches to solve the problem of too many independent variables and a relatively limited number of observations. First of all, the study uses univariate analysis as a precursor to identify some of the variables that are not significantly associated with IC disclosure measures. It then explores the impact of the remaining variables in three separate regression models, i.e. one model with corporate governance factors and company characteristics, the second model with audit committee characteristics controlling for variables that were identified to be significant in the first model where applicable, and the third model with market factors and company characteristics. As is discussed earlier, regression models should be developed based on the theoretical framework and should include all relevant variables. If the variables were examined in separate models, the models may be misspecified and the ‘omitted variables error’ is likely to incur. However, there are exceptional cases under which the omission of variables that ought to be included will not result in significantly biased estimations of the coefficients of the included variables (Dougherty, 1992; Wooldridge, 2006):

1) when there is no relationship between the included variables and the excluded variable(s). Under such circumstances, the bias term disappears;
2) if the coefficient of an excluded variable is 0, i.e. the excluded variable is not related to the dependent variable, the bias term would also be 0, but then the model misspecification issue does not arise.

Further, Mauro’s (1990) study presents a technique that enables the determination of when a variable omitted from a linear regression model can account for the effects attributed to an independent variable included in that model. It is suggested by the author that for an omitted variable to account for the effect of a specific independent variable the omitted variable must 1) have a substantial effect on the dependent variable, 2) be substantially correlated with the independent variable in question, and 3) not be substantially correlated with the other independent variables in the model. All three conditions must be met. If the omitted variable is related to the dependent variable and the independent variable in question, as well as the other independent variables in the model, the omission of the variable will have little influence on the estimate of the effect of the independent variable in question. However, omitting a relevant variable will increase the unexplained variance in the dependent variable. As is noted in Mauro (1990: 314) that in many cases, it is impossible to determine how variance in a dependent variable should be divided between correlated independent variables. In models with correlated independent variables, the coefficient for an independent variable may take on nonintuitive values – sometimes opposite in sign to the simple correlation of the predictor with the dependent variable, which could be denoted as multicollinearity problem. Hence, it is also necessary that the omitted variable be a measure of a factor not already included in the model. As the correlation between the omitted variable and an independent variable included in an analysis approaches unity, the model will become inestimable, and it will be impossible to 'separate' the effects of the two variables (Mauro, 1990: 315).

To ensure that the three regression models are not subject to significant omitted variables error,[56] the relationship between corporate governance (including audit committee characteristics) and market factors were examined, i.e. to see whether

[56] As is observed in Mauro (1990), in most cases, predictions are limited to the existence and direction of the effects. In these instances, a substantially different coefficient is one that is not significantly different from zero or one that is significant and of opposite sign from the value originally obtained. Otherwise, the effect of the omitted variables on the estimated impact of the included independent variables on the dependent variable is not considered to be significant.

corporate governance and market variables are significantly correlated (see Table 10.5 in Chapter 10), whether market factors are significantly correlated with company characteristics (see Chapters 9 and 10), and whether there are potential multicollinearity problems (see Chapter 10). The univariate analyses provide evidence toward the validity of the results found in the three separate regression models examined in Chapters 6, 8 and 9. Based on the results of the univariate and multivariate analyses, two 'full' regression models with reduced number of variables, i.e. variables that were identified to be significantly related to IC disclosure measures but are not potentially subject to serious multicollinearity problems, can then be examined (see Chapter 10). The 'full' models provide further evidence for the validity of the results found in the separate regression models.

4.7 SUMMARY

This chapter has provided a detailed discussion of the research methodology issues, including the data collection method, sample selection procedures, development of the research instrument, measurement of intellectual capital (IC) disclosure, operationalisation of independent variables, data sources of the research, and methods of data analysis. The study applies content analysis, which involves coding qualitative and quantitative information and quantifying the coded information. The approach and methods of analysis applied in this study differ from prior IC disclosure studies in the following ways:

1) they use a self-developed, more detailed (61 IC items) research instrument is used, which covers three formats of information disclosure, i.e. text, number and graph/picture. This enables IC information in the annual report to be captured with greater detail;
2) they provide greater transparency in the research method applied;

3) they offer a three-dimensional perspective on the level of IC disclosure - the disclosure index (ICDI-variety), word count (ICWC-volume), and word count percentage (ICWC%-focus). This offers a more holistic view on IC disclosure behaviour in the annual report;
4) they consider IC disclosure at the subcategory level. Unlike previous studies, this study also considers an item by item analysis of IC disclosures of sample firms and locations of disclosure in the annual report; and
5) they examine the determinants of IC disclosure, including corporate governance factors, company characteristics and market factors, using statistical analysis.