

# THE VALUE RELEVANCE OF VOLUNTARY INTELLECTUAL CAPITAL DISCLOSURE: NEW ZEALAND EVIDENCE

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## Abstract

The purpose of this study is to investigate the value relevance of voluntary intellectual capital disclosure (ICD) in New Zealand by examining the relationship between voluntary ICD and market value. The results suggest that the relationship between voluntary ICD and market value is not a simple, positive relationship across the board. That is, the benefits of different types of intellectual capital (IC)—namely human, relational and structural capital—may vary significantly, and there may even be some costs to disclosure. Positive relationships were found between human and relational capital as well as ICD overall. The results for structural capital disclosure, however, showed a significant and negative relationship. These results suggest that there may be a trade-off between the costs and benefits of disclosure. We also found that the relationship between voluntary ICD and market value is moderated by technologically intensive industries. This relationship is stronger for low-tech industries. This may be due to the fact that low-tech industries disclosed more IC information voluntarily, indicating that more disclosure strengthens the relationship between voluntary IC and market value.

**Keywords** Intellectual Capital, Human Capital, Relational Capital, Structural Capital, Value Relevance, Market Value

**Acknowledgement:** The authors acknowledge with thanks the helpful comments received from seminar participants of the department of Accountancy and Finance, University of Otago and a discussant and participants of the Annual Conference of the Asia-Pacific Management Accounting Association, Japan, November, 2013

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## 1 Introduction

The past 20 to 30 years have seen the world move into an age ruled by information. Subsequently, our economy has shifted from a manufacturing-based economy to an economy based on knowledge. In this new knowledge-based economy, intangible assets such as intellectual capital (IC) have been noted to be more important for value creation than physical assets (Whiting and Miller, 2008). This notion that IC drives firm performance and value has also been supported in the literature (Clarke *et al.*, 2011; Vafaei *et al.*, 2011). It would seem that these kinds of assets are becoming more important to companies. This established importance has not been recognised by regulators, however. Currently, there are insufficient mandatory standards for the disclosure of IC resources. Because of this, there has been a decrease in the book value of company assets in proportion to their market value (Cezair, 2008). This gap between market and book values (“hidden value”) has been attributed to the market valuation taking into account intellectual capital (Whiting and Miller, 2008).

The lack of a sufficient mandatory framework for the disclosure of IC resources means that the majority of intellectual capital disclosures (ICDs) have to be done voluntarily (if at all). The area of voluntary disclosure of IC is an interesting one, as understanding the drivers and effects of such voluntary disclosures is useful for making decisions about these important assets. The effect of such disclosures, however, has been given relatively little attention. Thus, the purpose of this study is to examine the value relevance of these voluntary ICDs of New Zealand firms over a three-year period from 2008 to 2010. It has been noted that if disclosures affect market value, they will be value relevant (Vafaei *et al.*, 2011).

Prior literature has found inconsistencies among different countries as to how voluntary ICD affects market value (Orens *et al.*, 2009). This study provides further evidence as to whether this relationship applies to a New Zealand context. In doing so, it examines the external validity of prior studies in different markets. This study is the first study to examine the relationship between voluntary ICDs and market value for New Zealand firms. This will provide further analysis as to how voluntary ICD and its relationship to market

value have changed over this time frame. Also, examining the relationship in the year 2008 may give some evidence as to how the global financial crisis has affected this relationship. This could have implications for the literature as to how a recession may affect these results.

The method of content analysis utilized, previously used by Birch and Whiting (2012) and Vergauwen *et al.* (2007), allows for the division of ICD into its three separate elements: human, relational and structural capital. This method allows this study to examine the individual effects of each of these elements of intellectual capital, to see which, if any, is the most significant in driving this relationship.

The present study also examines how high-technology industries differ to low-technology industries in respect to this relationship. This presents the following research questions addressed by this study: Is there a relationship between the voluntary ICD in the annual reports of New Zealand companies and their market value? Is this relationship moderated by technologically intensive industries?

The remainder of this study is structured as follows. Section 2 reviews prior literature relating to ICD and market values. Section 3 provides hypotheses development, while the research design used to test those relationships is described in section 4. The results are then reported, discussed and some conclusions are offered.

## 2 Literature review

It is important when discussing IC to define what is meant by the term and to explore its components. A universal definition of IC is elusive (Zambon, 2004). However, a widely used definition of IC in accounting literature can be found in the Swedish firm Skandia's first Annual Intellectual Capital Report, which defines IC as "the possession of knowledge, applied experience, organizational technology, customer relationships, and professional skills" (Edvinsson, 1997, p. 368). These descriptions were later classified into three IC components: human capital, structural (internal) capital and relational (external) capital (Sveiby, 1997; Roos *et al.*, 1998; Guthrie and Petty, 2000; Bozzolan *et al.*, 2003; Petty *et al.*, 2009; Martín-de Castro *et al.*, 2011). Human capital (HC) is the knowledge people possess as well as their ability to generate knowledge useful to the organisation's goals. It can be split into three dimensions: a person's knowledge (e.g. formal education, experience, and training), abilities (e.g. leadership, know how, communication) and behaviours (e.g. belonging, friendship, flexibility, creativity). Human capital also signifies "the skills/competences, training and education, and experience and value characteristics of an organisation's workforce" (Petty *et al.*, 2009, p. 2). Structural capital (SC) refers to capital that "provides the tools and architecture for retaining, packaging,

reinforcing and transforming knowledge along the business activity" (Martín-de Castro *et al.*, 2011, p. 656). It denotes "the knowledge embedded in organisational structures and processes, and includes patents, research and development, technology and systems" (Petty *et al.*, 2009, p. 2). Structural capital also refers to what remains in the company when employees go home for the night, such as brands, patents, organisational structure and concept (Roos *et al.*, 1998). Relational capital (RC) refers to the organisation's relationships between its main agents (e.g. its customers, suppliers and allies) and other social agents it works with (e.g. community). It comprises "relationships with customers and suppliers, brand names, trademarks and reputation" (Petty *et al.*, 2009, p. 2). Using these classifications, we can sort ICD into its three main categories to understand which of the three areas is the most significant and how each area interacts with firm value.

Intellectual capital can be disclosed either through regulation (mandatory disclosure) or through companies' voluntary disclosure.

### 2.1 Voluntary disclosure

Until now there has been no prescribed accounting standard for the disclosure of IC. Since most IC information is not mandatorily required by accounting standards and rules, it is primarily disclosed on a voluntary basis. This in turn leaves the bulk of IC resources being left out of financial statements. Kumar (2013) indicates that larger firms, firms with high ownership dispersion, firms with lower leverage, and firms with high-technology industries in the U.S.-listed Asian companies provide more voluntary disclosures of intangibles information using the disclosure index developed by Oliveira *et al.* (2006). Haji and Ghazali (2013) examine the relationship between ICDs and corporate governance attributes in Malaysia in 2007. Their results show that all corporate governance attributes namely board size, independent directors, board effectiveness and position of the chairman (except family members on the board) are significant in explaining the extent and quality of ICDs. Abhayawansa and Azim (2014) look at IC reporting practices of the Bangladeshi pharmaceutical industry in 2006. They find a clear awareness among firms of the significance of IC in corporate value creation and a commitment to communicate IC publicly. They also find firms do not adopt a consistent framework for IC reporting.

Overall levels of ICD are found to be relatively low worldwide (Whiting and Miller, 2008). However, presumably due to increasing awareness of the importance of intellectual capital, the literature has supported that ICD has been rising over time (Abdolmohammadi, 2005; Vandemaele *et al.*, 2005). Whiting and Miller (2008) state that evidence has

shown relational capital is the most frequently reported, followed by structural capital and lastly human capital. This is consistent with Guthrie and Petty (2000), who finds relational capital to be the most frequently reported.

## 2.2 Market value

In relation to voluntary ICD, the effects of such ICD have received relatively little attention. An important question to answer in this regard is whether this voluntary ICD is value relevant, or in other words, does it have any significant effects on user decisions. Vafaei *et al.* (2011) and Oliveira *et al.* (2010) suggest that if something affects the market price of a company, it is value relevant. It is then interesting to examine whether such voluntary ICD does have a significant effect on market price. Does the level of disclosure have any real effect on user decision making? To answer this question, drivers of market value will first be discussed, followed by literature specifically examining links between market value and ICD.

Basu (1981) shows that earnings have a significant predictability of market value; that is, firms with higher earnings yields were able to attract higher market values. This is because earnings are seen to be a predictor of firms' future cash flows. The higher the firms' earnings, the greater the future pay-outs will be, and hence the greater the market value. The Ohlson (1995) model has also been developed to predict market values based on firms' earnings. Earnings are then proposed as an important determinant of market value.

Book value is another potential determinant of market value, specifically for firms with low earnings. Ashton *et al.* (2003); Hayn (1995) and Burgstahler and Dichev (1997) all suggest that book value along with earnings is a better predictor than earnings alone. Ohlson (1995) incorporates earnings (abnormal earnings) as well as book value in his valuation model, providing support that both figures have effects on market values. The reasoning behind this is that book value is a proxy for the adaptation value or liquidation value of the firm. The value of a firm's resources will play a role on what the firm is worth, because simply put, the more a firm's resources are worth, the more the value of that firm will be. Next, we look at the effects of ICD on market value.

## 2.3 Effects of ICD on market value

Oliveira *et al.* (2010) have shown that disclosure of IC resources does have value relevance. More specifically, intangible ICDs such as goodwill, software costs, research and development, patents, brands and advertising have all been shown to have effects on market value[1]. Ji and Lu (2014)'s result shows that capitalised intangible assets are value

relevant in Australia, in both the pre- and post-adoption of International Financial Reporting Standards (IFRS) periods. Value relevance is higher in firms with more reliable information on intangible assets. They also find that the value relevance of intangibles has declined in the post-adoption period of IFRS. However, the positive relationship between the value relevance and the reliability of intangibles has remained unchanged in the post-adoption period.

Only a few studies have investigated the effects of ICD on the market capitalisation or market value of companies (Abdolomohammadi, 2005; Anam *et al.*, 2011; Orens *et al.*, 2009; Vafaei *et al.*, 2011; Abeysekera, 2011). Abdolomohammadi (2005), the first study to investigate the effects of ICD on market capitalization, examines a sample of 58 Fortune 500 companies in the USA. He uses a content analysis of the annual reports over a five-year period from 1993 to 1997. After controlling for net profit and book value, he finds a significant and positive relationship between ICD and market capitalisation. Another similar study, Anam *et al.* (2011) investigates the effects of ICD on the market capitalization of Malaysian companies for two years, 2002 and 2006. Their findings are consistent with those of Abdolomohammadi (2005). Thus, there are significant benefits for disclosing information on IC, as it affects market value. Orens *et al.* (2009) take a slightly different approach to Anam *et al.* (2011) and Abdolomohammadi (2005), as they collect data on ICD from a different medium, that is, company websites. They analyse the presence of certain terms on a sample of 267 companies from four European countries (Belgium, France, Germany and the Netherlands). Using Tobin's Q as a proxy for firm value, they find that ICD is significantly, and positively, associated with firm value, consistent with the findings of Anam *et al.* (2011) and Abdolomohammadi (2005). They also find that firms with greater ICD have a lower cost of finance. They conclude by suggesting that greater ICD increases investors' willingness to commit financial resources to a company. Orens *et al.* (2009) is the only previous study to examine the individual effects of human, relational and structural capital disclosures on market value. They find that only relational and structural disclosures have significant effects on market value. Human capital disclosure did not show any significant relationship. Vafaei *et al.* (2011) examine 220 listed companies from four different countries (Hong Kong, Singapore, UK and Australia). Using a content analysis approach, they examine the relationship between ICD in annual reports and market price for both pre- and post-adoption of international financial reporting standards (IFRS). They find support that the relationship of ICD and market price is affected by country- and industry-specific factors. The positive relationship between ICD and market price is only significant for the UK and Australia, and for non-

traditional industries. These results confirm that ICD may only be value relevant in certain areas. The results are partially consistent with those of Anam *et al.* (2011), Abdolomohammadi (2005) and Orens *et al.* (2009), but do shed some doubt as to the strength of this relationship and its worldwide external validity. Abeysekera (2011) investigates the effects of ICD on market value. It is slightly different, as it incorporates the effects of the disclosure of narrative, visual and numerical IC on market value, with the consideration of political setting as a moderating variable, the two political settings being a temporary truce and a period beset by civil war. They study a sample of 30 firms from Sri Lanka for the period 1998 to 2004. Their findings indicate that in times of temporary truce, there is a positive association between narrative ICD and market value (but not numerical or visual). Such a relationship does not hold for times of civil war.

Industry has been noted to play an important role in determining the level and effect of ICD. Bozzolan *et al.* (2003) find that companies that are in technologically intensive industries disclose significantly more IC information. Kumar (2013) also shows that firms with high-technology industries provide more voluntary disclosures of intangibles information. This relationship has been attributed to information asymmetry theory, where high-technology industries have more intangible intellectual assets which are not shown in their book value. To remedy and bridge this information gap, they are likely to voluntarily disclose this information. This relationship is also consistent with Vafaei *et al.* (2011) and Oliveira *et al.* (2006). Vafaei *et al.* (2011) also find that the relationship between ICD and market value is only significant for non-traditional industries (or high-tech industries). However, Birch and Whiting (2012) find inconsistent results with prior literature and state, for New Zealand and Australian firms, that low technologically intensive industries tend to disclose more IC information. They argue the reason for this inconsistency may be due to New Zealand and Australia not having many companies that are truly high-tech. The industry effects of the present study are expected to be similar to Birch and Whiting (2012), due to the sample country being New Zealand.

Overall, there seems to be strong evidence which indicates that there is a significant relationship between ICD and market value. There is further evidence that this relationship may be affected by operations in different countries, industries and with different political settings. The present study is the first to examine this relationship in a New Zealand context.

### 3 Hypotheses development

Prior studies that investigate the effects of ICD on the market capitalisation or market value of firms (Abdolomohammadi, 2005; Anam *et al.*, 2011; Orens

*et al.*, 2009; Vafaei *et al.*, 2011; Abeysekera, 2011) have shown significant positive relationships between ICD and market value. Accordingly, there are significant benefits for disclosing information on IC as it affects market value. In addition, agency theory assumes managers are self-interested. Because of this, steps have to be taken to align manager and shareholder goals (Jensen and Meckling, 1976). Voluntary ICD has been suggested as a step that can be taken to limit agency costs, as it gives shareholders a greater knowledge of the company (White, Lee, and Tower, 2007). It is contended that voluntary ICD could reduce information asymmetry between the shareholders and the managers, and as a consequence eliminate related agency problems and costs (Yi *et al.*, 2011). Singh and Van der Zahn (2008) argue that voluntary ICD could lower the cost of capital, as it enhances investors' confidence with respect to the impact of IC on the firm's value creation[2]. Other benefits to a firm by voluntarily disclosing information on IC are to improve corporate image and attract potential investors. It is thus hypothesised that there is a positive relationship between ICD and market value.

*H<sub>1</sub>*. There is a positive relationship between voluntary ICD and market value.

Orens *et al.* (2009) has specifically examined the relationship between the three components of ICD (human, relational and structural capital) and market value. They find that the relationship is only significant for relational and structural capital disclosure. Human capital disclosure did not show any significant relationship. Therefore, it is hypothesised that the positive impact on market value varies between the different components of ICD.

*H<sub>2a</sub>*. There is a no relationship between human ICD and market value.

*H<sub>2b</sub>*. There is a positive relationship between relational ICD and market value.

*H<sub>2c</sub>*. There is a positive relationship between structural ICD and market value.

Prior literature has shown the level of technological intensity affects the amount of IC disclosed (Birch and Whiting, 2012; Vafaei *et al.*, 2011; Oliveira *et al.*, 2006). Vafaei *et al.* (2011) have also shown that the relationship between ICD and market value is moderated by the technological intensity, and they find a significant relationship only in non-traditional (high-tech) industries. Therefore, it is expected that technological intensity will have a moderating effect on the relationship between ICD and market value. This leads to the development of hypotheses *H<sub>3</sub>* and *H<sub>4</sub>*.

*H*<sub>3</sub>. The technological intensity of the industry has a moderating effect on the relationship between ICD and market value.

*H*<sub>4</sub>. The technological intensity of the industry has a moderating effect on the relationship between components of ICD and market value.

## 4 Research design

### 4.1 Sample and data

The data for the dependent and control variables in this study were obtained from the OSIRIS database. Data for the independent variable were collected from annual reports which were obtained from the New Zealand Stock Exchange. As of the 8<sup>th</sup> of May 2012, there were 128 New Zealand companies listed on the OSIRIS database. To be included in this study, data had to be obtainable for a company's market capitalization, net profit or loss, total assets, leverage and book value for all three years, 2008, 2009 and 2010. After accounting for this, the sample was reduced to 109 companies. Of these 109 companies, 85 reports were readable in 2008, 98 reports were readable in 2009[3] and 101 reports were readable in 2010. This gave a total sample size of 284 annual reports over all three years.

### 4.2 Dependent variable

The dependent variable for this study is market value. The company's share price is used as a measure of market value (Vafaei *et al.*, 2011; Oliveria *et al.*, 2010). Market capitalisation figures and outstanding numbers of shares were obtained from the OSIRIS database. The market capitalization was then divided by the number of shares to give the share price.

To provide some robustness analysis, two different measures were used to test this relationship. First, a lagged market price taken six months after the balance date was tested. This was done in order to allow for the fact that it may take some time for disclosure to have any effect. A second model, Tobin's Q, was used as another measure of firm value (Orens *et al.*, 2009), and we run the test again.

### 4.3 Independent variable

The independent variable for this study is voluntary ICD. Its data were collected from annual reports which were obtained from the New Zealand Stock Exchange for 2008, 2009 and 2010. These annual reports were then indexed so that they could be examined using the ISYS search engine.

Measurement of voluntary ICD is fairly problematic. The nature of the information makes it

difficult to obtain a reliable measure of its level. The literature has primarily approached this measurement issue using content analysis. Content analysis is "a method of codifying the text of writing into various groups or categories based on selected criteria, assuming that the frequency indicates the importance of the subject matter" (Guthrie *et al.*, 2004, p. 285). When performed correctly, it should be a systematic, objective and reliable way to determine the meaning of content in disclosures (Whiting and Miller, 2008). The method in the current study is a slight variation of traditional content analysis, as it uses a computerised word search technique (Birch and Whiting, 2012; Vergauwen *et al.*, 2007). The traditional manual content analysis can be very time consuming. It is for this reason that the traditional content analysis has been restricted to relatively small sample sizes. This then impacts on the ability of such a sample size to produce significant and useful results. To get around this problem, Vergauwen *et al.* (2007), and Birch and Whiting (2012) use an adapted content analysis based on a computerised word search. This computerised word search increases the sample size over that used in manual content analysis studies, but some ICDs may not be captured as the annual report is not read for meaning (Birch and Whiting, 2012). A list of words pertaining to each component of IC (human, relational and structural capital) is adopted from Birch and Whiting (2012). This list was formulated by adapting another list, prepared by Vergauwen *et al.* (2007), from a European context to a New Zealand context. The use of this list is desirable, as the current study is conducted on New Zealand data. The use of a consistent ICD method also allowed the incorporation into the present study of some 2009 data obtained from the authors of Birch and Whiting (2012)[4]. The list comprises a total of 108 words and is divided into the three components of IC, namely human, relational and structural capital.

As mentioned earlier the ISYS search engine was used to screen the indexed annual reports. Individual annual reports were examined for each of the words in the word search list. Each word hit was manually examined as to whether it was a voluntary disclosure that related to IC. Decisions were made based on a decision document created by Birch and Whiting (2012). Each hit was coded either a 1 or a 0, depending on whether it was a legitimate hit or a false positive, respectively. A false positive is a word that shows up in the annual report, providing a word 'hit' to the search engine, but is not actually a valid voluntary ICD; for example, the word 'brands' under relational capital would return a number of false positives when searching the Restaurant Brands annual report. This is because the word hit would be related to the name of the company, and not to a valid ICD.

Three different measures were collected for the independent variable. These measures were count,

presence and score of an ICD. All these measures were calculated for each human, relational and structural capital. The sum of all three of these formed the total disclosure. The 'count' variable captures the extent of disclosure. It is calculated as the sum of all the valid ICDs contained in the annual report. The 'presence' variable captures the variety of disclosure. If a word from the search list is present in an annual report, then it is coded a 1, if it is not present it is coded a zero. The maximum presence any one company can have is then 108, which represents the 108 search terms used. Finally, the 'score' variable also captures the extent of disclosure. It is calculated by dividing the 'count' of valid word hits by the total number of words contained in the relevant sections of the annual report which were examined[5].

The use of an electronic word search does enhance objectivity overall to this measure (Vergauwen *et al.*, 2007; Birch and Whiting, 2012). However, because of the nature of content analysis, there is an element of subjectivity involved in gathering data. In the present study, this is due to the researcher making a decision as to whether a word hit is valid or not. The literature has approached this issue by conducting reliability testing. A total of 14 reports (seven in 2008 and seven in 2010) were recoded at different time periods by the author to test for stability (test-retest reliability) based on a number of decision rules. All values were above the minimum acceptable level of Krippendorff's alpha of 0.75[6]. A second coder was also used to test the reproducibility of the reports (inter-rater reliability) after reading the training document. This was conducted on an additional three annual reports. The values for reproducibility were also all above the minimum acceptable level (Krippendorff's alphas are 0.76, 0.78 and 0.82). Reliability testing thus indicates that the reliability of the data is satisfactory.

#### 4.4 Control variables

##### 4.4.1 Net profit

Net profit is an indicator of the recursion value of the company (Ashton *et al.*, 2003). Recursion value is the value of the future economic pay-outs a company will make. It represents the value the company is creating from continuing its current business operation. The greater the recursion value of the company, the greater the market value will presumably be. Net profit is then used to control for this effect. Net profit figures were obtained from OSIRIS. Net profit is then scaled by the number of shares outstanding at the balance date.

##### 4.4.2 Book value

Book value is a proxy for the value of the company's current resources. Current resources represent the ability of a company to adapt its business (Ashton *et*

*al.*, 2003; Hayn, 1995; Burgstahler and Dichev, 1997). Companies that have a greater resource pool behind them will then have a greater market value. Thus, book value is presumed to have a significant effect on market value. Book value was also obtained from OSIRIS and was calculated as assets minus liabilities. Book value is also scaled by the number of shares outstanding at the balance date.

##### 4.4.3 Leverage

Leverage has been shown to measure the financial risk of a company (Mandelker and Rhee, 1984). Of two investments with the same rates of return, the lower-risk investment will attract a higher market value. Because of this relationship, financial leverage may have significant effects on market values (Orens *et al.*, 2009; Anam *et al.*, 2011; Abeysekera, 2011). Leverage was calculated by dividing total liabilities by total equity. Data for this variable were obtained from OSIRIS.

##### 4.4.4 Industry

Industry has been noted to play an important role in determining the level and effect of ICD (Bozzolan *et al.*, 2003; Vafaei *et al.*, 2011; Oliveira *et al.*, 2006; Birch and Whiting, 2012). An industry dummy variable is included in the model and companies are coded a 1 if they are high-tech or 0 if they are low-tech.

##### 4.4.5 Year

Two dummy variables are included in the regression to control for year. These variables are coded 1 if an observation is related to the year that the dummy variable represents[7]. In 2008, there was a global financial crisis; the effects of this on this study are specifically unknown. Controlling for year in this study is done to make sure there are no significant differences between the three years. Separate regressions were also run for each year to see if there were any notable differences.

##### 4.4.6 Size

Size is controlled for in this study by scaling book value by number of shares. Size has been shown to affect voluntary disclosure as well as larger companies having larger market capitalizations.

#### 4.5 Moderating variable

Previous research discussed in the literature review section has shown that there is a difference in the level of intellectual capital disclosure between high- and low-tech industries. For these reasons technological intensity is proposed to moderate the relationship

between voluntary ICD and market value. Consistent with Birch and Whiting (2012), companies are coded a 1 if they are high-tech or 0 if they are low-tech. Classifications were made based on a company's Global Industry Classification Standard number obtained from OSIRIS. Interaction terms between each measure of ICD and industry were then created to test the moderating effect of industry.

$$P_{it} = \beta_0 + \beta_1 \text{TotalICD}_{it} + \beta_2 \text{EPS}_{it} + \beta_3 \text{BVPS}_{it} + \beta_4 \text{Leverage}_{it} + \beta_5 \text{Industry}_{it} + \beta_6 \text{Year}_{it} + \varepsilon_{it} \quad (1)$$

where  $P$  is market price, TotalICD is total voluntary ICD [8], EPS is net profit or loss after tax divided by the number of outstanding shares, BVPS is book value divided by the number of shares outstanding, Leverage is total liabilities over total equity, Industry is dummy variable coded 1 for high-tech industries and 0 for low-tech industries, Year is dummy variable,  $\beta_0$  is constant,  $t$  is year,  $i$  is company, and  $\varepsilon$  is error term.

$$P_{it} = \beta_0 + \beta_1 \text{HumanICD}_{it} + \beta_2 \text{RelationalICD}_{it} + \beta_3 \text{StructuralICD}_{it} + \beta_4 \text{EPS}_{it} + \beta_5 \text{BVPS}_{it} + \beta_6 \text{Leverage}_{it} + \beta_7 \text{Industry}_{it} + \beta_8 \text{Year}_{it} + \varepsilon_{it} \quad (2)$$

### Model 3 – Moderation effects of industry on total ICD

## 4.6 Empirical model

The four hypotheses to be empirically tested are reflected in the following four models.

### Model 1 – Total ICD

The main regression model used in this study, and to test  $H_1$ , is presented below:

### Model 2 – Component analysis of ICD

A second model was also formulated which separates Total ICD into its three components, namely human, relational and structural capital, to test  $H_{2a}$ ,  $H_{2b}$  and  $H_{2c}$ . Variable measurement in model 2 is the same as in model 1 except for where ICD has been split into its three components. This model is presented below:

Model 3 was developed in order to test the moderation effect of industry on  $H_3$ . This is done by creating an interaction term between voluntary ICD and industry to the regression.

$$P_{it} = \beta_0 + \beta_1 \text{TotalICD}_{it} + \beta_2 \text{EPS}_{it} + \beta_3 \text{BVPS}_{it} + \beta_4 \text{Leverage}_{it} + \beta_5 \text{Industry}_{it} + \beta_6 \text{Year}_{it} + \beta_7 \text{TotalICD}_{it} * \text{Industry}_{it} + \varepsilon_{it} \quad (3)$$

### Model 4 – Moderation effects of industry on components of total ICD

when conducting this analysis. Variable measurement is consistent with models 1 and 2. This model is used to test  $H_4$ .

Interaction terms were also created between each separate component of intellectual capital and industry

$$P_{it} = \beta_0 + \beta_1 \text{HumanICD}_{it} + \beta_2 \text{RelationalICD}_{it} + \beta_3 \text{StructuralICD}_{it} + \beta_4 \text{EPS}_{it} + \beta_5 \text{BVPS}_{it} + \beta_6 \text{Leverage}_{it} + \beta_7 \text{Industry}_{it} + \beta_8 \text{Year}_{it} + \beta_9 \text{HumanICD}_{it} * \text{Industry}_{it} + \beta_{10} \text{RelationalICD}_{it} * \text{Industry}_{it} + \beta_{11} \text{StructuralICD}_{it} * \text{Industry}_{it} + \varepsilon_{it} \quad (4)$$

All variables in this model 4 are measured the same as in models 1 and 2, except for where voluntary ICD has been separated into its three classifications, namely human, relational and structural capital, and with the addition of three interaction terms created by multiplying each human, relational and structural capital by industry.

## 5 Results

### 5.1 Descriptive statistics

#### 5.1.1 Differences in disclosure across classifications

Descriptive statistics presented at Table I indicate that structural capital is the most frequently reported in this sample, followed by relational capital and lastly human capital.

This is inconsistent with prior literature which has suggested that relational capital is the most frequently reported (Whiting and Miller, 2008; Guthrie and Petty, 2000). The reason for this inconsistency may be due to the present study using a different method to collect ICD data, or because the present study conducts research on years much later than the previous studies. However, it is consistent with Birch and Whiting (2012).

**5.1.2 Differences between high- and low-tech industries**

Due to non-normal data on some of the variables, the Mann-Whitney U test was used to investigate the differences between levels of disclosure from high- and low-tech companies. Results from this test show that total count, total presence, human presence and human score are significantly higher for low-tech firms, at the 5% significance level. Relational count, relational presence, relational score and human count were also significantly higher for low-tech firms, but

at the 1 % significance level[9]. This result is inconsistent with many prior studies (Bozzolan *et al.* 2003; Oliveira *et al.* 2006; Vafaei *et al.* 2011) but is consistent with Birch and Whiting (2012). It has been suggested that this inconsistency may be due to New Zealand not having very many ‘truly high-tech’ firms (Birch and Whiting, 2012) and a small sample size for high-tech’ firms. It could also be the case that the industry classification used is significantly different from other studies.

**Table I.** Descriptive statistics for selected variables

Variable	Minimum	Maximum	Mean	Median	Standard Deviation
HC Count	0	183	21	12	27
HC presence	0	16	5	5	3
HC Score	0.000	0.018	0.002	0.001	0.002
RC Count	0	390	27	17	35
RC presence	0	13	5	4	3
RC score	0.0000	0.019	0.002	0.001	0.003
SC count	0	1036	51	35	74
SC presence	0	83	8	7	6
SC score	0.0000	0.032	0.004	0.003	0.005
Total ICD count	1	1570	98	71	124
Total ICD presence	1	91	17	16	9
Total ICD score	0.000	0.062	0.008	0.005	0.009
Market price	0.00	8.94	1.79	1.35	1.83
Book value per share (BVPS)	-0.25	12.55	1.55	1.03	1.73
Net profit per share (EPS)	-2.06	5.04	0.08	0.06	0.39
Leverage	0.000	33.070	2.793	1.095	5.077

**Note:** HC = Human capital; RC = Relational capital; SC = Structural capital; ICD = Intellectual capital disclosure

**5.1.3 Differences between years**

The non-parametric test for the differences between two or more related samples is the Friedman two-way analysis of variance by rank test. This was conducted

on firms which had IC data for all three years in order to investigate the differences in ICD between the years. Results for total ICD for this analysis are shown below[10].

	Count	Presence	Score
	Mean Rank	Mean Rank	Mean Rank
Total ICD 2008	1.46	1.53	1.09
Total ICD 2009	1.67	2.19	2.79
Total ICD 2010	2.87	2.28	2.12
<b>Test Statistics</b>			
N	85	85	85
Chi-Square	99.714	30.025	123.741
df	2	2	2
p- value	.000***	.000***	.000***

\*\*\*significant at the 1% level



This analysis shows that measures of ICD are not the same between years, as indicated by their significance at the 1% level. Looking at the mean ranks, ICD seems to be consistently increasing over time for both count and presence, whereas for score the mean rank increases from 2008 to 2009 then drops back down from 2009 to 2010. Overall, there seems to be an increase in voluntary ICD over the three years. This is consistent with Abdolomohammadi (2005) and Vandemaele et al. (2005).

**5.2 Spearman’s correlations between market price, independent and control variables**

Initial results of the relationships between the dependent variable, market price, and independent variables, ICD, and control variables are shown in Table II.

**Table II.** Spearman correlations between market price, independent and control variables

	Market Price		
	Coefficient	P-value	Sig
HC Count	0.37	.000	***
HC presence	0.305	.000	***
HC Score	0.213	.000	***
RC Count	0.299	.000	***
RC presence	0.251	.000	***
RC score	0.176	.001	***
SC count	0.23	.000	***
SC presence	0.164	.003	***
SC score	0.041	.246	ns
Total ICD count	0.315	.000	***
Total ICD presence	0.267	.000	***
Total ICD score	0.126	.017	**
Book value per share (BVPS)	0.773	.000	***
Net profit per share (EPS)	0.649	.000	***
Leverage	0.518	.000	***

**Note:** \*\*\* indicates  $p < .01$ , \*\* indicates  $p < .05$ , \* indicates  $p < .10$  and “ns” indicates  $p > .10$ .

There is significant correlation between market price and all measures of ICD except structural score[11]. All correlations are significant at the 1% level except for Total ICD score, which is significant at the 5% level. This analysis indicates support for hypotheses 1 and 2. Significant correlations between price and each book value, net profit and leverage are observed. This gives some indication that these control variables do have significant effects on market price.

**5.3 Regression analysis—pooled results**

Table III presents the results of the regression analysis of firm valuation for total ICD. Total ICD is significant for both count and presence at the 1% level. Total score is, however, found to be insignificant. This indicates support for the hypothesis that ICD is value relevant. Coefficients are all positive and consistent with expectations.

**Table III.** Multiple regression analysis of firm valuation for Total ICD – Pooled sample results (2008 to 2010) – Model 1

	Count			Presence			Score		
	Coefficient	t-value	p-value	Coefficient	t-value	p-value	Coefficient	t-value	p-value
(Constant)	.331	1.867	.063	.210	.955	.341	.627	3.724	.000***
Book value per share (BVPS)	.633	13.263	.000***	.636	13.166	.000***	.646	13.215	.000***
Net profit per share (EPS)	.785	3.772	.000***	.830	3.954	.000***	.880	4.145	.000***
Leverage	.022	1.438	.151	.024	1.535	.126	.025	1.541	.125
Industry	-.088	-.558	.578	-.034	-.213	.831	-.069	-.422	.673
YearDummy2008	.146	.747	.456	.047	.242	.809	-.024	-.121	.903
YearDummy2009	.255	1.354	.177	.030	.161	.872	-.022	-.103	.918
Total ICD	.003	4.005	.000***	.027	2.987	.003***	8.191	.781	.436
Adjusted R squared		.514			.502			.487	

**Note:** \*\*\* indicates  $p < .01$ .

$$\text{Model 1: } P_{it} = \beta_0 + \beta_1 \text{TotalICD}_{it} + \beta_2 \text{EPS}_{it} + \beta_3 \text{BVPS}_{it} + \beta_4 \text{Leverage}_{it} + \beta_5 \text{Industry}_{it} + \beta_6 \text{Year}_{it} + \varepsilon$$

$P_t$  = Market capitalisation at balance date divided by the number of outstanding shares; **TotalICD** = Voluntary intellectual capital disclosure as measured by the count, presence or score; **EPS** = Net profit or loss after tax divided by the number of outstanding shares; **BVPS** = Assets minus liabilities divided by the number of shares outstanding; **Leverage** = Total liabilities divided by total equity; **Industry** = Dummy variable coded 1 for high-tech industries and 0 for low-tech industries; **Year** = Dummy variable;  $\beta_0$  is constant;  $t$  = year;  $i$  = company;  $\varepsilon$  = Error term

The model also indicates that both book value and net profit have significant effects on market value which are consistent with Anam *et al.* (2011); Orens *et al.* (2009); Vafaei *et al.* (2011); and Abeysekera (2011). Leverage, industry and year seem to have no effect on market value. The insignificance of leverage was not expected, but is consistent with Orens *et al.* (2009) but inconsistent with Abeysekera (2011), who found leverage to be significant only in times of truce. Interpretation of the coefficients of the model suggests that for each extra ICD, or count, market value is increased by \$0.003. For a firm disclosing 50 extra ICD-related words, the model predicts share price to be increased by \$0.15, or 15 cents. Likewise for every extra type of ICD (presence), the model predicts share price to be increased by \$0.027. For an extra 10 types

of ICD, the model predicts a \$0.27, or 27-cent increase in the share price. Although a strict interpretation like this is unlikely to hold in the real world, this does show that levels of disclosure could have some practical significance in influencing share prices (as values such as 15 and 27 cents are significant changes in share price). This analysis shows that overall total ICD does have a significant and positive relationship with market value and thus shows support for  $H_1$ .

Results were then examined further to investigate the individual effects of each component of ICD. Results from this regression are presented in Table IV.

**Table IV.** Multiple regression analysis of firm valuation for IC components – Pooled sample results (2008 to 2010) – Model 2

	Count			Presence			Score		
	Coefficient	t-value	p-value	Coefficient	t-value	p-value	Coefficient	t-value	p-value
(Constant)	.335	2.005	.046**	.063	.280	.780	.634	3.752	.000***
Book value per share (BVPS)	.617	13.615	.000***	.629	13.022	.000***	.652	13.312	.000***
Net profit per share (EPS)	.614	3.087	.002***	.831	3.972	.000***	.835	3.884	.000***
Leverage	.016	1.090	.277	.023	1.440	.151	.025	1.543	.124
Industry	.169	1.084	.279	.070	.423	.673	.008	.047	.963
YearDummy2008	-.223	-1.146	.253	.009	.047	.963	-.092	-.455	.650
YearDummy2009	.085	.470	.638	.048	.262	.793	-.020	-.089	.929
Human ICD	.018	4.833	.000***	.034	1.012	.312	37.814	.717	.474
Relational ICD	.013	3.353	.001***	.097	2.615	.009***	68.833	1.681	.094*
Structural ICD	-.007	-3.541	.000***	-.003	-.179	.858	-39.060	-1.333	.184
Adjusted R squared		.568			.509			.489	

**Note:** \*\*\* indicates  $p < .01$ , \*\* indicates  $p < .05$ , and \* indicates  $p < .10$ .

Model 2:  $P_{it} = \beta_0 + \beta_1 \text{HumanICD}_{it} + \beta_2 \text{RelationalICD}_{it} + \beta_3 \text{StructuralICD}_{it} + \beta_4 \text{EPS}_{it} + \beta_5 \text{BVPS}_{it} + \beta_6 \text{Leverage}_{it} + \beta_7 \text{Industry}_{it} + \beta_8 \text{Year}_{it} + \varepsilon$

$P_t$  = Market capitalisation at balance date divided by the number of outstanding shares; **Human ICD**, **Relational ICD** and **Structural ICD** = Voluntary intellectual capital disclosure as measured by the count, presence or score; **EPS** = Net profit or loss after tax divided by the number of outstanding shares; **BVPS** = Assets minus liabilities divided by the number of shares outstanding; **Leverage** = Total liabilities divided by total equity; **Industry** = Dummy variable coded 1 for high-tech industries and 0 for low-tech industries; **Year** = Dummy variable;  $\beta_0$  is constant;  $t$  = year;  $i$  = company;  $\varepsilon$  = Error term

Human count, relational count and structural count are all significant at the 1% level. Both human count and relational count show a positive and significant relationship with market value. Interestingly, however, and against expectations, structural count is significant but negatively related to market value. As explained later in the discussion section, this negative relationship has been attributed to the erosion of competitive advantage.

The 'presence model' showed that relational presence was positively significant at the 1% level. Human presence and structural presence did not show any significant relationships. Finally, the 'score model' showed that relational score was positively significant at the 10% level, while the human score and the structural score did not show any significant relationships. Overall, the results seem to indicate there is both a positive and significant relationship between human capital disclosure and relational capital disclosure. Interestingly, results showed that, inconsistent with expectations, there was a negative relationship between structural capital disclosure (count) and market value. This suggests that there may be both costs and benefits to increases in voluntary ICD. Interpretation of the coefficients in the 'IC components model' in Table IV shows large increases

from the coefficients in the 'total ICD model' in Table III. The coefficient for Total ICD under the 'count model' increases from 0.003 (see Table III) to 0.018 for human capital, 0.013 for relational capital and -0.007 for structural capital. As shown in Tables III and IV, these increases in coefficients are also seen in the presence and score models. This would indicate that it is not just the quantity of ICD that matters, but that the type (human, relational or structural) of disclosure is also relevant. Different disclosures seem to have varying benefits and costs because if there were consistent benefits from each component, we would expect consistent coefficients. Overall, the results seem to indicate that there are positive benefits from both human and relational capital disclosure. However, the results indicate that structural disclosure has some negative costs.

#### 5.4 Regression analysis—yearly results

A year-by-year analysis was conducted to see if there were any significant differences in the relationship between ICD and market value over the three years 2008, 2009 and 2010. This was done by partitioning the sample into its three separate years as subsamples

and then rerunning models 1 and 2 within each year subsample.

Table V summarises the differences in significance of ICD over the three years.

**Table V.** Yearly regression results of firm valuation for Total ICD and its components from 2008 to 2010

	Count			Presence			Score		
	Coefficient t	t-value	p-value	Coefficient t	t-value	p-value	Coefficient t	t-value	p-value
Total ICD2010	0.001	1.827	.071*	0.055	2.742	.007***	61.408	1.07	.287
Total ICD2009	0.006	3.039	.003***	0.013	1.272	.207	2.165	0.219	.827
Total ICD2008	0.003	2.384	.020**	0.045	2.25	.027**	251.086	3.565	.001***
		Count		Presence		Score			
Human2010	0.02	3.245	.002***	0.072	1.018	.311	405.422	1.884	.063
Human2009	0.011	1.025	.308	-0.003	-0.065	.949	-23.348	-0.449	.654
Human2008	0.015	2.774	.007***	0.12	1.83	.071 *	546.802	2.733	.008***
		Count		Presence		Score			
Relational2010	0.011	1.939	.056*	0.074	0.95	0.344	200.164	1.233	.221
Relational2009	0.017	2.326	.022**	0.079	1.614	.110	75.866	1.926	.057*
Relational2008	0.016	1.944	.056*	0.058	0.779	0.439	425.453	2.06	.043**
		Count		Presence		Score			
Structural2010	-0.006	-2.577	.012**	0.032	0.595	.553	-185.808	-1.498	.138
Structural2009	-0.007	-0.845	.400	-0.001	-0.064	.949	-27.356	-0.961	.339
Structural2008	-0.01	-2.001	.049**	-0.025	-0.376	.708	-227.948	-0.991	.325

**Note:** \*\*\* indicates  $p < .01$ , \*\* indicates  $p < .05$ , and \* indicates  $p < .10$ .

This shows that 2008 seems to show the most significant relationships, with 2009 showing the least significant. Overall, this analysis shows that relationships are not overly different between the years. This justifies the use of a pooled cross-sectional analysis.

### 5.5 The moderating effect of industry

To test whether industry has a moderating effect on the relationship between ICD and market value,

interaction terms between industry and ICD were created and added to the model.

Results from this analysis are presented in Tables VI and VII for the moderating effect of industry on total ICD and three components of ICD respectively. Table VI shows interaction terms are significant for both total count and presence at the 1% level, while interaction for score was not significant. This suggests that industry does have a moderating effect.

**Table VI.** Multiple regression results – Test of the moderating effect of industry on total ICD: Pooled regression (2008 to 2010) – Model 3

	Count			Presence			Score		
	Coefficient	t-value	p-value	Coefficient	t-value	p-value	Coefficient	t-value	p-value
(Constant)	-.291	-1.417	.158	-.196	-.738	.461	.653	3.754	.000***
Book value per share (BVPS)	.602	13.122	.000***	.628	13.106	.000***	.647	13.207	.000***
Net profit per share (EPS)	.838	4.218	.000***	.872	4.188	.000***	.881	4.144	.000***
Leverage	.018	1.229	.220	.024	1.523	.129	.025	1.546	.123
Industry	.631	3.113	.002***	.732	2.227	.027**	-.151	-.712	.477
YearDummy2008	.340	1.788	.075*	.073	.379	.705	-.021	-.106	.916
YearDummy2009	.441	2.408	.017**	.028	.155	.877	-.023	-.107	.915
Total ICD	.008	6.725	.000***	.050	4.022	.000***	4.877	.412	.681
TotalICD*industry	-.007	-5.335	.000***	-.046	-2.666	.008***	10.821	.605	.545
Adjusted R squared		.558			.513			0.486	

**Note:** \*\*\* indicates  $p < .01$ , \*\* indicates  $p < .05$ , and \* indicates  $p < .10$ .

Model 3:  $P_{it} = \beta_0 + \beta_1 \text{TotalICD}_{it} + \beta_2 \text{EPS}_{it} + \beta_3 \text{BVPS}_{it} + \beta_4 \text{Leverage}_{it} + \beta_5 \text{Industry}_{it} + \beta_6 \text{Year}_{it} + \beta_7 \text{TotalICD} * \text{Industry}_{it} + \varepsilon$   
 $P_t$  = Market capitalisation at balance date divided by the number of outstanding shares; **TotalICD** = Voluntary intellectual capital disclosure as measured by the count, presence or score; **EPS** = Net profit or loss after tax divided by the number of outstanding shares; **BVPS** = Assets minus liabilities divided by the number of shares outstanding; **Leverage** = Total liabilities divided by total equity; **Industry** = Dummy variable coded 1 for high-tech industries and 0 for low-tech industries. **Year** = Dummy variable; **TotalICD\*Industry** = Interaction effect;  $\beta_0$  is constant;  $t$  = year;  $i$  = company;  $\varepsilon$  = Error term

**Table VII.** Multiple regression results – Test of the moderating effects of industry on three components of intellectual capital: Pooled regression (2008 to 2010) – Model 4

	Count			Presence			Score		
	Coefficient	t-value	p-value	Coefficient	t-value	p-value	Coefficient	t-value	p-value
(Constant)	.026	.109	.913	-.148	-.554	.580	.686	3.927	.000***
Book value per share (BVPS)	.608	13.255	.000***	.634	13.206	.000***	.641	13.030	.000***
Net profit per share (EPS)	.697	3.404	.001***	.890	4.255	.000***	.895	4.133	.000***
Leverage	.016	1.084	.279	.026	1.664	.097	.029	1.786	.075*
Industry	.452	2.095	.037**	.710	1.969	.050	-.158	-.747	.456
YearDummy2008	-.024	-.105	.917	-.008	-.040	.968	-.093	-.460	.646
YearDummy2009	.221	1.115	.266	.001	.005	.996	-.025	-.114	.909
Human ICD	.015	3.125	.002***	.087	2.022	.044**	95.039	1.606	.109
Relational ICD	.016	3.159	.002***	.071	1.496	.136	91.932	1.743	.082*
Structural ICD	-.002	-.493	.622	.005	.138	.890	-90.947	-2.270	.024**
HumanICD*Industry	-.003	-.307	.759	-.182	-2.526	.012**	-222.022	-1.716	.087*
RelationalICD*Industry	-.005	-.620	.536	.064	.808	.420	7.129	.081	.936
StructuralICD*Industry	-.003	-.610	.542	-.011	-.272	.786	117.270	2.109	.036**
Adjusted R squared		.569			0.518			0.494	

**Note:** \*\*\* indicates  $p < .01$ , \*\* indicates  $p < .05$ , and \* indicates  $p < .10$ .

Model 4:  $P_{it} = \beta_0 + \beta_1 \text{HumanICD}_{it} + \beta_2 \text{RelationalICD}_{it} + \beta_3 \text{StructuralICD}_{it} + \beta_4 \text{EPS}_{it} + \beta_5 \text{BVPS}_{it} + \beta_6 \text{Leverage}_{it} + \beta_7 \text{Industry}_{it} + \beta_8 \text{Year}_{it} + \beta_9 \text{HumanICD} * \text{Industry}_{it} + \beta_{10} \text{RelationalICD} * \text{Industry}_{it} + \beta_{11} \text{StructuralICD} * \text{Industry}_{it} + \varepsilon$

$P_i$  = Market capitalisation at balance date divided by the number of outstanding shares; **Human ICD**, **Relational ICD** and **Structural ICD** = Voluntary intellectual capital disclosure as measured by the count, presence or score; **EPS** = Net profit or loss after tax divided by the number of outstanding shares; **BVPS** = Assets minus liabilities divided by the number of shares outstanding; **Leverage** = Total liabilities divided by total equity; **Industry** = Dummy variable coded 1 for high tech industries and 0 for low tech industries; **Year** = Dummy variable; **HumanICD\*Industry**, **RelationalICD\*Industry** and **StructuralICD\*Industry** = Interaction effects;  $\beta_0$  is constant;  $t$  = year;  $i$  = company;  $\epsilon$  = Error term

Examination of the coefficients shows that they also have negative values. This indicates that the strength of the positive relationship between count and presence and market value is more significant for low-tech industries (as high-tech industries are coded 1 in this model). When examining the individual interaction with each component, significance was found in human presence at the 5 % level and human score at the 10% level (see Table VII). Both of these also had negative coefficients, suggesting that human capital disclosure is more positively significant for low technologically intensive industries. An interaction between structural score and industry was also found at the 5% significance level. This has a positive coefficient, indicating that the negative relationship is more significant for low-tech industries.

Overall, it can be concluded that industry does have some moderating effect on the relationship between ICD and market value. This indicates that ICDs are more relevant for low-tech industries and one could argue that more disclosure enhances the relationship between ICD and market value. This

$$P_{it+6\text{ months}} = \beta_0 + \beta_1 \text{TotalICD}_{it} + \beta_2 \text{EPS}_{it} + \beta_3 \text{BVPS}_{it} + \beta_4 \text{Leverage}_{it} + \beta_5 \text{Industry}_{it} + \beta_6 \text{Year}_{it} + \epsilon_{it}$$

This model was formulated to incorporate the idea that it may take some time for ICD to have an impact on market value. Results from this regression are by and large consistent with the results from the price model (i.e., model 1), the only difference being that the relational score is no longer significant. This adds some element of robustness to the results and shows that relationships last over a lagged effect[12].

$$\text{Tobin's } Q_{it} = \beta_0 + \beta_1 \text{TotalICD}_{it} + \beta_2 \text{Netprofit}_{it} + \beta_3 \text{Bookvalue}_{it} + \beta_4 \text{Leverage}_{it} + \beta_5 \text{Industry}_{it} + \beta_6 \text{Year}_{it} + \beta_7 \text{Size}_{it} + \epsilon_{it}$$

Tobin's Q is defined by Chung and Pruitt (1994)[13] as:

$$\text{Tobin's } Q = (\text{MVE} + \text{PS} + \text{LTD} + \text{STD} - \text{CA})/\text{TA}$$

where MVE is the market value of equity or market capitalisation. PS is the value of preference share, LTD is the book value the firm's non-current liabilities, STD is the book value the firm's current liabilities, CA is the book value the firm's current assets and TA is the book value of the firm's total assets. Due to the nature of the calculation of Tobin's Q, there were a number of significant outliers created in the regression. Because Tobin's Q is calculated by dividing by total assets, very high-tech firms which still have significant market values but work off a very low amount of physical assets will return extreme values of Tobin's Q. These outliers were shown to significantly bias the results of the regression. It is hard to exclude these outliers, as they are technically

result is consistent with Birch and Whiting (2012). However, this is inconsistent with Vafaei *et al.* (2011), who find a significant relationship only for non-traditional (high-tech) companies which disclosed more.

## 5.6 Additional analysis

In order to provide robustness to the results, two extra models with different dependent variables were formulated to provide increased reliability to the results. Models were rerun using a lagged market price and Tobin's Q. Results from this analysis are now discussed.

### 5.6.1 Lagged market price model

The lagged price model is identical in every way to models 1 and 2, aside from the fact that the dependent variable, market price, has been substituted for a lagged price figure, taken six months after balance date. This model is presented below:

### 5.6.2 Tobin's Q model

The next robustness model replaces the dependent variable, market price, with Tobin's Q. The rest of this model is consistent with models 1 and 2. The Tobin's Q model is presented below:

valid observations. Exclusion of the outliers was performed to remove the bias they were creating, justified by the fact that this test was only used for the purposes of robustness testing. With the removal of outliers, the results generally support the results obtained from the price model, where the relationships seems to be slightly weaker, but still apparent. Structural score also became negatively significant at the 10% level in this model. The use of Tobin's Q is consistent with Orens *et al.* (2009).

Overall, the results from the robustness test by and large show that the relationships observed in the price model are supported and reliable.

## 6 Discussion and conclusion

This study investigates the value relevance of ICD of 284 New Zealand annual company reports from 2008 to 2010, via content analysis. Results from this study suggest that voluntary ICDs are value relevant. The total count and total presence of voluntary ICD disclosures showed significant and positive relationships with market price. These relationships were also backed up by all robustness checks. This result was further investigated through examination of the individual effects of each component of intellectual capital. This provided interesting results, with the positive relationship between ICD and market value only apparent with human and relational capital, whereas structural capital indicated a negative relationship with market value. This would suggest that there is a trade-off between the costs and the economic benefits of ICDs. A possible justification for the negative relationship, or for the cost of voluntary ICD, is the erosion of competitive advantage (Vergauwen *et al.*, 2007). Public disclosure of ICD resources may actually be harmful to companies because they could potentially reveal practices which companies use to maintain their competitive advantage. Competitors could use this released information to the detriment of the disclosing company, therefore costing the company. Another possible explanation is that the voluntary disclosure relating to structural disclosure was primarily bad disclosure, which would then presumably reduce market value. The specific reason for this negative relationship cannot be solved by the present study but does give some good ideas for future research.

We also found that the relationship between voluntary ICD and market value is moderated by technologically intensive industries. This relationship is stronger for low-tech industries.

Based on the results of this study, it can be concluded that voluntary ICD is value relevant. However, this value relevance is not simply a positive relationship. The results suggest that there may be costs and benefits to voluntary disclosure, and these may vary between the different types of disclosure. In light of this, companies must think hard about what they disclose and about what effects it may have. In addition, results from this study will be of interest to a number of parties. Investors, company management, regulators and other stakeholders could significantly benefit from a greater understanding of the relationship between voluntary ICD and market value. For example, regulators may want to be aware of how such disclosures influence and inform users. Understanding this relationship could call for stricter regulation of such disclosure to prevent exploitation of any relationship. Investors could use such information to decide whether they should base decisions on such voluntary ICDs before investing. Finally, management may be wary of how and when they should make

ICDs, in light of understanding the effects they may have on firm value and future profitability.

One limitation in this study is that ICD was not classified as to whether it is forward or backward looking. It also assumes all ICD is good disclosure. In order to mitigate this assumption future research could code ICDs to either good or bad. Another potential avenue for future research is to employ a survey based (or qualitative data collection) study that could be used to investigate the perceptions of users as to whether they are actually considering voluntary ICDs in their valuations of companies. This could help to understand the value relevance of ICDs in greater detail.

## Notes

1. Goodwill (Oliveira *et al.*, 2010; Higson, 1998); software costs (Aboody and Lev, 1998); research and development (Bublitz and Ettredge, 1989; Lev and Sougiannis, 1996; Sougiannis, 1994); patents (Hirschey *et al.*, 2001); brands (Barth *et al.*, 1998; Kallapur and Kwan, 2004); and advertising (Shah *et al.*, 2009).
2. There are four main theories as to why companies may disclose intellectual capital. These four theories are agency theory, stakeholder theory, legitimacy theory and information asymmetry theory (Whiting and Miller, 2008; Yi *et al.*, 2011).
3. Of the 98 reports in 2009, voluntary ICD data for 80 of them were provided by Birch and Whiting (2012). We thank them for providing this data.
4. Repetitive items in a sentence were all recorded. Exclusions were pictures, graphs and sentences besides them. Other exclusions were report titles and job titles.
5. All sections of the annual reports were examined except for details of board and executive board members, the corporate directory, the auditor's independence declaration, all financial report information (such as income statement, balance sheet, statement of cash flows and notes to financial statements), auditor's report, shareholders' information and glossary.
6. Krippendorff's alpha varies from 0.79 to 0.94. An  $\alpha$  of 0.75 is deemed to be acceptable standard of reliability (Milne and Adler, 1999).
7. The first year is represented by observations with all other year dummies equal to zero, therefore a third dummy is not required as it results in redundancy in the model (Clarke *et al.*, 2011, p. 516).
8. Measured as the count, presence and score.
9. See Appendix 1 for results.
10. Results for each human, relational and structural capital differences can be found in Appendix 2.
11. Spearman correlation analysis was also used in order to examine correlations between the independent variable and control variables, to test the multicollinearity assumption of the multiple

regressions. Significant correlations were found between the variables. Further analysis and examination of the variance inflation factor (VIF) scores, however, indicated any correlation was not significant enough to violate this assumption.

12. The robustness test results of the lagged market price model and the Tobin's Q model can be obtained from the author.

13. Tobin's Q in its original formulation is the market value of the firm's assets divided by the replacement value of the firm's assets. As it is difficult to obtain accurate measures of both market value and replacement value of the firm's assets, an approximation of Tobin's Q developed by Chung and Pruitt (1994) was used instead. Chung and Pruitt (1994) argue that their approximation explains 96.6% of the total variability in the theoretical Tobin's Q by Lindenberg and Ross (1981).

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