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KEY PERFORMANCE INDICATORS AND ANALYSTS' EARNINGS FORECAST ACCURACY: AN APPLICATION OF CONTENT ANALYSIS

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ABSTRACT

We examine the association between the extent of change in key performance indicator (KPI) disclosures and the accuracy of forecasts made by analysts. KPIs are regarded as improving both the transparency and relevancy of public financial information. The results of using linear regression models show that contrary to our prediction and the hypothesis of this paper, there is no significant association between the change in non-financial KPI disclosures and the accuracy of analysts' forecasts. Nonetheless, when we employ a non-linear regression and deflate the absolute value of forecast errors (the dependent variable in this study) by the stock price, the results support the hypothesis of an association between a change in non-financial KPI reporting and the accuracy of analyst forecasts. These results have policy implications, as worldwide policymakers, regulators, corporations and analysts underscore the importance of KPI disclosures.

Keywords: Key Performance Indicators (KPI), non-financial KPIs, analysts, analysts forecast accuracy

INTRODUCTION

More transparent and relevant disclosure can reduce market uncertainty and help investors to make better and more efficient investment decisions. By transparency, we mean the disclosure of information of interest to users of financial statements (Angluin & Scapens, 2000). Key Performance Indicators (KPIs) are regarded as improving both the transparency and relevancy of public financial information. The importance of KPI disclosures can be found in the

U.K. Companies Act of 1985, which requires the publication of certain financial KPIs in accordance with the EU Accounts Modernisation Directive for all, except small, companies. However, this reporting requirement is mainly limited to financial KPIs. Rezaee (2007) argues that there is a need for reporting both financial and non-financial KPIs, as non-financial KPIs often complement financial KPIs. Furthermore, the importance of KPI reporting can also be observed in the final report of the Advisory Committee on Improvements to Financial Reporting (ACIFR) to the United States Securities and Exchange Commission (SEC) in 2008, which recommends the extensive use of KPIs. In addition, Barth and Landsman (2010) call for disclosure of more disaggregated information and argue that lack of transparency and disclosure prevented investors from better evaluating the risk of their investments during the current economic crisis. Details and different perspectives of KPI disclosures are shown in Appendix A.

This paper mainly focuses on stock market analysts as a separate group of users of financial and non-financial information. The results of using linear regression models show that contrary to our prediction and the hypothesis of this paper, there is no significant association between non-financial KPI disclosure and the accuracy of analysts' forecasts. Nonetheless, when we employ a non-linear regression and deflate the absolute value of forecast errors (the dependent variable of this study) by the stock price, the results support the hypothesis of an association between non-financial KPI reporting and analyst forecast accuracy only for a sample of S&P 500 companies and a sample of manufacturing companies. For a sample of oil and gas companies, the results suggest that KPI disclosures are either not fully utilised by financial analysts or that these disclosures do not have much impact on analysts' forecast accuracy.

In providing empirical evidence regarding the recommendations made by the ACIFR in 2008, the policy implication of this study is to encourage the SEC and the Financial Accounting Standards Board (FASB) to define specific KPIs and require companies in each industry to consistently report them. This study shows that there are some cases in which analysts can benefit from the utilisation of KPI information in their analyses. Finally, this paper opens a new line of research in KPI empirical studies.

The remainder of the paper is organised as follows. Next section includes a discussion of prior studies and the development of the hypothesis. Then, the next section explains the sample design, data, and methodology. Next section presents the results and their analyses, and conclusions and implications are discussed in the last section.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Earnings estimates that are more accurate require access to more information about critical key measures of management performance, which requires management to present measures considered to be critical success factors (De Geuser, Moorai, & Oyon, 2009; Sundin, Granlund, & Brown, 2010). These critical success factors are considered according to eight different perspectives: investor, employee, customer, supplier, social community, internal process, innovation and learning, and environmental perspectives (Kaplan & Norton, 1996; Boesso, 2004). In short, we posit that the additional disclosure of key success factors can help analysts to make more accurate earnings estimates. The following are summaries of studies that support the link between analysts' forecast accuracy and additional disclosure and transparency.

Barron, Kim, Lim, & Stevens (1998) use an analytical model to show that analysts' forecast accuracy is affected by two main factors. The first factor relates to information that is publicly available and to which all analysts have access. The second factor considers idiosyncratic information that analysts collect through their own efforts. McEwen and Hunton (1999) use a survey to examine the association between analysts' forecast accuracy and specific accounting information items used for financial statement analyses. McEwen and Hunton (1999) conclude that more accurate analysts consider more accounting items than analysts who are less accurate, and thus, the authors document a positive association between specific accounting information items and the quality of analyst decisions. In another study, Hope (2002) uses 85 variables from annual reports divided into seven broad categories–general information, income statement, balance sheet, funds/cash flow statement, accounting policies, stockholder's information, and supplementary information–to construct an annual report score. Further, the author employs a sample of 22 countries to investigate the association between the analysts' forecast accuracy and the level of annual report disclosure as well as the association between forecast accuracy and the degree of enforcement of accounting standards. He documents a positive association between analysts' forecast accuracy and the level of reporting disclosure as well as a positive association between forecast accuracy and the level of enforcement of accounting standards. Along the same lines of study, Clement and Tse (2003) investigate whether investors take into account all of the characteristics of analysts' forecasts. They conclude that investors only utilise some of the forecast characteristics that correspond to future forecast accuracy. Clement (1999) finds that the forecast accuracy is positively associated with analysts' experience and employer size and negatively associated with the number of firms and industries followed by the analysts. Finally, Brown (2001) discusses the importance of the accuracy of analysts' forecasts.

Several studies investigate the effects of the Regulation Fair Disclosure (FD) act issued by the SEC in October 2000, which prohibits public companies from disseminating their private information on estimates made by analysts to a selective group of users without simultaneously disclosing the same information to other users. In general, prior studies find that the Regulation FD act has decreased differential access to information by analysts (e.g., Sunder, 2003; Brown, Hillegeist, & Lo, 2004; Eleswarapu, Thompson, & Venkataraman, 2004). In addition, Heflin, Subramanyam and Zhang (2003) find no evidence that Regulation FD decreases the quality and amount of information available to investors prior to earnings announcements. Mathew and Findlay (2006) find that, on average, analysts' forecast accuracy post FD declined; however, analysts who were less accurate before the regulation became more accurate post FD, and those who were more accurate pre regulation became less accurate post regulation. This trend indicates that the discrepancy of access to selective information among analysts has declined after the Regulation FD. Mohanram and Sunder (2006) find that after the implementation of Regulation FD, there has been a smaller difference in the amount of effort exerted by analysts to detect idiosyncratic information.

Baiman and Verrecchia (1995) as well as Leuz and Wysocki (2006) conclude that more disclosure affects market liquidity and lowers the cost of capital. They argue that more disclosure reduces the information asymmetries among investors and causes uninformed or less informed investors not to worry about trade with informed investors. They conclude that more disclosure reduces uncertainty about firm value. In another study, Stulz (2009) concludes that disclosure helps to reduce agency costs.

In short, prior studies suggest that the market rewards companies that meet or beat the analysts' expectations, such that the forecasts made by analysts and the accuracy of the forecasts play an important role in the efficiency of the market. Prior research, however, does not address whether and to what extent analysts use KPIs in their forecasts. In short, access to more reliable and timely information reduced market uncertainty as a result of KPI reporting, and higher reporting quality can result in more accurate and reliable forecasts by analysts. Any effort to improve the accuracy of the forecasts adds value to the efficiency of the stock market. Our study contributes to the findings of prior research by examining the possible association between the change in KPI disclosures and analysts' forecast accuracy. We posit that more transparency through more KPI disclosure contributes to more accurate analyst forecasts. In particular, we hypothesise that the disclosure of more non-financial KPIs is expected to increase the amount of idiosyncratic information available to analysts, which will increase the overall analysts' forecast accuracy. Therefore, we hypothesise that:

H: KPI reporting disclosure is positively associated with analysts' forecast accuracy.

SAMPLE, DATA AND METHODOLOGY

Sample

Our data include a random sample of 156 companies listed on the S&P 500, a random sample of 135 manufacturing companies listed on the NYSE, and a random sample of 113 oil and gas companies listed on the NYSE. The choice of S&P 500 companies is based on the importance of the economic impacts of large companies, and the choice of manufacturing and oil and gas companies is based on the importance of social, environmental, and sustainability reporting in these companies. All samples are randomly selected from their populations. Given the nature of manual collection of KPI data, the sample sizes are sufficiently increased to be more cost-effective and reliable in extending the results obtained from samples to the whole population. The main reason for choosing three different samples is to compare the degree of observed association between KPI disclosure and forecast accuracy among selected industries.

Contrary to prior research studies, such as Lambert and Larcker (1987) and Ittner and Larcker (1998), which have employed a cross-sectional regression model with only a one-year observation period, we have examined a two-year period, 2006 and 2007, with manually collected data from approximately 400 companies and 800 observations. Furthermore, in some cases, to calculate the change in the lag of some variables and the variances of some variables, we have extracted data for three to five years.

Data

We have collected our data from company websites, the Research Insight database, CRSP database, and 10-Ks filed with the SEC. Furthermore, to determine the extent of KPI disclosure, the data from the Research Insight database and the LexisNexis Academic Business library database for 10-K filings were for the fiscal years ending on 31 December 2006 and 2007. We then examined the sample companies' 10-K filings, the Management Discussion and Analysis (MD&A) and other information disclosed in these documents and search for disclosures of factors that prior studies consider to be critical success factors beyond conventional financial reporting. Using the detailed information listed in Appendix A, we determined the extent of both financial and non-financial KPI disclosure according to the following eight KPI perspectives:

1. investor perspective
2. employee perspective
3. customer perspective
4. supplier perspective
5. social perspective
6. internal perspective
7. innovation perspective
8. environmental perspective

To calculate KPI variables, we have used content analysis, whereby the KPI index is calculated as a ratio of the total number of KPI key words disclosed to the total number of words included in the companies' Management Discussions and Analyses. We use content analysis, which has become a widely accepted method in the business literature (e.g., Marston & Polei, 2004; Guthrie et al., 2004; Striukova et al., 2008), to identify the extent of KPIs being disclosed in MD&As. The method of content analysis for analysing non-financial information has also been extensively used in accounting literature (e.g., Unerman, 2000; Furrer et al., 2008). We used the "myWORDCOUNT" software to count the sentences and words in MD&As. The words were further classified into financial and non-financial KPIs. While this approach may not be considered the most robust measure of KPI disclosure, it is the simplest, the most dependable, and the least subjective way of analysing the contents of MD&As and determining the extent of KPI disclosures. All analysts' earnings forecasts are calculated based on the individual analysts' forecasts reported in the latest edition of the Institutional Brokers' Estimate System (I/B/E/S). Financial data are mainly extracted from the Research Insight database and the Center for Research in Security Prices (CRSP).

Methodology

We examine the association between the extent of change in KPI disclosure and the accuracy of the forecasts made by analysts. This study includes three sets of data for two years (2006 and 2007). We originally began with a sample of 200 companies from each industry and concluded with companies that had complete data for both 2006 and 2007. All companies in related populations are numbered starting from 1, and we used a table of random numbers to select our sample companies from each industry. Our final samples include a random sample of 156 companies listed on S&P 500, a random sample of 135 manufacturing companies listed on the New York Stock Exchange (NYSE), and a random sample of 113 oil and gas companies listed on the NYSE. We choose a random sample of S&P 500 companies because of the importance of the economic impacts of large companies. Furthermore, the choice of manufacturing and oil and gas companies is based on the importance of social, environmental, and sustainability reporting in these industries (e.g., Laine, 2010; Johansen, 2010).

Consistent with prior studies (e.g., Gu & Wu, 2003; Dhaliwal et al., 2010), to test the association between the change in KPI reporting (DFKPI and DNFKPI) and analyst forecast accuracy (ABSFE), we have employed the following multivariate linear regression model. In this model, we control for the variance of Return on Equity (VAROE), sales growth (SALG), size of the company (SIZE), market risk (DBETA), leverage or borrowing (DLVRG), liquidity (DCASH), growth (DMK/BK), profitability (DPROFIT), and industry classification (INDs).

$$ABSFE_i = \beta_0 + \beta_1 DFKPI_i + \beta_2 DNFKPI + \beta_3 VAROE_i + \beta_4 SALG_i + \beta_5 SIZE_i + \beta_6 DBETA +$$

$$\beta_7 DLVRG + \beta_8 DCASH + \beta_9 DMK / BK + \beta_{10} DPROFIT + \sum_{j=11}^{K+9} \beta_j INDS_{ji} + v_i \tag{1}$$

We have employed the most recent I/B/E/S median analysts' earnings-per-share available prior to each earnings announcement date to determine the absolute value of analysts' forecast errors (ABSFE) as the difference between the actual (AE) and forecasted earnings per share (EE):

$$ABSFE_i = \left| AE_i - EE_i \right| \tag{2}$$

The definitions of all variables are presented in Appendix B. The control variables are chosen based on the same justifications applied in prior studies. The significance of the coefficient of change in KPIs indicates an association between KPI disclosure and the analyst forecast accuracy. We expect the sign to be negative.

ANALYSES AND RESULTS

Descriptive Statistics and Univariate Analysis

Table 1 shows the descriptive statistics for the independent variables used in this study. In Table 1, the first two columns show the descriptive statistics for a random sample of 156 companies listed on the S&P 500, the second two columns show the descriptive statistics for a random sample of 135 manufacturing companies listed on the NYSE, and the last two columns show the descriptive statistics for a sample of 113 oil and gas companies listed on the NYSE. The correlation matrices for these three random samples are presented in Table 2.

Table 1
Descriptive statistics for analysts' forecasts

S&P 500 Companies			Manufacturing		Oil and Gas	
Variable	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
DFKPI	.028	1.951	.038	1.563	.195	2.789
DNFKPI	.013	.879	–.022	.784	.223	1.305
VAROE	41	238	15	76	81	373
SALG	.232	.584	.172	.355	.731	4.247
SIZE	7.193	2.197	7.114	2.372	6.582	2.242
DBETA	.0348	.781	.1121	.680	.180	1.027
DLVRG	.0118	.111	.006	.107	.361	3.524
DCASH	–.0135	.102	–.0137	.100	–.015	.120
DMK/BK	.207	4.867	1.401	14.981	–.371	5.602
DPROFIT	–.031	.183	–.0268	.164	–1.623	16.830

All panels of Table 2 demonstrate that financial and non-financial KPIs are highly correlated with each other; therefore, to avoid the problem of multicollinearity, we have dropped the financial KPIs and focused only on disclosure of non-financial KPIs. As a result, we have modified the original model used in our analyses. That is, the model that we have employed in our analyses does not include the change in financial KPI.

Table 2
Pearson correlations for the sample of all industries

Panel A: A random sample of 156 companies from S&P 500

Variable	DFKPI	DNFKPI	VAROE	SALG	SIZE	DBETA	DLVRG	DCASH	DMK/BK
DFKPI	1.00								
DNFKPI	0.90***	1.00							
VAROE	0.05	0.06	1.00						
SALG	0.00	0.01	0.36***	1.00					
SIZE	–0.03	–0.06	–0.06	–0.16**	1.00				
DBETA	0.01	0.00	–0.09	–0.09	0.05	1.00			
DLVRG	0.12	0.19**	0.10	0.16*	–0.23**	0.07	1.00		
DCASH	0.05	0.11	0.05	–0.09	0.11	0.11	–0.13	1.00	
DMK/BK	0.01	0.02	–0.08	–0.05	0.12	0.03	0.01	0.06	1.00
DPROFIT	0.03	–0.03	–0.04	0.19**	0.19**	0.06	–0.15*	–0.05	0.14

Panel B: A random sample of 135 companies from manufacturing industry

Variable	DFKPI	DNFKPI	VAROE	SALG	SIZE	DBETA	DLVRG	DCASH	DMK/BK
DFKPI	1.00								
DNFKPI	0.87***	1.00							
VAROE	0.01	0.11	1.00						
SALG	–0.11	–0.21**	–0.08	1.00					
SIZE	–0.10	–0.09	–0.03	–0.04	1.00				
DBETA	0.02	0.02	0.02	0.02	0.05	1.00			
DLVRG	0.09	0.08	–0.19**	0.14	–0.19**	–0.04	1.00		
DCASH	0.07	0.08	0.06	–0.06	0.22***	0.04	–0.18**	1.00	
DMK/BK	0.00	0.00	0.17**	–0.02	0.01	–0.03	–0.11	–0.02	1.00
DPROFIT	–0.05	–0.07	–0.16**	0.02	0.13	0.14	–0.53***	0.12	–0.01

Panel C: A random sample of 113 companies from oil and gas industry

Variable	DFKPI	DNFKPI	VAROE	SALG	SIZE	DBETA	DLVRG	DCASH	DMK/BK	DPROFIT
DFKPI	1.00									
DNFKPI	0.93***	1.00								
VAROE	0.01	–0.02	1.00							
SALG	0.17*	0.31***	0.25***	1.00						
SIZE	–0.07	–0.08	–0.12	–0.14	1.00					
DBETA	–0.06	–0.04	–0.3***	–0.16	–0.05	1.00				
DLVRG	–0.02	–0.05	–0.07	0.18*	–0.5***	–0.18	1.00			
DCASH	0.11	0.15	0.01	–0.18*	0.19*	0.26**	–0.53***	1.00		
DMK/BK	0.10	0.10	–0.17*	–0.06	0.15	0.08	–0.04	0.12	1.00	
DPROFIT	0.02	0.05	0.15	0.22**	0.49***	0.18	–.90***	0.53***	0.04	1.00

***, **, *, significance at 0.01, 0.05, and 0.10 level, respectively.

Multivariate Analysis

Our multivariate model tests the association between the analysts' forecast accuracy and the extent of non-financial KPI disclosures. Prior studies use both deflated earnings forecast errors (the dependent variable of this study), to correct for error variance, and non-deflated earnings forecasts. Those who deflate earnings forecasts argue that the deflation corrects for heteroscedasticity and non-normality. To deflate earnings forecasts, some researchers use the absolute value of actual earnings per share (e.g., Capstaff et al., 1995, 2001), some use the standard deviation of prior earnings (e.g., De Bondt & Thaler, 1990), and others use the stock price (e.g., Duru & Reeb, 2002, Easterwood & Nutt, 1999; Keane & Runkle, 1998). However, Clatworthy et al. (2007) argue that the approach used in prior studies to deflate actual and forecasted Earnings Per Share (EPS) invalidates the inferences made from the regression results. In this study, we have used both non-deflated and deflated approaches and have reported the results separately for (a) results with no deflation and (b) results using the stock price for deflating the dependent variable.

Results with no deflation

The results of testing our hypothesis with no deflation of the dependent variable using linear regression are shown in Table 3. The first two columns of Table 3 show the results of estimating the model using data from a random sample of companies from all industries listed on the S&P 500. As these two columns demonstrate, the coefficient of change in non-financial KPIs is not significant, indicating that our hypothesis is not supported. The second two columns of Table 3 show the results of estimating the model using data from a sample of manufacturing companies. As these two columns show, the coefficient of change in non-financial KPIs is not significant, again indicating that the hypothesis is not supported when the study is limited to companies in the manufacturing industry. Finally, the last two columns of Table 3 show the results of estimating the model using data from a sample of companies in the oil and gas industry. Similar to the other two samples discussed above, the results show that the coefficient of change in non-financial KPIs is not significant, indicating that the hypothesis is not supported for when the study is limited to the companies in the oil and gas industry.

The diagnostic tests of the residuals of the above linear regressions and the use of an econometric technique of goodness of fit for model selection have shown that a non-linear model can better explain the association between the absolute value of forecast errors and a change in the non-financial KPI index and other independent variables. The application of non-linear models is common in the accounting literature, and the most commonly used non-linear models are the Logit models, in which the dependent variable is a dichotomous variable (i.e., Stone & Rasp, 1991; Barniv & McDonald, 1999; Jones & Hensher, 2004, 2007; Ge & Whitmore, 2005; Baxter et al., 2007). Another non-linear model that we have used in our study is the optimal scaling model.

ZDNet (2003) briefly reviewed the optimal scaling regression and posits that the Data Theory Group at Leiden University in the Netherlands has developed the optimal scaling approach; this approach was applied to the analysis of multivariate data that are not quantitative, not distributed normally, or are incomplete. The paper posits that the optimal scaling can easily account for the non-linear relationship between the variables of interest. Therefore, in our study, we rerun our models using the optimal scaling regression to account for the observed non-linearity.

Table 3

The results for analysts' forecast accuracy using first digit SIC industry codes with no deflation of dependent variable

$$ABSFE_i = \beta_0 + \beta_1 DNFKPI + \beta_2 VAROE_i + \beta_3 SALG_i + \beta_4 SIZE_i + \beta_5 DBETA +$$
$$\beta_6 DLVRG + \beta_7 DCASH + \beta_8 DMK / BK + \beta_9 DPROFIT + \sum_{j=10}^{K+8} \beta_j INDS_{ji} + v_i$$

Sample of:	S&P 500 (N = 156)		Manufacturing (N = 135)		Oil and Gas (N = 113)	
	Coeffi.	*t*-stat	Coeffi.	*t*-stat	Coeffi.	*t*-stat
(Constant)	–.002	–.004	.642	1.515	.033	1.903*
DNFKPI	.012	.103	.136	.966	–.003	–1.269
VAROE	–.000	–.188	–.000	–.391	–.000	–1.438
SALG	.068	.229	.526	1.418	.022	2.284**
SIZE	.030	.567	–.047	–.877	–.003	–1.480
DBETA	.057	.352	.349	2.189**	–.006	–1.035
DLVRG	.075	.072	1.603	1.048	.014	.519
DCASH	.168	.174	–1.946	–1.709	.057	1.480
DMK/BK	.011	.535	.035	.528	–.004	–1.233
DPROFIT	–.780	–1.036	–.338	–.373	–	–
INDS_1	.001	.002				
INDS_2	–.124	–.175				
INDS_3	.145	.605				
INDS_4	–.260	–.468				
INDS_5	–.166	–.236				
INDS_6	2.139	3.56***				
INDS_7	–.288	–.540				
Adj. R-quared		.009		.047		.015
F-stat		1.057		1.597		1.096

***, **, * Significance at the 0.01, 0.05 and 0.10 level, respectively.

Where:

$ABSFE_j$ = absolute value of forecast error per share (actual minus forecasted earnings per share) for firm j.

$DBETA_j$ = Change in Firm's exposure to systematic risk (beta)

$DCASH_j$ = Change in the sum of cash and short term investments divided by total assets for firm j.

$DLVRG_j$ = Change in total liabilities divided by total assets for firm j.

DMK / BK_j = Change in market to book ratio at the end of the year for firm j.

$DPROFIT_j$ = Change in earnings divided by total assets for firm j.

$DNFKPI_j$ = firm *j*'s change in nonfinancial KPIs in year *T* (total number of nonfinancial KPI key words disclosed to total words included in the company's MD&A)
$INDS_j$ = *K* industry dummy variables (*K* is the number of industries included in the sample) for firm *j*.
$SALG_j$ = Growth in sales revenue (sales in current year minus sales in previous year divided by sales in the previous year) for firm *j*.
$SIZE_j$ = Size measured as the natural log of total assets for firm *j*.
$VAROE_j$ = variance of ROE, measured based on yearly average of historical data for the last five years before 2007 for firm *j*.

Table 4
The results for analysts' forecast accuracy using optimal scaling with no deflation of dependent variable

$$ABSFE_i = h(DNFKPI_i, VAROE_i, SALG_i, SIZE_i, DBETA_i, DLVRG_i, DCASH_i, DMK / BK_i, DPROFIT_i)$$

Sample of:	S&P 500 (*N* = 156)		Manufacturing (*N* = 135)		Oil and Gas (*N* = 113)	
	Coeffi.	*F*-stat	Coeffi.	*F*-stat	Coeffi.	*F*-stat
DNFKPI	–.156	2.97*	–.363	17.84***	–.315	6.91***
VAROE	–.109	1.462	–.233	6.69***	–.354	4.484**
SALG	–.153	2.459	.185	4.394**	–	–
SIZE	–.182	3.54**	–.165	3.735*	.272	4.433**
DBETA	.339	13.22***	.235	7.85***	–.522	10.79***
DLVRG	–.215	4.82***	.050	.343		
DCASH	–.167	3.030*	–.119	1.973	.309	6.619**
DMK/BK	.063	.496	–.051	.332	–.389	9.48***
DPROFIT	–	–	–.325	13.66***	–	–
Adj. R-squared		.127		.252		.215
F-stat		2.008**		3.298***		2.348**

***, **, * Significance at the 0.01, 0.05 and 0.10 level, respectively.

Where:
$ABSFE_j$ = absolute value of forecast error per share (actual minus forecasted earnings per share) for firm *j*.
$DBETA_j$ = Change in Firm's exposure to systematic risk (beta)
$DCASH_j$ = Change in the sum of cash and short term investments divided by total assets for firm *j*.
$DLVRG_j$ = Change in total liabilities divided total assets for firm *j*.
DMK / BK_j = Change in market to book ratio at the end of the year for firm *j*.

$DPROFIT_j$ = Change in earnings divided by total assets for firm *j*.
$DNFKPI_j$ = firm *j*'s change in nonfinancial KPIs in year *T* (total number of nonfinancial KPI key words disclosed to total words included in the company's MD&A)
$INDS_j$ = *K* industry dummy variables (*K* is the number of industries included in the sample) for firm *j*.
$SALG_j$ = Growth in sales revenue (sales in current year minus sales in previous year divided by sales in the previous year) for firm *j*.
$SIZE_j$ = Size measured as the natural log of total assets for firm *j*.
$VAROE_j$ = variance of ROE, measured based on yearly average of historical data for the last five years before 2007 for firm *j*.

The results of rerunning the non-linear regression models are shown in Table 4. The first two columns of Table 4 show the results of estimating the model using data from a sample of S&P 500 companies. As these two columns show, the coefficient of change in non-financial KPIs is marginally significant, thereby marginally supporting the hypothesis of this paper. Other significant coefficients are those of SIZE (negative), DBETA (positive), DLVRG (negative), and change in liquidity (DCASH), which is marginally significant (negative). The second two columns of this table show the results of estimating the model using data from a sample of manufacturing companies. As these two columns show, the coefficient of change in non-financial KPIs is highly significant, thereby supporting the hypothesis of this paper. Other significant coefficients are those of VAROE (negative), SALG (positive), DBETA (positive), DPROFIT (negative), and SIZE, which is marginally significant (negative). The last two columns of Table 4 show the results of estimating the model using data from the sample of oil and gas companies. As these two columns show, the coefficient of change in non-financial KPIs is highly significant, which provides support for the hypothesis of this paper. Other significant coefficients are those of VAROE (negative), SIZE (positive), DBETA (negative), change in liquidity (DCASH) (positive), and change in the market-to-book ratio (DMK/BK) (negative).

Results using stock price for deflating the dependent variable

Table 5 summarises the results for when the stock price at the end of the year is used to deflate the dependent variable of this study. As the results indicate, compared with the results reported in Table 3, the explanatory powers of regressions for all three samples have clearly improved. However, the coefficients of change in non-financial KPIs are not statistically significant, providing no support for the hypothesis of this study. It appears that using the stock price to deflate the dependent variable for the sample of S&P 500 companies is inappropriate. The first two columns of Table 5 show that for a random sample of S&P 500 companies, the coefficients of SIZE and DLVRG are significant and the coefficient of change in liquidity (DCASH) is marginally significant. These three coefficients have negative signs, while the coefficient of change in BETA (DBETA) is significant and has a positive sign. The second two columns of Table 5 show that for a random sample of manufacturing companies, the coefficients of VAROE and change in PROFIT (DPROFIT) are significant and the coefficient of SIZE is marginally significant, with all coefficients having negative signs, while the coefficients of change in BETA (DBETA) and SALG are significant with positive signs. Finally, the last two columns of Table 5 show that for a sample of companies from the oil and gas industry, the coefficients of change in BETA and change in market-to-book ratio (DMK/BK) are significant and negative. The coefficient of VAROE is also significant and negative. Finally, the coefficients of SIZE and change in liquidity (DCASH) are significant with positive signs. These results generally indicate that analysts are more accurate in their earnings forecasts for large and risky companies and less accurate for companies that have sales growth.

The results for running the non-linear version of the above model (after deflating the dependent variable) are presented in Table 6. The first two columns of Table 6 show the results for estimating the model using data from a sample of S&P 500 companies. As these two columns indicate, the coefficient of change in non-financial KPIs (DNFKPI) is highly significant and has the expected sign, thereby supporting the hypothesis of this paper. This finding indicates that for S&P 500 sample companies, the disclosure of non-financial KPIs is associated with analysts' forecast accuracy. Other significant coefficients are those of VAROE (negative), SALG (positive), SIZE (negative), change in BETA (DBETA) (negative), and change in LVRG (DLVRG) (positive). The second two columns of this table show the results of estimating the model using data from a sample of manufacturing companies. As these two columns indicate, the coefficient of change in non-financial KPIs (DNFKPI) is highly significant, thereby supporting the hypothesis of this paper and indicating an association between non-financial KPI reporting and analysts' forecast accuracy. Other significant coefficients are those of VAROE (negative), SALG (negative), SIZE (negative), and change in market-to-book ratio (DMK/BK) (negative). The last two columns of Table 6 show the results of estimating the model using data from the sample of oil and gas companies. As these two columns indicate, the coefficient of change in non-financial KPIs (DNFKPI) is not significant, which does not support the hypothesis of this paper for oil and gas companies. Other significant coefficients are those of VAROE (negative), SIZE (negative), DBETA (negative), change in liquidity (DCASH) (positive), and change in market-to-book ratio (DMK/BK) (negative).

Table 5
The results for analysts' forecast accuracy using first digit SIC industry codes using stock price for deflation of dependent variable

$$ABSFE_i = \beta_0 + \beta_1 DNFKPI + \beta_2 VAROE_i + \beta_3 SALG_i + \beta_4 SIZE_i + \beta_5 DBETA + \beta_6 DLVRG + \beta_7 DCASH + \beta_8 DMK/BK + \beta_9 DPROFIT + \sum_{j=10}^{K+8} \beta_j INDS_{ji} + v_i$$

Sample of:	S&P 500 (N = 156)		Manufacturing (N = 135)		Oil and Gas (N = 113)	
	Coeffi.	t-stat	Coeffi.	t-stat	Coeffi.	t-stat
(Constant)	.118	3.63***	.234	4.00***	.033	1.903*
DNFKPI	–.005	–.551	.003	.147	–.003	–1.269
VAROE	–.000	–1.450	–.000	–.032	–.000	–1.438
SALG	–.019	–.979	.049	.970	.022	2.284**
SIZE	–.012	–3.36***	–.028	–3.77***	–.003	–1.480
DBETA	–.004	–.408	.024	1.113	–.006	–1.035
DLVRG	.141	1.98**	.331	1.544	.014	.519
DCASH	.037	.599	–.260	–1.69*	.057	1.480
DMK/BK	.001	.709	–.004	–.497	–.004	–1.233
DPROFIT	–.160	–3.32***	–.094	–.771	–	–
INDS_1	.021	.463				
INDS_2	.005	.120				
INDS_3	–.001	–.036				
INDS_4	.016	.458				
INDS_5	–.003	–.057				
INDS_6	.021	.536				
INDS_7	.005	.143				
Adj. R-squared		.142		.152		.157
F-stat		2.049**		3.106***		2.177**

***, **, * Significance at the 0.01, 0.05, and 0.10 level, respectively.

Where:
$ABSFE_j$ = absolute value of forecast error per share (actual minus forecasted earnings per share) for firm j.
$DBETA_j$ = Change in Firm's exposure to systematic risk (beta)
$DCASH_j$ = Change in the sum of cash and short term investments divided by total assets for firm j.
$DLVRG_j$ = Change in total liabilities divided by total assets for firm j.
DMK / BK_j = Change in market to book ratio at the end of the year for firm j.
$DPROFIT_j$ = Change in earnings divided by total assets for firm j.

$DNFKPI_j$ = firm *j*'s change in nonfinancial KPIs in year *T* (total number of nonfinancial KPI key words disclosed to total words included in the company's MD&A)
$INDS_j$ = *K* industry dummy variables (*K* is the number of industries included in the sample) for firm *j*.
$SALG_j$ = Growth in sales revenue (sales in current year minus sales in previous year divided by sales in the previous year) for firm *j*.
$SIZE_j$ = Size measured as the natural log of total assets for firm *j*.
$VAROE_j$ = variance of ROE, measured based on yearly average of historical data for the last five years before 2007 for firm *j*.

Table 6
The results for analysts' forecast accuracy using optimal scaling regression using stock price for deflation of dependent variable

$$ABSFE_i = h(DNFKPI_i, VAROE_i, SALG_i, SIZE_i, DBETA_i, DLVRG_i, DCASH_i, DMK/BK_i, DPROFIT_i)$$

Sample of:	S&P 500 (*N* = 156)		Manufacturing (*N* = 135)		Oil and Gas (*N* = 113)	
	Coeffi.	*F*-stat	Coeffi.	*F*-stat	Coeffi.	*F*-stat
DNFKPI	–.232	8.67***	–.125	6.798***	–.143	2.119
VAROE	–.362	17.70***	–.174	13.22***	–.551	17.31***
SALG	.177	5.76**	–.389	60.66***	–	–
SIZE	–.502	50.52***	–.637	207.2***	–.344	10.55***
DBETA	–.177	4.54**	.070	2.356	–.701	29.52***
DLVRG	.524	34.26***	–.065	2.109	–	–
DCASH	.071	.877	.048	1.108	.252	6.27**
DMK/BK	–.038	.256	–.180	13.04***	–.402	15.92***
Adj. R-squared		.481		.405		.495
F-stat		7.668***		30.09***		6.17***

***, **, * Significance at the 0.01, 0.05, and 0.10 level, respectively.

Where:
$ABSFE_j$ = absolute value of forecast error per share (actual minus forecasted earnings per share) for firm *j*.
$DBETA_j$ = Change in Firm's exposure to systematic risk (beta)
$DCASH_j$ = Change in the sum of cash and short term investments divided by total assets for firm *j*.
$DLVRG_j$ = Change in total liabilities divided by total assets for firm *j*.
DMK / BK_j = Change in market to book ratio at the end of the year for firm *j*.
$DPROFIT_j$ = Change in earnings divided by total assets for firm *j*.

$DNFKPI_j$ = firm *j*'s change in nonfinancial KPIs in year *T* (total number of nonfinancial KPI key words disclosed to total words included in the company's MD&A)
$INDS_j$ = *K* industry dummy variables (*K* is the number of industries included in the sample) for firm *j*.
$SALG_j$ = Growth in sales revenue (sales in current year minus sales in previous year divided by sales in the previous year) for firm *j*.
$SIZE_j$ = Size measured as the natural log of total assets for firm *j*.
$VAROE_j$ = variance of ROE, measured based on yearly average of historical data for the last five years before 2007 for firm *j*.

CONCLUSIONS

In this paper, we investigated the association between the change in non-financial KPI disclosures and the accuracy of analysts' forecasts using the absolute value of forecast errors, both with and without deflation. The stock price at the end of 2007 is used for deflation. The results of this study provide some preliminary evidence demonstrating that, in general, there is no significant association between the change in non-financial KPI disclosure and analysts' forecasts accuracy when a linear multivariable regression model is employed for analysis. However, using a nonlinear (optimal scaling) model, we have found a significant negative association between analysts' forecast accuracy, measured by the absolute value of forecast errors deflated by the stock price, and a change in non-financial KPI disclosures for a random sample of S&P 500 companies and a random sample of manufacturing companies, supporting the hypothesis of this study. The evidence shows that this association does not hold for a random sample of companies from the oil and gas industry. To some extent, our results are consistent with the findings of prior studies documenting the relevance of social disclosure for analysts in international financial markets (e.g., Dhaliwal et al., 2010) and the importance of disclosure for analysts' forecasts at the international level (e.g., Hope, 2002).

Additional findings of this study indicate that for a random sample of companies from the S&P 500, the accuracy of analysts' forecasts is higher when the variance of return on equity is larger, the company is larger in size, and the company is riskier, and the accuracy is lower when the company has a lower growth rate and has more debt. For a random sample of companies from manufacturing companies, the accuracy of analysts' forecasts is higher when the variance of return on equity is larger, the sales growth is larger, and the ratio of market-to-book value is larger. For a random sample of oil and gas companies, the accuracy of analysts' forecasts is higher when the variance of return on equity is larger, the company is larger in size, the company is riskier, and the market-to-book ratio is larger, and the accuracy is lower when the company has more cash and short-term investments.

This study is expected to contribute to the literature in several ways. First, we investigate the association between the extent of change in non-financial KPI reporting and analysts' forecast accuracy. To the best of our knowledge, this is the first study to address this issue. Second, we documented the existence of a non-linear relationship and questioned the use of linear regression models in these studies. Third, we extended the literature on the relevance of corporate voluntary disclosures. Finally, while the SEC and the U.S. Treasury department have shown growing interest in KPI disclosure, no empirical results are available to support such interest. The policy implication of this study in providing empirical evidence regarding the recommendations made by the ACIFR in 2008 is to encourage the SEC or FASB to define specific KPIs and require companies in each industry to consistently report them. The cross-sectional analysis conducted in this paper focuses only on data for a two-year period between 2006 and 2007. Future research is encouraged to focus on multiple-year observations of KPI disclosure as well as research on comparing mandatory versus voluntary KPI reporting.

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APPENDIX A

List of Key Performance Indicators (Adapted from Boesso, 2004, which is mainly based on Kaplan and Norton, 1996)

Investor Perspective

1. Stocks performance, shareholder and investor return (dividends, trends, EPS, stock and debt ratings)
2. Management's presentation of measures adopted as critical success factors (Balanced scorecard, milestone achievements, goals) (Sundin et al., 2010; De Geuser et al., 2009)
3. Non-mandatory analyses of profitability and financial structure (VA, Cash flow, ROI, ROE, Debts ratios, Pro-forma data)
4. Description of a total results by business/geographic units (% of total export)
5. Intangible Assets Monitor or Intellectual Capital Statement (value of assets internally developed)
6. Economic profit and value based management (EP, EVA)

Employee Perspective

7. Wages, contracts and benefits other than stock options (and pensions for U.S.) (avg. amount by category)
8. Training and internal education (hours, number of employees involved)
9. Employee compositions by professional category, age, country, minority (%, trends)
10. Number of employees, turnover and hiring/firing procedures (numbers, %, trends)
11. Productivity (volumes/sales/value added by employee)
12. Employee satisfaction, competence and commitment (indices, surveys)

Customer Perspective

13. Main customers, contractual relationships, prices, bargaining power (average numbers, purchases, products or services bought)
14. Geographic diversification and characteristic of retail network (%, number of dealers)
15. Market share, penetration and benchmarking with competitors (%, trends)
16. Brands, license and trademarks (numbers, value creation, evaluation)
17. Customer satisfaction, retention, loyalty (indices, surveys, complains, defects, warranty claims, repeat sales)
18. Customer profitability and reliance (indices, trends)

Supplier Perspective

19. Main suppliers, contractual relationship and bargaining power (average numbers, discounts)
20. Geographic diversification and policies (%, trends)
21. Partnership, alliances' operational data and firm specific investments (value, %)
22. Certified quality of partners and inputs (numbers, quantities of raw materials, services)
23. Supplier satisfaction, retention, commitment (indices, surveys)
24. Cost accounting for suppliers (cost saving and indices)

Social Community Perspective

25. Donations and other social expenses, without quoting the programs' details and results (amount, %)
26. Description of social, ethic activities and projects (information about the project)

27. Diversity and equal opportunities (%, distribution)

Internal Processes Perspective

28. Product capacity, acquisition, synergies, reorganisations project. Analysis of services and investments for banks and insurances
29. Nature of the main industry: structure, cyclicability, seasonality (timing, %, trends) - direct quote to company's performance/strategy
30. Total quality management products and services (warranty claims, defects, ranking, ISO9000, ratings for banks' products)
31. Cost accounting and cost saving by country, production line or project (%, amounts, operating cost per employee)
32. Manufacturing cycle time, internal service responsiveness, effectiveness, and productivity (hours, days, delivery and waiting time)
33. Outsourcing, digitalisation and internationalisation of processes (%, geographical distribution, volumes)

Innovation and Learning Perspective

34. Processes' innovations, patents, standards, suggestion developed (numbers, value)
35. R&D projects and expenditure (numbers, employees, %, trends) – description of specific projects or growth
36. New products, projects, reserves, services, customers (numbers, objective, market share, investments)
37. Decision making, segment strategy and responsibilities maps (levels, objectives, parameters)
38. Time to market of new products/strategies/contracts (days, months, costs)
39. Historical product's life cycle analysis (timing, market share, trends)

Environmental Perspective

40. Environmental performance and social impact (awards, consumption rate, toxic emission, etc.)
41. Litigations, legal actions and claims, included accounting litigations (expenses, number)
42. Environmental profitability and cost accounting (ratios, trends, indices, value added)

APPENDIX B

Definitions of Variables

$ABSFE_j$ = absolute value of forecast error per share (actual minus forecasted earnings per share) for firm j.
$DBETA_j$ = Change in firm's exposure to systematic risk (beta)
$DCASH_j$ = Change in the sum of cash and short term investments divided by total assets for firm j.
$DLVRG_j$ = Change in total liabilities divided by total assets for firm j.
DMK / BK_j = Change in market to book ratio at the end of the year for firm j.
$DPROFIT_j$ = Change in earnings divided by total assets for firm j.
$DFKPI_{j,T}$ = firm j's change in financial KPIs in year T (total number of financial KPI key words disclosed to total words included in the company's MD&A)
$DNFKPI_j$ = firm j's change in nonfinancial KPIs in year T (total number of nonfinancial KPI key words disclosed to total words included in the company's MD&A)
$INDS_j$ = K industry dummy variables (K is the number of industries included in the sample) for firm j.
$SALG_j$ = Growth in sales revenue (sales in current year minus sales in previous year divided by sales in the previous year) for firm j.
$SIZE_j$ = Size measured as the natural log of total assets for firm j.
$VAROE_j$ = variance of ROE, measured based on yearly average of historical data for the last five years before 2007 for firm j.