Can the Balanced Scorecard Help in Designing Conference Calls? The Effect of Balanced Information Composition on the Cost of Capital

Firk, Sebastian; Hennig, Jan Christoph; Wolff, Michael

Published in:
European Accounting Review

DOI:
10.1080/09638180.2019.1709523

Can the Balanced Scorecard Help in Designing Conference Calls? The Effect of Balanced Information Composition on the Cost of Capital

Sebastian Firk, Jan C. Hennig & Michael Wolff

European Accounting Review, 2020
Vol. 29, No. 1, 115–146, https://doi.org/10.1080/09638180.2019.1709523

Check for updates

Can the Balanced Scorecard Help in Designing Conference Calls? The Effect of Balanced Information Composition on the Cost of Capital

SEBASTIAN FIRK*, JAN C. HENNIG** and MICHAEL WOLFF**

*Department of Accounting, University of Groningen, Groningen, Netherlands; **Chair of Management and Control, University of Goettingen, Goettingen, Germany*

(*Received: November 2017; accepted: December 2019*)

Abstract Most recent studies on conference calls focus on the costs for firms that can arise from the calls' open nature. We study the benefits of conference calls and hypothesize that firms could use the balanced scorecard concept as a framework for presenting the information (i.e. balanced information composition) in conference calls to lower the cost of capital. Our results show a negative association between a more balanced information composition in conference calls and a firm's cost of capital. Additional tests substantiate that the effect of such a balanced information composition on the cost of capital is driven by a reduction in information asymmetry. Overall, the findings suggest that firms can benefit from the balanced scorecard concept by using it as a framework for preparing their conference calls.

Keywords: Earnings Conference Calls; Cost of Capital; Balanced Scorecard; Textual Analysis

JEL classifications: G14; L2; M41

1. Introduction

Earnings conference calls are an important capital market channel to communicate information. Insights from practice and research reveal uncertainty among firms when facing a variety of design choices in the open nature of conference calls. For example, instead of experimenting with more informative formats (Rehm, 2013), managers adhere to predetermined scripts and even refrain from answering questions as they fear the risks arising from the unintended disclosure of negative information (Hollander, Pronk, & Roelofsen, 2010; Lee, 2016). However, given the variety of design choices in conference calls, there may be potential for firms to lower their cost of capital by reducing information asymmetries (Brown, Hillegeist, & Lo, 2004). This falls in

Correspondence Address: Jan C. Hennig, Chair of Management and Control, University of Goettingen, Goettingen, Germany.
Email: jan-christoph.hennig@wiwi.uni-goettingen.de

Paper accepted by Reuven Lehavy and Florin Vasvari, Guest editors for the Special issue on Textual analysis research in accounting.

line with practitioners, who have started to push for advice on handling conference calls more effectively (Rehm, 2013).

In the recent literature, the predominant perspective on the open nature of conference calls seems to focus on firms' costs (e.g. from the unintended disclosure of negative information) instead of on the potential benefits (e.g. Brochet, Loumioti, & Serafeim, 2015; Hollander et al., 2010; Lee, 2016). This is surprising, because initial conference call studies stressed the specific benefits of conference calls in bridging the gap between managers and investors by reducing information asymmetry in the long term (Brown et al., 2004; Frankel, Johnson, & Skinner, 1999; Tasker, 1998). However, these initial studies focused on the decision regarding whether to hold a conference call, while specific courses of action about how firms can exploit the design choices of conference calls are rather limited in the literature.[1] To provide a specific course of action, in this study we propose the balanced scorecard concept as a framework for firms to better present the information in conference calls.

The balanced scorecard complements financial information with customer, internal processes, and learning and growth information to overcome the shortcomings of purely financial information (Kaplan & Norton, 1992). Kaplan and Norton proposed the balanced scorecard as a tool for internal communications to help managers implement their corporate strategy (Kaplan & Norton, 1993, 1996). The balance among the four perspectives should thereby enable a more holistic presentation of a firm's business in a condensed form (De Geuser, Mooraj, & Oyon, 2009; Kaplan & Norton, 1993). This balance may also be beneficial in the context of external communications as financial analysts and investors require both non-financial as well as financial information (Brown, Call, Clement, & Sharp, 2015). In this light, we argue that firms and their investor relations (IR) teams could lean on the balanced scorecard concept as a framework with which to prepare the information content of their conference calls (i.e. balanced information composition). By doing so, firms could reduce information asymmetry and consequently lower their cost of capital.[2]

To test our prediction, we develop a proxy for information composition in line with the balanced scorecard concept using computer-aided text analysis (CATA). We construct word lists for the four balanced scorecard perspectives: finance, customer, internal processes, and learning and growth. For each perspective, we measure the occurrences (i.e. word counts) in firms' quarterly conference calls. Next, based on the word counts of the four perspectives, we calculate a reversed version of the Gini coefficient to derive a measure of balanced information composition (*BIC*) for each call.[3] We use a sample of S&P 500 firms for the period from 2004 to 2013 consisting of 7536 quarterly earnings conference call transcripts. To proxy for the cost of capital, we rely on extensive previous research and use the average of several different proxies for the implied cost of capital (e.g. Dhaliwal, Judd, Serfling, & Shaikh, 2016; Hail & Leuz, 2006). Using generalized method of moments (GMM) regressions, we find that firms with a more balanced information composition in conference calls experience a lower cost of capital, thus suggesting that the open

[1]In addition to this, the study by Matsumoto et al. (2011) goes further and demonstrates the informativeness of the content of conference calls beyond accompanying press releases from an investor-focused perspective. In contrast, our study intends to take a managerial perspective by proposing a framework that lays out a specific course of action for firms to prepare their information composition in a beneficial (value-creating) manner.

[2]We follow a frequent assumption in the disclosure literature and expect a reduction in information asymmetry to lower a firm's cost of capital (e.g., Armstrong et al., 2011; Brown et al., 2004; Diamond & Verrecchia, 1991). A lower cost of capital resulting from the presentation of information in conference calls seems plausible as conference calls are meant to help investors and analysts comprehend existing information from the earnings announcement.

[3]The Gini coefficient determines the inequality among values of a frequency distribution using the Lorenz curve. It measures the ratio of the area between the Lorenz curve and the egalitarian line (i.e., a 45-degree line) relative to the entire area under the egalitarian line. Larger values of the Gini coefficient imply greater inequality.

nature of conference calls can bring benefits to firms. To substantiate our findings, we run a battery of robustness tests with alternative specifications including alternative variable specifications and a two-stage least squares (2SLS) model. Across all of the robustness tests, the results remain quantitatively and qualitatively similar.

In additional tests, we focus on the underlying mechanism that explains the negative relation between the balanced information composition and the cost of capital. First, we investigate whether the observed effect is simultaneously determined by alternative information dimensions. We find that after controlling for the influence of a set of selected information dimensions (i.e. forward-looking to backward-looking, long-term to short-term, non-financial to financial, non-quantitative to quantitative, and corporate social responsibility (CSR) to other), the effect of our measure of balanced information composition remains robust. Second, we analyze the relevance of the balance between the four perspectives in contrast to alternative composition forms for the observed cost of capital effect. Therefore, we construct variables proxying for alternative forms of information composition based on our self-developed word lists (such as the ratio of the three non-financial perspectives to the financial perspective) that gradually converge to the proposed balance between the four perspectives. The results highlight the relevance of more balance between all four perspectives. Third, we conduct a contextual analysis to gain a better understanding of the channel (i.e. reduced information asymmetry) underlying the reduction in the firms' cost of capital. Specifically, we investigate situations involving increased uncertainty when information asymmetry tends to be higher and where voluntary disclosure should be particularly effective (Chen, DeFond, & Park, 2002). We find that the effect of a balanced information composition on the cost of capital is more pronounced when the firm's capital market environment faces greater uncertainty. Fourth, we relate balanced information composition to potential drivers of the cost of capital. Based on prior literature, we consider a reduction in information asymmetry (e.g. Armstrong, Core, Taylor, & Verrecchia, 2011; Lambert, Leuz, & Verrecchia, 2012), decreased illiquidity (e.g. Balakrishnan, Billings, Kelly, & Ljungqvist, 2014; Diamond & Verrecchia, 1991), and the simultaneous generation of positive new information (Kothari, Li, & Short, 2009) as potential drivers of a lower cost of capital. The tests show a negative relation between balanced information composition and information asymmetry as well as illiquidity, which is frequently associated with a reduction in information asymmetry (Balakrishnan et al., 2014; Leuz & Verrecchia, 2000). Simultaneously, we find no change in cumulative abnormal returns, which indicates that the generation of new information as the main driver behind the effect is unlikely. In sum, the tests show that information asymmetry is the main driver behind the effect on the cost of capital.

This paper contributes to the literature in several ways. First, we add to the previous conference call literature by highlighting how firms can make use of the benefits of the open nature of conference calls (e.g. Hollander et al., 2010; Lee, 2016). Specifically, our study indicates that conference calls can bridge the gap between managers and investors by reducing information asymmetry (Brown et al., 2004; Tasker, 1998). Second, we specify how firms can better communicate with the market. We propose the use of the balanced scorecard concept, which complements the financial perspective with additional information perspectives in conference calls and we demonstrate how this can support a lower cost of capital. In this vein, we expand the application of the balanced scorecard concept to the field of capital market communications. Third, we contribute to the literature investigating the determinants of the firms' cost of capital (Dhaliwal et al., 2016; Evans, 2016; Mishra, 2014) by extending previous work by Brown et al. (2004). We show that not only the existence of conference calls but also the conference call design can lower the cost of capital.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops the hypothesis. Section 3 describes the sample, the variables and the analytical model.

Section 4 discusses the empirical findings and robustness checks. Section 5 presents additional tests and Section 6 concludes.

2. Literature Review and Hypotheses Development

2.1. The Inherent Conflict in the Use of Conference Calls

Academic interest in quarterly earnings conference calls has been growing (e.g. Brochet et al., 2015; Larcker & Zakolyukina, 2012; Lee, 2016). Conference calls usually have two components: a management discussion (MD) session in which the management presents results and a question and answer (Q&A) session in which analysts ask the management questions.[4] The initial literature stressed the specific benefits of conference calls as a vehicle for capital market communications that can bridge the gap between managers and investors (Frankel et al., 1999; Tasker, 1998). In line with the seminal work of Diamond and Verrecchia (1991),[5] Brown et al. (2004) provide evidence that conference calls lead to a long-term reduction in information asymmetry and, consequently, to a lower cost of capital. Despite these promising benefits, most recent research has focused on the costs of conference calls (Hollander et al., 2010; Lee, 2016; Mayew, 2008). In this vein, Lee (2016) states that the open nature of conference calls comes at a cost because firms relinquish some of the control over their communications and thus run the risk of the potential unintended disclosure of bad news. In this context, Lee (2016) provides evidence that managers adhere to predetermined scripts when answering questions to avoid undesirable outcomes. Similarly, Mayew (2008) shows that firms prefer that favorable analysts participate in conference calls and Hollander et al. (2010) find support for the hypothesis that firms regularly abstain from answering analysts' questions. Therefore, the developing line of prior studies depicts how managers intend to circumvent potential downsides when holding conference calls.

2.2. Managing Conference Calls to Create Value

In contrast, an upcoming stream of IR research hints at the upside potential of managing conference calls (Brown, Call, Clement, & Sharp, 2019; Chapman, Miller, & White, 2019; Karolyi & Liao, 2017). First, Brown et al. (2019, p. 2) show in their survey that IR officers consider conference calls the 'most important venue for corporate management to convey its message to institutional investors,' suggesting that firms could use conference calls more intentionally. Second, Karolyi and Liao (2017) and Chapman et al. (2019) show that firms with well-provided-for IR teams manage to better communicate with the market and thereby reduce information asymmetry. Specifically, Chapman et al. (2019) provide evidence for lower stock price volatility and lower analyst forecast errors, while Karolyi and Liao (2017) find lower analyst forecast errors and a lower cost of capital. These studies show that enhanced capital market communications can be beneficial for firms by reducing information asymmetry.

Aiming at the communication benefits of conference calls, the question arises as to how firms can specifically make use of these benefits and embrace this opportunity. The most relevant target groups for firms' conference calls (sell- and buy-side analysts) clearly stress the value of more balanced information consisting of a large variety of aspects covering different areas such as

[4]The literature commonly stresses that the less formal disclosure format, the lower standard of legal liability, and the opportunity for extemporaneous disclosure vest conference calls with a more open nature (e.g., Frankel et al., 1999; Hollander et al., 2010; Matsumoto et al., 2011).

[5]Diamond and Verrecchia (1991) suggest that revealing information to lower information asymmetry can reduce firms' cost of capital.

trends, processes, logistics, customers, and management teams, as well as financials, and of how these aspects intertwine (Brown et al., 2015, 2019). For firms, this translates into the necessity to compose information about the critical areas of the business and to portray aspects from different perspectives.

2.3. Composing Information for Conference Calls in Line with the Balanced Scorecard

In the context of internal communications, the successful diffusion of the balanced scorecard has entailed a popular illustration of the firms' business along four major perspectives (i.e. finance, customer, internal processes, and learning and growth). Kaplan and Norton developed the balanced scorecard to overcome the shortcomings of a purely financial focus in performance measurement systems, and included the customer, internal processes, and learning and growth perspectives (Kaplan & Norton, 1992). The composition of these four perspectives is frequently highlighted to represent the critical areas of a business (Banker, Chang, & Pizzini, 2004; Kaplan & Norton, 1992, 1993). Specifically, the four perspectives facilitate the understanding of the strategy by demonstrating how the different areas of the business interact (Sundin, Granlund, & Brown, 2010; Wiersma, 2009). The holistic presentation of the firms' business is intended to aid in communicating and implementing corporate strategies (Kaplan & Norton, 1993; Malina & Selto, 2001). In conclusion, the literature widely agrees on the positive information effect of the balanced scorecard for firms' internal communication purposes (e.g. De Geuser et al., 2009; Malina & Selto, 2001).

In this sense, the balanced scorecard concept with its four perspectives might also advance external communications by providing a valuable framework for IR teams for composing information for conference calls. Specifically, Kaplan and Norton's idea to enrich the finance focus in performance measurement systems with non-financial information might also help to attenuate the predominant finance focus in conference calls. Considering the time restrictions in capital market communications with investors and analysts, composing both financial and non-financial information poses a great challenge for firms. As information could be composed in many respects, a generally applicable framework that represents the critical areas of a business is crucial. To this end, the balanced scorecard literature has extensively invested in the identification of the most critical areas of a business (Kaplan & Norton, 1993). Thus, similar to internal purposes, focusing on the four perspectives from the balanced scorecard concept could be particularly relevant for firms' conference calls as they complement the principal finance focus and illustrate the critical areas of a business. IR teams could present information based on the four perspectives to better illustrate the execution of the firms' strategy and to round out their equity story for market participants. Accordingly, we propose that higher levels of balanced information composition should translate into an improved information environment for analysts and investors, thus leading to a reduction in information asymmetry (Diamond & Verrecchia, 1991; Leuz & Verrecchia, 2000).[6] Following a frequent assumption in the disclosure literature, we expect a reduction in information asymmetry to lower the firms' cost of capital (e.g. Armstrong

[6]In line with previous studies, we do not explicitly refer to information quality or quantity as the driver of the reduction in information asymmetry as both are empirically hard to disentangle. Instead, we refer to Leuz and Verrecchia (2000, p. 91), who state that 'theory is sufficiently broad as to allow the notion of 'increased levels of disclosure' to be interpreted as either an increase in the quantity of disclosure or an increase in the quality of disclosure (or both).' For example, in our case, a more balanced information composition could lead to an increase in information quantity, which could then be used to assess information that is already available, thereby improving information quality.

et al., 2011; Brown et al., 2004; Diamond & Verrecchia, 1991).[7] Consequently, we hypothesize that:

H1. A more balanced information composition in conference calls is associated with a lower cost of capital.

3. Data and Empirical Methodology

3.1. Sample Selection

We obtain conference call transcripts for S&P 500 firms between 2004 and 2013 from Thomson StreetEvents. For our analysis, we selected only listed firm-quarters that met the following criteria: (1) the firm is listed in the S&P 500 Index in at least one year of the investigated period; (2) the firm is non-financial (excluding SIC codes 6000–6999); (3) all necessary cost of capital data are available; (4) all necessary financial data for the control variables from Datastream are available; and (5) the conference call transcript is available. The resulting sample comprises a total of 7536 firm-quarter observations. Panels A and B of Table 1 describe the sample construction and industry composition.[8]

3.2. Dependent Variable: Implied Cost of Capital

We empirically estimate the ex-ante expected cost of equity capital implied in current stock prices and analysts' earnings forecasts. The idea is to insert the market price and analyst forecasts into the valuation equation to back out the internal rate of return (i.e. the implied cost of capital) that equates the current stock price and the future residual incomes or abnormal earnings, respectively. Previous research introduced various models for calculating the implied cost of capital. To mitigate the effect of measurement errors, we follow several researchers (e.g. Dhaliwal et al., 2016; Hail & Leuz, 2006; Mishra, 2014) and employ the average implied cost of capital (*r_avg*) estimate from different models. In constructing the measure, we follow Dhaliwal, Li, Tsang, and Yang (2011) and Mishra (2014), and include models by Claus and Thomas (2001 *r_ct*), Gebhardt, Lee, and Swaminathan (2001 *r_gls*), and Easton (2004 *r_es*).[9]

3.3. Independent Variable: Balanced Information Composition

Balanced information composition should capture the balance of the information in the MD sessions[10] in earnings conference calls in terms of the four balanced scorecard perspectives: finance,

[7] While many empirical studies exploit the assumed link between a reduction in information asymmetry and a lower cost of capital, the theorists' debate revolves around various positions. The theory widely agrees on the indirect effect of information asymmetry on the cost of capital as information asymmetry among investors poses the problem of adverse selection in capital markets leading to illiquidity (Amihud & Mendelson, 1986; Leuz & Verrecchia, 2000; Welker, 1995). Information asymmetry is linked with price protection by uninformed investors facing informed investors (Welker, 1995). Investors' behavior then reduces the liquidity in the market and exacerbates selling or buying shares. In turn, illiquidity imposes trading costs on investors, for which they expect to receive compensation linking information asymmetry with the cost of capital (Amihud & Mendelson, 1986; Brennan & Subrahmanyam, 1996). Besides the indirect link, the theory also considers a direct link between information asymmetry and the cost of capital as increased information asymmetry results in higher estimation risks (Lambert, Leuz, & Verrecchia, 2007; Lambert et al., 2012). In order to investigate the effect of balanced information composition on the cost of capital in more detail, we conduct additional tests on other capital market outcomes linked to information asymmetry and liquidity risk in Section 5.

[8] Because we exclude firm-quarters without conference calls, a potential selection bias is inherent in this sample based on the firms' choice regarding whether to hold conference calls. We employ a sample selection correction suggested by Heckman (1979) by including a correction factor derived from a first-stage probit regression in the subsequent regression. In unreported tables, we obtain similar results.

[9] The calculation models and their components are described in detail in Appendix A.

[10] In unreported regressions, we consider all words spoken by the management including those from the Q&A session and obtain similar results.

Table 1. Sample selection and industry composition

Panel A: Sample Selection

Description	No. of observations
Listed firm-quarters of firms that have been in the S&P 500 between 2004 and 2013	23,133
Excluding firm-quarters of financial firms (SIC 6000–6999)	(3543)
Excluding firm-quarters with missing cost of capital data	(4251)
Excluding firm-quarters with missing data in the control variables	(2625)
Excluding firm-quarters without available conference call transcript	(5178)
Final sample	7536

Panel B: Industry Composition

Two-Digit SIC Industry Sector	Number of observations	% of observations
Mining (10–14)	441	5.85
Construction (15–17)	56	0.75
Manufacturing (20–39)	3890	51.62
Telecommunication, Transportation, and Utilities (40–49)	1113	14.77
Wholesale (50–51)	311	4.12
Retailing (52–59)	617	8.19
Services (70–88)	1108	14.70
Total	7536	100

customer, internal processes, and learning and growth. To measure balanced information composition, we employ CATA and use QDA Miner along with the Wordstat module, a common text analysis tool (Short, Broberg, Cogliser, & Brigham, 2010). First, we developed four individual word lists to measure the word counts for the four perspectives of the balanced scorecard in each conference call. Second, we take the word counts per perspective and calculate the Gini coefficient using the following formula: $1 + \frac{1}{n} - \frac{2}{n^2 \bar{z}} \sum_{i=1}^{n} (i * z_i)$, where $n = 4$ is the number of perspectives, z_1, z_2, z_3, and z_4 are the word counts for each of the four perspectives in descending order, and $\bar{z}$ is the mean word count of the perspectives. The Gini coefficient has been commonly applied to measure (in-) equality or balance (He & Huang, 2011).[11] Third, similar to other scholars, we normalize and standardize the Gini coefficient on a 0-to-1 scale (Chen & Hambrick, 2012). Fourth, as the Gini coefficient is an inequality measure, we then reverse the scale to turn it into our equality measure of balanced information composition (*BIC*) so that it is more intuitive to the reader. For a succinct description of the word lists and their development as well as numerical examples for the computation of the measure of balanced information composition, see Appendix C. For a more detailed explanation and a stepwise description of the whole development process, see the supplementary online Appendix S1.[12]

[11]We also calculate other common inequality measures such as the relative mean deviation, the coefficient of variance, the Mehran measure, Piesch measure, Kakwani measure, and the Theil entropy measure (He & Huang, 2011). The correlation between these measures and the Gini coefficient is mostly above 0.96 and is 0.82 at the lowest, indicating the reliability of the Gini coefficient.

[12]The extensive description of the word list development in the online Appendix might prove particularly fruitful for researchers who intend to develop their own dictionaries. Thereby, the applied development procedure in this paper might help to uncover new measurements.

3.4. Methodology

We are aware that our research setting is prone to endogeneity issues because voluntary disclosure is a choice variable that can be affected by many factors (Larcker & Rusticus, 2010). This is particularly true in light of conference calls, where various corporate factors that also potentially affect the cost of capital intervene.

Given these endogeneity concerns, recent research has shown that GMM is an appropriate choice (Firk, Schmidt, & Wolff, 2019; Wintoki, Linck, & Netter, 2012). The use of GMM involves certain advantages over other multivariate regression methods (e.g. ordinary least squares (OLS) or fixed-effects regression) and other instrument variable methods (e.g. 2SLS): First, GMM solves the issue of reverse causality by using instrumental variable estimates that are retrieved from the lagged values, thereby eliminating the need for external instruments (Roodman, 2006; Wintoki et al., 2012).[13] Second, GMM accounts for unobservable heterogeneity by including firm-fixed effects, which can also be assessed even though they are constant over time (Firk et al., 2019; Wintoki et al., 2012).[14] Third, GMM considers the dynamic relationship between disclosure and the cost of capital by allowing for the inclusion of the lagged cost of capital value (Wintoki et al., 2012).

In our analysis, we use the two-step GMM estimator instead of the first difference or one-step estimator, which may suffer from weak instruments when variables vary little over time, as might be the case with disclosure choices (Blundell & Bond, 1998). To operationalize the two-step GMM estimator, we employ the *xtabond2* module in Stata provided by Roodman (2006). In doing so, we need to treat strictly exogenous regressors separately (Roodman, 2006). We assume time and industry dummies to be exogenous and include them in the *ivstyle* option. We include the remaining variables in the *gmmstyle* option. To avoid instrument proliferation, we further specify the *collapse* option (Wintoki et al., 2012).

To indicate the appropriateness of the GMM regressions, we display a set of consistency measures to validate the regression results. We implemented the tests for autocorrelation in differences (AR1) and levels (AR2), as suggested by Arellano and Bond (1991), to check the validity of the instrumented estimates. Moreover, we use Hansen's J statistic to indicate whether the restrictions are overidentified; that is, whether the number of moment conditions surpasses the parameters to be estimated.

Specifically, we estimate the following model to investigate the first hypothesis:

$$
\begin{aligned}
r\_avg_{it} = {} & \beta_0 + \beta_1 BIC_{it} + \beta_2 Beta_{it} + \beta_3 Size_{it} + \beta_4 Book\ to\ market_{it} + \beta_5 Leverage_{it} \\
& + \beta_6 Analyst\ forecast\ dispersion_{it} + \beta_7 Long\ term\ growth\ rate_{it} \\
& + \beta_8 Capital\ intensity_{it} + \beta_9 R\&D\ intensity_{it} + \beta_{10} Operating\ margin_{it}
\end{aligned}
$$

[13]The challenge with 2SLS is to find a suitable instrument variable that is correlated with the independent variable but uncorrelated with the error terms (Larcker & Rusticus, 2010). Due to a lack of fitting instruments, the use of industry averages is quite common but far from perfect (Larcker & Rusticus, 2010). The same would be true for the use of 2SLS in this study. In the regression results in the robustness section, we employ the industry average of the balanced information composition as the instrument and find that the results for our hypothesis using 2SLS hold. When considering the advantage that GMM does not require external instruments, we chose GMM over 2SLS.

[14]The issue with a potential fixed-effects model in our case is that the independent variable and, even more so, the dependent variable are not independent of past realizations, and thus are relatively sticky over time. This issue is even more pronounced when examining the cost of capital, which is why the majority of studies investigating the cost of capital abstain from using the fixed-effects model.

$$+ \beta_{11} Management\ tone_{it} + \beta_{12} Analyst\ tone_{it} + \beta_{13} Analyst\ coverage_{it}$$
$$+ \beta_{14} Call\ structure_{it} + \beta_{15} Length_{it} + \beta_{16} BSC\ volume_{it} + \beta_{17} ID_i$$
$$+ \beta_{18} Year_j + \beta_{19} Quarter_k + \varepsilon_{it}, \quad (1)$$

where *r_avg* is the measure of the estimated implied cost of capital for firm i in time period t, as a combination of year j and quarter k. The independent variable is balanced information composition (*BIC*). The controls include the key financial variables for the implied cost of capital consistent with previous research (e.g. Dhaliwal et al., 2016; Gebhardt et al., 2001; Hail & Leuz, 2006; Mishra, 2014). These controls are the firm-level beta (*Beta*), firms' market value as size (*Size)*, the book to market ratio (*Book to market)*, leverage (*Leverage)*, analysts' forecast dispersion (*Analyst forecast dispersion)*, and the consensus long-term growth forecast (*Long-term growth rate)*. Given that a firm's strategy closely relates to the independent variable *BIC* and the dependent variable *r_avg*, we control for a set of additional firm-specific variables (*Capital intensity*, *R&D intensity*, and *Operating margin*). Moreover, we account for confounding effects at the conference call level. As the perception of the conference call highly depends on the tone (Loughran & McDonald, 2011), we include two measures for positivity: one for managers' language (*Management tone*) and one for analysts' language (*Analyst tone*). Due to the central role of analysts as information intermediaries, we control for the number of analysts participating in the conference call in relation to analysts issuing forecasts for the firm (*Analyst coverage*). To account for a firm's leeway in setting up conference calls, we employ the ratio of words spoken in the MD and the Q&A sessions (*Call structure*). Considering that *BIC* captures the information composition, we included controls assessing the information amount in conference calls. As a rather generic proxy, we employed the length of the presentation (*Length*) measured as the number of words, and as a more specific proxy in line with the proposed concept of the balanced scorecard, we added the accumulated counts of the four balanced scorecard perspectives scaled by the length of the presentation (*BSC volume)*. *ID*, *Year,* and *Quarter* control for industry (Fama and French 17), year, and quarter effects.[15]

4. Empirical Results

4.1. Descriptive Statistics

Panel A of Table 2 displays the summary statistics for the regression variables. The firms' average estimated cost of capital (*r_avg*) has a mean of 9.45% and a median of 8.97%. The average balanced information composition (*BIC*) is 0.50 and varies substantially. In Panel B of Table 2, we ran univariate tests to provide a first indication that analysts require a more balanced information composition in conference calls. In line with our argumentation, we assume that analysts will benefit from a more balanced information composition. Given the prevailing focus on financial information in the MD sessions of conference calls,[16] we argue that analysts on average have an interest in an incremental provision of the three non-financial information perspectives (customer, internal processes, and learning and growth). In order to attain a more balanced information composition, we expect that would analysts ask for relatively more non-financial information in the Q&A sessions than is provided in the MD sessions. Thus, we compare the proportion of non-financial information in the analyst part of the Q&A sessions to the MD sessions of conference calls. Panel B reports that analysts in the Q&A sessions on average ask for 19.48%

---

[15] A detailed description of the variables and their sources is provided in Appendix B.
[16] In 95% of our sample's observations, the finance perspective is the most dominant.

Table 2. Descriptive statistics

Panel A: Summary Statistics

Variables	Mean	SD	Min	Q1	Median	Q3	Max
r_avg[a]	9.446	2.431	4.197	7.875	8.967	10.371	26.323
BIC[b]	0.496	0.211	0.000	0.354	0.497	0.643	1.000
Beta[a]	0.784	0.443	– 0.417	0.473	0.745	1.025	4.305
Size[a]	9.035	1.101	5.412	8.260	8.934	9.729	12.030
Book to market[a]	0.775	0.429	0.125	0.468	0.709	1.027	7.914
Leverage[a]	0.047	0.070	0.000	0.002	0.021	0.062	0.708
Analyst forecast dispersion[a]	0.111	0.164	0.000	0.036	0.065	0.123	3.526
Long-term growth rate[a]	12.608	6.412	– 23.320	9.000	12.000	15.000	63.450
Capital intensity	0.387	0.313	0.003	0.142	0.269	0.564	1.722
R&D intensity	2.332	4.330	0.000	0.000	0.321	2.937	76.703
Operating margin	0.217	0.137	– 0.606	0.131	0.194	0.286	0.890
Management tone	0.234	0.203	– 0.578	0.101	0.246	0.382	0.775
Analyst tone	0.037	0.241	– 1.000	– 0.111	0.048	0.200	1.000
Analyst coverage	2.861	0.429	0.693	2.639	2.890	3.135	4.043
Call structure	0.635	0.371	0.023	0.400	0.557	0.781	6.470
Length	8.150	0.383	5.043	7.933	8.184	8.406	9.951
BSC volume	0.039	0.010	0.006	0.032	0.039	0.045	0.076
r_avg_alt[a]	9.728	2.398	4.207	8.253	9.278	10.653	27.338
BIC_alt[b]	0.610	0.213	0.000	0.477	0.633	0.770	1.000
Forward-looking to backward-looking	1.183	0.475	0.214	0.863	1.092	1.405	4.461
Long-term to short-term	1.529	1.789	0.061	0.704	1.082	1.747	36.342
Non-financial to financial	2.543	4.080	0.000	0.497	1.187	2.839	57.666
Non-quantitative to quantitative	1.084	1.366	0.038	0.436	0.730	1.271	33.205
CSR to other	1.072	0.556	0.126	0.729	0.971	1.251	5.860
Firm volatility	29.629	15.051	6.609	19.420	25.917	35.437	188.126
Industry volatility	32.639	13.390	11.575	24.500	29.303	37.370	172.384
Index volatility	34.115	13.681	22.992	26.656	28.469	37.035	101.797
Bid-ask spreads[a]	0.010	0.005	0.003	0.007	0.009	0.012	0.069
Amihud illiquidity	0.017	0.095	0.000	0.006	0.010	0.017	6.184
Firm idio. volatility	0.227	0.112	0.060	0.151	0.201	0.273	1.328
Cumulative abnormal returns	0.004	0.064	– 0.476	– 0.031	0.001	0.037	0.480

Panel B: Analysts' Demand for Non-Financial Information

Demand for customer, internal processes, and learning and growth information in the Q&A session:	
if MD session is less balanced	+ 37.08%
if MD session is averagely balanced	+ 19.48%
if MD session is more balanced	+ 1.88%

Notes: Panel A presents descriptive statistics for the regression variables of our sample of 7536 firm-quarter observations over the period 2004–2013. Appendixes A and B provide definitions and data sources for the regression variables. (a) Winsorized at the 1st and 99th percentiles; (b) normalized and standardized; (c) dummy variable. Panel B reports the demand for customer, internal processes, and learning and growth information in the form of analysts' questions. We measure the demand as the difference in customer, internal processes, and learning and growth information between the MD session and analysts' questions. We measure customer, internal processes, and learning and growth information as opposing to financial information according to the perspectives of the balanced scorecard. For the categorization in less and more balanced MD sessions, we used a sample split into firms lying below and above the median.

more non-financial information compared to the non-financial information provided in the MD sessions. Further, the results show that this tendency is stronger for less balanced MD sessions, where analysts ask for 37.08% more non-financial information (i.e. a higher analyst demand for balanced information composition). These descriptive results provide a first indication that analysts do demand a more balanced information composition in conference calls.

4.2. *Effect of a Balanced Information Composition on the Cost of Capital*

To investigate the relation between balanced information composition and the cost of capital, we run GMM regressions controlling for various confounding effects. Model 2 of Table 3 reports the results of our analysis. We find a highly statistically significant and negative effect of a balanced information composition (*BIC*) on the cost of capital. In terms of economic significance, the marginal effect of a balanced information composition on the cost of capital is −48.2 basis points.[17] To put this result into perspective, the average cost of capital in the sample is 9.45%, which translates into a 5.10% (=0.474/9.45) decrease in the firms' cost of capital. Against the backdrop of prior findings, the economic magnitude seems plausible. At the lower end, Brown et al. (2004) find that merely holding conference calls irrespective of the design reduces the firms' cost of capital by 15 basis points. At the upper end of the range, Brochet, Limbach, Bazhutov, Betzer, and Doumet (2019) document the firms' cost of capital to vary by 58 basis points for a one-standard-deviation change in the IR quality. To assess the economic significance from a different angle, we examine the effect of an increase in the balanced information composition from the 50th percentile value to the 75th percentile value on the cost of capital and observe a reduction of 33.2 basis points. Overall, the findings support our hypothesis suggesting that firms with a more balanced information composition experience a lower cost of capital.

4.3. *Robustness Tests*

To validate the results of the analysis, we conduct a number of sensitivity tests. First, we consider alternative specifications of the variables used in the regression. Second, to further address endogeneity concerns, we repeat the analysis using a 2SLS model.

4.3.1. *Alternative specifications*

In Panel A of Table 4, we validate whether the results hold for alternative variable specifications and conduct several tests substituting the set of control variables, the cost of capital variable, and the balanced information composition variable. First, we reduce the control variables to the standard set commonly included when investigating the cost of capital, which are *Beta*, *Size*, *Book to market*, *Leverage*, *Analyst forecast dispersion*, and *Long-term growth rate* (Dhaliwal et al., 2016, 2011; Gebhardt et al., 2001; Mishra, 2014). With this test, we intend to alleviate concerns that the results are driven by our choice of control variables. Model 1 shows that we obtained similar results. Second, we test an alternative specification of the cost of capital variable. In the main tests, we excluded the model by Ohlson and Juettner-Nauroth (2005) for reasons of high similarity in the derivation of the model with the Easton (2004) model. To provide assurance that the results are not sensitive to the choice of the specific models, we repeat the analysis using a cost of capital proxy based on all four models. Model 2 shows that we obtained similar results. Third, we determine whether the results are sensitive to alternative calculations of our balanced information composition measure. Apart from the Gini coefficient, previous studies also considered other inequality measures such as the relative mean deviation, the coefficient of variance, the Mehran measure, Piesch measure, Kakwani measure, and the Theil entropy measure (He & Huang, 2011). While most inequality measures are almost perfectly correlated with the Gini coefficient (above 0.96), the Theil entropy measure only shows a high similarity (0.82) and serves best for a robustness test. We repeated the analysis using the Theil entropy measure, and Model 3 shows that we obtained similar results.

---

[17]To obtain the marginal effect, we multiply the coefficient with the standard deviation of the balanced information composition measure (*BIC*): $-2.283 \times 0.211 = -0.482$.

Table 3. Balanced information composition and the implied cost of capital

Model	1	2
Method	GMM	GMM
Dependent variable	*r_avg*[a]	*r_avg*[a]
Independent variable		
BIC[b]		– 2.283***
		(– 3.263)
Control variables		
Lagged cost of capital[a]	0.433***	0.477***
	(7.550)	(9.538)
Beta[a]	0.141	0.112
	(0.588)	(0.419)
Size[a]	– 0.752*	– 0.702
	(– 1.771)	(– 1.474)
Book to market[a]	1.261***	1.319***
	(4.252)	(4.359)
Leverage[a]	0.016	0.080
	(0.023)	(0.092)
Analyst forecast dispersion[a]	2.343*	2.299
	(1.873)	(1.483)
Long-term growth rate[a]	0.032**	0.042***
	(2.263)	(2.865)
Capital intensity	– 0.581	– 1.085
	(– 0.556)	(– 0.928)
R&D intensity	0.194***	0.259***
	(2.801)	(3.428)
Operating margin	2.911	3.360**
	(1.589)	(2.000)
Management tone	0.110	1.105
	(0.136)	(1.198)
Analyst tone	– 1.150	– 1.880**
	(– 1.620)	(– 2.116)
Analyst coverage	– 0.763	– 0.336
	(– 1.275)	(– 0.525)
Call structure	– 0.444	– 0.125
	(– 0.715)	(– 0.187)
Length	– 24.204	– 17.130
	(– 1.381)	(– 0.890)
BSC volume	0.116	0.080
	(0.198)	(0.132)
Constant	12.145**	10.365
	(2.001)	(1.597)
Industry effects	yes	yes
Year effects	yes	yes
Quarter effects	yes	yes
Model fit		
Wald Chi2 statistic	1292.70 (45)	1466.14 (46)
Arellano-Bond test (AR1)	– 7.54 [0.000]	– 7.52 [0.000]
Arellano-Bond test (AR2)	– 1.07 [0.284]	– 0.82 [0.410]
Hansen J-statistic	35.87 [0.118]	34.64 [0.180]
N	7536	7536

Notes: This table reports GMM regression analyses of the balanced information composition (*BIC*) on cost of capital (*r_avg*). ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Z-statistics are provided in parentheses. Industry effects comprise 17 Fama & French industry dummies. Appendixes A and B provide definitions and data sources for the regression variables. (a) Winsorized at the 1st and 99th percentiles; (b) normalized and standardized.

Table 4. Robustness tests – alternative variable and model specifications

Panel A: Alternative Variable Specifications

Model	1	2	3
Method	GMM	GMM	GMM
Alternative specification	Control variables	Dependent variable	Independent variable
Dependent variable	*r_avg*[a]	*r_avg_alt*[a]	*r_avg*[a]
Independent variable			
BIC[b]	– 2.060**	– 2.627***	
	(– 2.313)	(– 2.870)	
BIC_alt[b]			– 1.498**
			(– 1.963)
Control variables			
Lagged cost of capital[a]	0.294***	0.479***	0.466***
	(3.548)	(7.780)	(10.349)
Beta[a]	0.305	0.328	0.278
	(1.127)	(1.063)	(1.147)
Size[a]	– 0.188	– 0.375	– 0.457
	(– 0.371)	(– 0.723)	(– 1.101)
Book to market[a]	0.968*	1.177***	1.305***
	(1.704)	(3.517)	(4.671)
Leverage[a]	0.618	0.016	0.010
	(0.783)	(0.018)	(0.014)
Analyst forecast dispersion[a]	7.938***	1.973	2.962**
	(3.047)	(1.149)	(2.344)
Long-term growth rate[a]	0.027**	0.037**	0.034**
	(2.017)	(2.200)	(2.510)
Capital intensity		– 0.953	– 1.123
		(– 0.817)	(– 1.072)
R&D intensity		0.229***	0.271***
		(2.624)	(3.991)
Operating margin		2.582	3.506**
		(1.193)	(2.425)
Management tone		1.612	0.799
		(1.498)	(0.827)
Analyst tone		– 2.656***	– 1.409*
		(– 2.672)	(– 1.779)
Analyst coverage		– 0.475	– 0.169
		(– 0.713)	(– 0.334)
Call structure		– 0.150	– 0.044
		(– 0.182)	(– 0.071)
Length		0.450	– 0.192
		(0.661)	(– 0.333)
BSC volume		– 13.823	– 25.342
		(– 0.652)	(– 1.306)
Constant	6.657	5.462	10.168*
	(1.406)	(0.786)	(1.827)
Industry effects	yes	yes	yes
Year effects	yes	yes	yes
Quarter effects	yes	yes	yes
Model fit			
Wald Chi2 statistic	1020.35 (39)	1590.13 (48)	1962.85 (48)
Arellano-Bond test (AR1)	– 6.38 [0.000]	– 7.13 [0.000]	– 8.80 [0.000]
Arellano-Bond test (AR2)	– 1.59 [0.112]	– 0.81 [0.419]	– 1.22 [0.223]
Hansen J-statistic	15.59 [0.211]	40.17 [0.125]	43.11 [0.226]
N	8072	7536	7536

(*Continued*).

Table 4. Continued.

Panel B: Alternative Model Specification		
Model	1	2
Method	2SLS -1. stage	2SLS -2. stage
Dependent variable	*BIC*[b]	*r_avg*[a]
Independent variable		
BIC[b] *industry peers*	0.885***	
	(12.284)	
BIC[b] *(instrumented)*		− 1.307***
		(− 3.118)
Control variables		
Beta[a]	− 0.002	0.869***
	(− 0.130)	(9.382)
Size[a]	− 0.019***	0.019
	(− 2.740)	(0.425)
Book to market[a]	− 0.013	1.704***
	(− 0.884)	(8.080)
Leverage[a]	0.065	2.112***
	(0.544)	(3.625)
Analyst forecast dispersion[a]	0.004	3.601***
	(0.186)	(9.756)
Long-term growth rate[a]	(0.000)	0.025***
	(− 0.408)	(3.684)
Capital intensity	(0.018)	0.175
	(− 0.616)	(1.033)
R&D intensity	0.004**	0.003
	(2.387)	(0.264)
Operating margin	0.096**	− 0.891***
	(2.183)	(− 2.618)
Management tone	0.202***	− 0.459**
	(6.368)	(− 2.409)
Analyst tone	(0.018)	(0.363)***
	(− 1.245)	(− 3.117)
Analyst coverage	0.081***	− 0.162
	(4.000)	(− 1.422)
Call structure	0.027*	− 0.289***
	(1.749)	(− 2.615)
Length	0.063***	0.878***
	(2.713)	(7.579)
BSC volume	2.291***	− 7.728*
	(3.087)	(− 1.920)
Constant	− 0.683***	− 0.547
	(− 3.755)	(− 0.561)
Industry effects	yes	yes
Year effects	yes	yes
Quarter effects	yes	yes
adj. r-squared	27.84	40.57
N	7961	7536

Notes: Panel A reports GMM regression analyses of the balanced information composition (*BIC*) on cost of capital (*r_avg*) with alternative variable specifications. Model 1 reports the regression analyses using a reduced set of control variables. Model 2 reports the regression analyses using alternative cost of capital (*r_avg_alt*). Model 3 reports the regression analyses using alternative balanced information composition (*BIC_alt*). Panel B reports 2SLS regression analyses of the balanced information composition (*BIC*) on cost of capital (*r_avg*) using the average balanced information composition of industry peers (*BIC industry peers*) as the instrument in the first stage. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Z-statistics and t-statistics are provided in parentheses. Industry effects comprise 17 Fama & French industry dummies. Appendixes A and B provide definitions and data sources for the regression variables. (a) Winsorized at the 1st and 99th percentiles; (b) normalized and standardized.

4.3.2. Alternative model

To mitigate concerns regarding the robustness of the results in terms of the applied method, we run a 2SLS approach. The accounting literature has frequently used 2SLS and highlighted it as an effective method for tackling endogeneity concerns in the form of omitted variable bias (Larcker & Rusticus, 2010). Similar to GMM, 2SLS makes use of instruments but leads to the challenge of finding an appropriate instrument. In line with previous research, we decided to use the industry average of the second stage-dependent variable as an instrument (e.g. Chen, Huang, & Wei, 2013; Dhaliwal et al., 2016). Thus, we estimated a first-stage regression using the industry average of balanced information composition as the instrument variable. In the second stage, we repeat our main analyses using the fitted values from the first-stage regression. Panel B of Table 4 reports the results for the first stage (Model 1) and the second stage (Model 2). We find that the instrumented variable of balanced information composition has a negative and highly statistically significant effect on the cost of capital. Hence, this test further supports our preceding analysis.

5. Additional Tests

To investigate the underlying mechanism that explains the negative relation between balanced information composition and the firms' cost of capital, we run a series of additional tests. First, we examine whether alternative information dimensions in conference calls simultaneously drive the observed effect. Second, we test alternative composition forms of the information in conference calls to verify whether the balanced information composition is indeed responsible for our results. Third, we assess the mechanism through a contextual analysis by investigating the effect in uncertain capital market environments. Fourth, we focus on a set of alternative dependent variables to investigate whether the reduction in information asymmetry is the main driver behind the effect on the cost of capital.

5.1. Alternative Information Dimensions

Beyond the information composition in line with the balanced scorecard concept, firms could focus on other information dimensions in conference calls at the same time. To validate whether the results are not affected by such simultaneous behavior, we test alternative information dimensions that might also play to market participants. Specifically, we contemplate the dimensions *Forward-looking to backward-looking* (Matsumoto, Pronk, & Roelofsen, 2011), *Long-term to short-term* (Brochet et al., 2015), *Non-financial to financial* (Dhaliwal et al., 2011; Matsumoto et al., 2011), *Non-quantitative to quantitative* (Pan, McNamara, Lee, Haleblian, & Devers, 2018), and *CSR to other* (Pencle & Mălăescu, 2016).[18] Some of these dimensions might be partially reflected by the balanced information composition measure (e.g. quantitative from the financial perspective or CSR from the customer perspective). Given these overlaps, it is essential to verify the effect of the balanced information composition in the presence of the alternative information dimensions. The additional tests including the alternative information dimensions are presented in Table 5.

[18]In addition to the prominence of the information dimensions, we also looked for established and readily available word lists to avoid developing new word lists. For *Forward-looking to backward-looking*, *Long-term to short-term*, *Non-financial to financial*, and *CSR to other* we used the word lists directly from the papers, and for *Non-quantitative to quantitative* we used the quoted word lists numbers and quantifiers from the software Linguistic Inquiry and Word Count (LIWC). While Brochet et al. (2015) provided two word lists, all other sources provided one word list (e.g., forward), so we calculated the counterpart (e.g., backward) by subtracting the frequency count from all words in the MD session. We then standardized and normalized the values and created the ratio.

Table 5. Additional tests – alternative information dimensions

Model	1	2	3	4	5	6
Method	GMM	GMM	GMM	GMM	GMM	GMM
Dependent variable	*r_avg*[a]	*r_avg*[a]	*r_avg*[a]	*r_avg*[a]	*r_avg*[a]	*r_avg*[a]
Independent variable						
BIC[b]	– 2.107***	– 2.162***	– 2.301***	– 2.274***	– 2.089***	– 2.075***
	(– 3.414)	(– 3.192)	(– 3.491)	(– 3.222)	(– 3.195)	(– 3.535)
Forward-looking to backward-looking	0.403					0.417
	(0.860)					(0.918)
Long-term to short-term		0.029				0.032
		(1.209)				(1.305)
Non-financial to financial			– 0.023			– 0.017
			(– 0.491)			(– 0.341)
Non-quantitative to quantitative				– 0.037		– 0.074
				(– 0.219)		(– 0.485)
CSR to other					– 0.126	– 0.165
					(– 0.279)	(– 0.328)
Control variables	yes	yes	yes	yes	yes	yes
Industry effects	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes
Quarter effects	yes	yes	yes	yes	yes	yes
Model fit						
Wald Chi2 statistic	2025.05 (49)	1729.90 (49)	1712.67 (49)	1653.49 (49)	1867.78 (49)	2193.23 (53)
Arellano-Bond test (AR1)	– 9.72 [0.000]	– 8.99 [0.000]	– 8.78 [0.000]	– 8.68 [0.000]	– 9.48 [0.000]	– 9.57 [0.000]
Arellano-Bond test (AR2)	– 1.03 [0.303]	– 0.82 [0.414]	– 1.01 [0.313]	– 0.81 [0.416]	– 1.09 [0.278]	– 1.41 [0.158]
Hansen J-statistic	37.47 [0.313]	34.88 [0.379]	38.82 [0.261]	35.15 [0.367]	38.15 [0.286]	43.82 [0.274]
N	7536	7536	7536	7536	7536	7536

Notes: This table reports GMM regression analyses of the balanced information composition (*BIC*) on cost of capital (*r_avg*) controlling for alternative balanced dimensions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Z-statistics are provided in parentheses. Industry effects comprise 17 Fama & French industry dummies. Appendixes A and B provide definitions and data sources for the regression variables. (a) Winsorized at the 1st and 99th percentiles; (b) normalized and standardized.

We find that the effect of the balanced information composition (*BIC*) on the cost of capital holds after we included the alternative information dimensions. We see that some alternative information dimensions also exhibit a negative sign; however, without being statistically significant. These results also hold when we include all alternative information dimensions and our measure of balanced information composition at the same time in Model 6. The findings substantiate the representation of the critical areas of a business via the balanced scorecard construct as a favorable approach for capital market communications.

5.2. Alternative Forms of Information Composition

In addition to balancing the four balanced scorecard perspectives, there could be other forms of composing information dimensions (e.g. balancing the financial perspective against the sum of the three non-financial perspectives). To alleviate concerns that other composition forms might be more favorable, we test several variables proxying for alternative forms of the information composition. We follow a procedure in which the form of the tested independent variable gradually converges to the proposed form of the information composition in line with the balanced scorecard concept. Specifically, we alternate the form by changing the calculation method of the information composition. We begin with a simple ratio (which only compares two dimensions) and then proceed stepwise to the Gini coefficient (which allows us to compare all four dimensions). Simultaneously, we narrow the scope of the applied word lists from broad non-financial information to the information perspectives of the balanced scorecard concept.

Table 6 presents the results and reports no significant effect of the alternative forms of information composition on the cost of capital in Models 1 through 3. Notably, the Gini coefficient based on the three non-financial information perspectives of the balanced scorecard approaches the significance level of 10%, while the forms based on ratios remain far from being significant. In Model 4 we inserted the main result for the sake of comparison. The findings suggest that a higher level of balance between the multiple information perspectives based on the balanced scorecard concept is responsible for the observed effect.

5.3. Impact of Uncertain Capital Market Environments

Economic theory implies that voluntary disclosure is particularly effective in situations of increased information asymmetry between the firm and the market (Diamond & Verrecchia, 1991). Following this, we expect the effect of a balanced information composition on the cost of capital to be particularly pronounced when the firms' capital environment faces greater uncertainty. To test this relation, we include an interaction term between our measure of balanced information composition (*BIC*) and one of three uncertainty variables. We specify the firm, industry, and index level as the firms' capital market environment. To obtain our uncertainty variables, we aggregate volatility measures in the form of the annualized volatility of daily stock returns (Campbell, Lettau, Malkiel, & Xu, 2001).

Models 1 through 3 in Table 7 report the results of the analyses. Across all three models, the interactions between *BIC* and the moderators *Firm volatility* (Model 1), *Industry volatility* (Model 2), and *Index volatility* (Model 3) exhibit statistical significance with the anticipated negative sign. Moreover, we continue to find a highly statistically significant and negative effect of balanced information composition on the cost of capital. These findings support our claim that a more balanced information composition in conference calls is particularly effective in reducing information asymmetry.

Table 6. Additional tests – alternative forms of information composition

Model	1	2	3	4
Method	GMM	GMM	GMM	GMM
Dependent variable	*r_avg*[a]	*r_avg*[a]	*r_avg*[a]	*r_avg*[a]
Calculation for information compositon measure	(All words – All finance words) / All words	Customer, internal processes, learning & growth words / All words	Gini coefficient of customer, internal processes, learning & growth words	Gini coefficient of finance, customer, internal processes, learning & growth words
Independent variable				
Information composition measure	– 0.541 (– 0.569)	– 0.845 (– 0.838)	– 1.348 (– 1.478)	– 2.283*** (– 3.263)
Control variables	yes	yes	yes	yes
Industry effects	yes	yes	yes	yes
Year effects	yes	yes	yes	yes
Quarter effects	yes	yes	yes	yes
Model fit				
Wald Chi2 statistic	1885.80 (48)	2055.84 (48)	1887.82 (48)	1648.62 (48)
Arellano-Bond test (AR1)	– 9.07 [0.000]	– 8.23 [0.000]	– 9.38 [0.000]	– 8.76 [0.000]
Arellano-Bond test (AR2)	– 1.13 [0.258]	– 1.03 [0.302]	– 0.95 [0.341]	– 0.79 [0.432]
Hansen J-statistic	40.93 [0.162]	38.87 [0.157]	43.31 [0.108]	34.78 [0.337]
N	7536	7536	7536	7536

Notes: This table reports GMM regression analyses of different information composition measures on cost of capital (*r_avg*). ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Z-statistics are provided in parentheses. Industry effects comprise 17 Fama & French industry dummies. Appendixes A and B provide definitions and data sources for the regression variables. (a) Winsorized at the 1st and 99th percentiles; (b) normalized and standardized.

Table 7. Additional tests – impact of uncertain capital market environments

Model	1	2	3
Method	GMM	GMM	GMM
Dependent variable	*r_avg*^{a}	*r_avg*^{a}	*r_avg*^{a}
Independent variable			
BIC^{b}	– 2.470***	– 2.412***	– 1.691**
	(– 3.996)	(– 3.589)	(– 2.494)
Firm volatility	0.013**		
	(2.477)		
BIC^{b} *x Firm volatility*	– 0.075**		
	(– 2.550)		
Industry volatility		0.023***	
		(6.151)	
BIC^{b} *x Industry volatility*		– 0.069***	
		(– 2.618)	
Market volatility			0.025***
			(8.938)
BIC^{b} *x Market volatility*			– 0.034*
			(– 1.875)
Control variables	yes	yes	yes
Industry effects	yes	yes	yes
Year effects	yes	yes	yes
Quarter effects	yes	yes	yes
Model fit			
Wald Chi2 statistic	2472.22 (50)	1713.09 (50)	1772.70 (50)
Arellano-Bond test (AR1)	– 8.36 [0.000]	– 7.71 [0.000]	– 7.48 [0.000]
Arellano-Bond test (AR2)	– 0.62 [0.534]	– 0.55 [0.582]	– 1.05 [0.294]
Hansen J-statistic	37.69 [0.225]	31.33 [0.500]	34.82 [0.249]
N	7512	7536	7536

Notes: This table reports GMM regression analyses of the balanced information composition (*BIC*) on cost of capital (*r_avg*) and the moderating effect of firm volatility, industry volatility, and index volatility, respectively. For these regressions BIC and the measures for uncertain capital market environments were mean-centered. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Z-statistics are provided in parentheses. Industry effects comprise 17 Fama & French industry dummies. Appendixes A and B provide definitions and data sources for the regression variables. (a) Winsorized at the 1st and 99th percentiles; (b) normalized and standardized.

5.4. Balanced Information Composition and Other Capital Market Outcomes

The finding of a negative effect of a balanced information composition on the firms' cost of capital could be subject to different potential channels. Empirical studies often imply that managers use voluntary disclosure to reduce information asymmetry and thereby lower a firm's cost of capital, while theoretical studies have developed a more nuanced perspective. Theorists essentially distinguish between a direct and an indirect channel regarding how information asymmetry can affect the firms' cost of capital. First, for the direct channel, information asymmetry might cause higher estimation risks directly resulting in an increased cost of capital. Second, for the indirect channel, information asymmetry leads uninformed investors to price-protect, which increases illiquidity. This in turn imposes trading costs on investors, for which investors expect to receive compensation, thus causing a higher cost of capital. A third channel could be that the balanced information composition coincides with positive new information and increases expectations for future earnings, which mitigates investor uncertainty and thus reduces the cost of capital (Kothari et al., 2009).[19]

[19] Kothari et al. (2009) find that positive news reduces uncertainty and thus has a directional link with a lower cost of capital. Thus, balanced information composition could systematically coincide with positive news.

Table 8. Additional tests – balanced information composition and other capital market outcomes

Model	1	2	3	4	5
Method	GMM	GMM	GMM	GMM	GMM
Dependent variable	*Bid-ask spreads*	*Amihud illiquidity*	*Analyst forecast dispersion*	*Idiosyncratic firm volatility*	*Cumulative abnormal returns*
Independent variable					
BIC^{b}	– 0.009**	– 0.287*	– 0.420**	– 0.369***	– 0.025
	(– 2.268)	(– 1.844)	(– 2.032)	(– 2.610)	(– 0.926)
Control variables	yes	yes	yes	yes	yes
Industry effects	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes
Quarter effects	yes	yes	yes	yes	yes
Model fit					
Wald Chi2 statistic	1157.08 (48)	155.61 (48)	667.11 (47)	800.97 (48)	142.78 (48)
Arellano-Bond test (AR1)	– 4.57 [0.000]	– 2.35 [0.019]	– 2.09 [0.037]	– 4.43 [0.000]	– 10.20 [0.000]
Arellano-Bond test (AR2)	0.01 [0.995]	– 1.65 [0.100]	– 0.33 [0.741]	– 1.58 [0.114]	– 0.32 [0.745]
Hansen J-statistic	41.30 [0.102]	15.10 [0.818]	29.87 [0.472]	24.71 [0.311]	45.30 [0.164]
N	9827	9688	9930	9925	9913

Notes: This table reports GMM regression analyses of the balanced information composition (*BIC*) on alternative dependent variables. Model 1 tests the influence on bid-ask spreads, Model 2 on the Amihud illiquidity measure, Model 3 on analyst forecast dispersion, Model 4 on idiosyncratic firm volatility, and Model 5 on cumulative abnormal returns. In Model 5 we do not include the lagged dependent variable, since a causal relationship between historical and current cumulative abnormal returns to a specific event is hard to envisage. ***, **, and * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Z-statistics are provided in parentheses. Industry effects comprise 17 Fama & French industry dummies. Appendixes A and B provide definitions and data sources for the regression variables. (a) Winsorized at the 1st and 99th percentiles; (b) normalized and standardized.

The third channel would simply indicate that firms only use balanced information composition when disclosing positive news, but the first and second channels would support the role of the balanced information composition as a permanent tool for capital market communications either due to a direct or an indirect effect through liquidity. To shed more light on these potential channels, we study a battery of alternative capital market outcomes. To this end, we apply measures closely related to information asymmetry (*Bid–ask spreads,*[20] *Analyst forecast dispersion,*[21] and *Idiosyncratic firm volatility*), illiquidity (*Amihud illiquidity*), and the generation of new information (*Cumulative abnormal returns*).

The results in Table 8 show negative and statistically significant effects of the balanced information composition on all measures related to information asymmetry and illiquidity while we find no statistical evidence for the generation of new information. Thus, balanced information composition can be an essential tool for a firm's capital market communications to lower the cost of capital by reducing information asymmetry (directly or indirectly through liquidity risk), ultimately adding to a firm's value creation.

6. Conclusion

In this study we explore the association between a conference call design in line with the concept of the balanced scorecard and the firms' cost of capital. Using textual analysis, we develop a novel measure to capture the balance of the information composition in conference calls. Our results suggest that a more balanced information composition in conference calls can lower the firms' cost of capital. Additional tests substantiate our findings and show that the observed effect is driven by a reduction in information asymmetry. These findings should be of particular interest to firms and IR teams as we propose the balanced scorecard concept as a framework to lean on when composing the information for conference calls.

We contribute to the literature in several ways. First, we add to the literature on conference calls by investigating the benefits of the open nature of conference calls in contrast to the potential costs of disclosing unfavorable information (Frankel et al., 1999; Hollander et al., 2010; Lee, 2016; Tasker, 1998). Our study emphasizes the view that firms can use this information dissemination opportunity to their advantage by bridging the gap between managers and investors. Second, we provide a specific course of action for enhanced capital market communications by proposing the use of the balanced scorecard concept as a framework for the information composition in conference calls. Specifically, we show how the concept of the balanced scorecard can support firms' value creation through a lower cost of capital in the field of capital market communications. Third, we contribute to the cost of capital literature (Dhaliwal et al., 2016; Evans, 2016; Mishra, 2014). In addition to previous work by Brown et al. (2004), we reveal that not only the existence of conference calls but also the conference call design has an impact on firms' cost of capital.

Our findings are subject to a number of limitations. First, although we devoted particular attention to developing the word lists, the balanced information composition measure cannot account for the varying quality of the word occurrences nor the connection between two

---

[20] Bid–ask spreads are a common proxy for information asymmetry (Lee, 2016; Leuz & Verrecchia, 2000). Some studies, however, have also employed bid–ask spreads as a measure for illiquidity as they are closely linked to 'price protection that uninformed market participants demand as compensation for the perceived information risk associated with trading in equity markets' (Welker, 1995, p. 802).

[21] In unreported regressions, we test the effect of balanced information composition on analyst forecast errors and obtain similar results.

related words from different perspectives. Second, beyond the four perspectives of the balanced scorecard there might be other information dimensions that investors prefer. In additional tests, we observe that the effect of the balanced information composition measure remains robust after controlling for several alternative information dimensions, but naturally we cannot account for all potential information dimensions. Third, we are unable to deny the existence of other unobserved design features (e.g. alternative forms of information composition), which could affect the cost of capital. In this context, we control for some obvious alternative features. Fourth, given that investors' information demand is likely to vary over time and that some information might already be available in the market, we cannot advocate for an exact balance as the best fit for investors at all times. Generally, however, we find indications that steps toward a more balanced information composition lead to positive capital market outcomes.

Despite these limitations, our study provides avenues for future research. Specifically, future research could apply the proposed balanced information composition measure in different corporate disclosure settings (e.g. capital market days). Moreover, beyond the balance composition future studies could delve deeper into the intentional design of conference calls and identify alternative frameworks. Finally, future research could shed light on aspects that drive firms' decisions on whether to exploit the open nature of conference calls by experimenting with more informative designs.

Acknowledgments

We thank the editors, Reuven Lehavy and Florin Vasvari, and two anonymous reviewers for their constructive guidance during the review process. We are also grateful for the helpful comments from Nico Lehmann, Jason Chen, Naomi Soderstrom, Anastasiya Zavyalova, Federico Aime, Jonathan Bundy, and Stefan Wagner. Moreover, we would like to thank participants at the Content Analysis Workshop at the Annual Meeting of the Academy of Managament in Anaheim (August 2016), the Finance, Accounting, and Taxes Research Colloquium at University of Goettingen (May 2017), the Annual Meeting of the Academy of Management in Anaheim (August 2016), the Annual Meeting of the European Accounting Association in Valencia (May 2017), the Annual Meeting of the American Accounting Association in San Diego (August 2017), and the Annual Meeting of the German Academic Association for Business Research (VHB) in Magdeburg (May 2018).

Supplemental Data and Research Materials

Supplemental data for this article can be accessed on the Taylor & Francis website, doi:10.1080/09638180.2019.1709523.
Appendix S1. Development of a Word List for Balanced Information Composition

References

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, *17*(2), 223–249.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297.

Armstrong, C. S., Core, J. E., Taylor, D. J., & Verrecchia, R. E. (2011). When does information asymmetry affect the cost of capital? *Journal of Accounting Research*, *49*(1), 1–40.

Balakrishnan, K., Billings, M. B., Kelly, B., & Ljungqvist, A. (2014). Shaping liquidity: On the causal effects of voluntary disclosure. *The Journal of Finance*, *69*(5), 2237–2278.

Banker, R. D., Chang, H., & Pizzini, M. J. (2004). The balanced scorecard: Judgmental effects of performance measures linked to strategy. *The Accounting Review*, *79*(1), 1–23.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Brennan, M. J., & Subrahmanyam, A. (1996). Measuring market liquidity. *Journal of Financial Economics*, *41*, 441–464.

Brochet, F., Limbach, P., Bazhutov, D., Betzer, A., & Doumet, M. (2019). *Where do investor relations matter the most?* Working paper.

Brochet, F., Loumioti, M., & Serafeim, G. (2015). Speaking of the short-term: Disclosure horizon and managerial myopia. *Review of Accounting Studies*, *20*(3), 1122–1163.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2015). Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research*, *53*(1), 1–47.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2019). Managing the narrative: Investor relations officers and corporate disclosure. *Journal of Accounting and Economics*, *67*(1), 58–79.

Brown, S., Hillegeist, S. A., & Lo, K. (2004). Conference calls and information asymmetry. *Journal of Accounting and Economics*, *37*(3), 343–366.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance*, *56*(1), 1–43.

Chapman, K. L., Miller, G. S., & White, H. D. (2019). Investor relations and information assimilation. *The Accounting Review*, *94*(2), 105–131.

Chen, G., & Hambrick, D. C. (2012). CEO replacement in turnaround situations: Executive (mis)fit and its performance implications. *Organization Science*, *23*(1), 225–243.

Chen, S., DeFond, M. L., & Park, C. W. (2002). Voluntary disclosure of balance sheet information in quarterly earnings announcements. *Journal of Accounting and Economics*, *33*(2), 229–251.

Chen, Z., Huang, Y., & Wei, K. C. J. (2013). Executive pay disparity and the cost of equity capital. *Journal of Financial and Quantitative Analysis*, *48*(3), 849–885.

Claus, J., & Thomas, J. (2001). Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets. *The Journal of Finance*, *56*(5), 1629–1666.

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, *67*(2), 719–760.

De Geuser, F., Mooraj, S., & Oyon, D. (2009). Does the balanced scorecard add value? Empirical evidence on its effect on performance. *European Accounting Review*, *18*(1), 93–122.

Dhaliwal, D. S., Judd, J. S., Serfling, M., & Shaikh, S. (2016). Customer concentration risk and the cost of equity capital. *Journal of Accounting and Economics*, *61*(1), 23–48.

Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. G. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review*, *86*(1), 59–100.

Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance*, *46*(4), 1325–1359.

Easton, P. D. (2004). PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital. *The Accounting Review*, *79*(1), 73–95.

Evans, M. E. (2016). Commitment and cost of equity capital: An examination of timely balance sheet disclosure in earnings announcements. *Contemporary Accounting Research*, *33*(3), 1136–1171.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E., & French, K. (1997). Industry costs of equity. *Journal of Financial Economics 43*, 153–193.

Firk, S., Schmidt, T., & Wolff, M. (2019). CFO emphasis on value-based management: Performance implications and the challenge of CFO succession. *Management Accounting Research*, *44*, 26–43.

Frankel, R., Johnson, M., & Skinner, D. J. (1999). An empirical examination of conference calls as a voluntary disclosure medium. *Journal of Accounting Research*, *37*(1), 133–150.

Gebhardt, W. R., Lee, C. M. C., & Swaminathan, B. (2001). Toward an implied cost of capital. *Journal of Accounting Research*, *39*(1), 135–176.

Hail, L., & Leuz, C. (2006). International differences in the cost of equity capital: Do legal institutions and securities regulation matter? *Journal of Accounting Research*, *44*(3), 485–531.

He, J., & Huang, Z. (2011). Board informal hierarchy and firm financial performance: Exploring a tacit structure guiding boardroom interactions. *Academy of Management Journal*, *54*(6), 1119–1139.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*(1), 153–161.

Hollander, S., Pronk, M., & Roelofsen, E. (2010). Does silence speak? An empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research*, *48*(3), 531–563.

Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard - measures that drive performance. *Harvard Business Review*, *70*(1), 71–79.

Kaplan, R. S., & Norton, D. P. (1993). Putting the balanced scorecard to work. *Harvard Business Review*, *71*(5), 131–140.

Kaplan, R. S., & Norton, D. P. (1996). *The balanced scorecard: Translating strategy into action*. Boston, MA: Harvard Business School Press.

Karolyi, G. A., & Liao, R. C. (2017). *The economic consequences of investor relations: A global perspective*. Working paper.

Kothari, S. P., Li, X., & Short, J. E. (2009). The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. *The Accounting Review*, *84*(5), 1639–1670.

Lambert, R. A., Leuz, C., & Verrecchia, R. E. (2007). Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research*, *45*(2), 385–420.

Lambert, R. A., Leuz, C., & Verrecchia, R. E. (2012). Information asymmetry, information precision, and the cost of capital. *Review of Finance*, *16*(1), 1–29.

Larcker, D. F., & Rusticus, T. O. (2010). On the use of instrumental variables in accounting research. *Journal of Accounting and Economics*, *49*(3), 186–205.

Larcker, D. F., & Zakolyukina, A. A. (2012). Detecting deceptive discussions in conference calls. *Journal of Accounting Research*, *50*(2), 495–540.

Lee, J. (2016). Can investors detect managers' lack of spontaneity? Adherence to predetermined scripts during earnings conference calls. *The Accounting Review*, *91*(1), 229–250.

Leuz, C., & Verrecchia, R. E. (2000). The economic consequences of increased disclosure. *Journal of Accounting Research*, *38*(2000), 91–124.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35–65.

Malina, M. A., & Selto, F. H. (2001). Communicating and controlling strategy: An empirical study of the effectiveness of the balanced scorecard. *Journal of Management Accounting Research*, *13*(1), 47–90.

Matsumoto, D., Pronk, M., & Roelofsen, E. (2011). What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. *The Accounting Review*, *86*(4), 1383–1414.

Mayew, W. J. (2008). Evidence of management discrimination among analysts during earnings conference calls. *Journal of Accounting Research*, *46*(3), 627–659.

Mishra, D. R. (2014). The dark side of CEO ability: CEO general managerial skills and cost of equity capital. *Journal of Corporate Finance*, *29*, 390–409.

Ohlson, J. A., & Juettner-Nauroth, B. E. (2005). Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies*, *10*(2–3), 349–365.

Pan, L., McNamara, G., Lee, J. J., Haleblian, J. J., & Devers, C. E. (2018). Give it to us straight (most of the time): Top managers' use of concrete language and its effect on investor reactions. *Strategic Management Journal*, *39*(8), 2204–2225.

Pencle, N., & Mălăescu, I. (2016). What's in the words? Development and validation of a multidimensional dictionary for CSR and application using prospectuses. *Journal of Emerging Technologies in Accounting*, *13*(2), 109–127.

Rehm, W. (2013). Three steps to a more productive earnings call. *McKinsey on Finance*, *August*, 2–4.

Roodman, D. (2006). *How to do xtabond2: An introduction to "difference" and "system" GMM in Stata. Center for Global Development working paper 103*. Working paper.

Short, J. C., Broberg, J. C., Cogliser, C. C., & Brigham, K. H. (2010). Construct validation using computer-aided text analysis (CATA): An illustration using entrepreneurial orientation. *Organizational Research Methods*, *13*(2), 320–347.

Sundin, H., Granlund, M., & Brown, D. A. (2010). Balancing multiple competing objectives with a balanced scorecard. *European Accounting Review*, *19*(2), 203–246.

Tasker, S. (1998). Bridging the information gap: Quarterly conference calls as a medium for voluntary disclosure. *Review of Accounting Studies*, *3*(1/2), 137–167.

Welker, M. (1995). Disclosure policy, information asymmetry, and liquidity in equity markets. *Contemporary Accounting Research*, *11*(2), 801–827.

Wiersma, E. (2009). For which purposes do managers use balanced scorecards? *Management Accounting Research*, *20*(4), 239–251.

Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the dynamics of internal corporate governance. *Journal of Financial Economics*, *105*(3), 581–606.

Appendices

Appendix A: Data Sources and Variable Definitions: Dependent Variable

Variable	Description/Calculation	Source
Dependent variables:		
r_gls	Implied cost of capital estimated using the Gebhardt et al. (2001) model for each quarter. Winsorized at the 1st and 99th percentiles. $P_t = B_t + \sum_{\tau=1}^{11} \frac{FROE_{\tau+t} - r\_gls}{(1+r\_gls)^{\tau}} B_{t+\tau-1} + \frac{FROE_{t+12} - r\_gls}{r\_gls(1+r\_gls)} B_{t+11}$ where $B_{t+\tau} = B_{t+\tau-1}(1 - DPR_{t+\tau})$ The explicit forecast horizon is set to 3 years. From year four to year twelve, the FROE linearly converges to the industry ROE in the 12th year. Industries are defined according to Fama and French (1997) and the industry ROE is estimated as the median over the past 5 years, excluding loss firms. The dividends per share are assumed to be constant. *P* is the stock price, B is the book value, FROE is the forecasted return on equity, and DPR is the expected dividend payout ratio.	Authors' calculations based on Datastream
r_es	Implied cost of capital estimated using the Easton (2004) model (kES) for each quarter. Winsorized at the 1st and 99th percentiles. $P_t = \frac{FEPS_{t+2} + r\_es * DPS_{t+1} - FEPS_{t+1}}{(r\_es)^2}$ The explicit forecast horizon is set to 2 years, beyond which forecasted abnormal earnings grow in perpetuity at a constant rate.	As above
r_ct	Implied cost of capital estimated using the Claus and Thomas (2001) model for each quarter. Winsorized at the 1st and 99th percentiles. $P_t = B_t + \sum_{\tau=1}^{5} \frac{ae_{t+\tau}}{(1+r\_ct)^{\tau}} + \frac{ae_{t+5}(1+g)}{(r\_ct - g)(1+r\_ct)^5}$ where $ae = FEPS_{t+\tau} - r\_ctB_{t+\tau-1}$ $B_{t+\tau} = B_{t+\tau-1} + FEPS_{t+\tau}(1 - DPR_{t+\tau})$ $DPR_{t+\tau} = 0.5$ $g = r_f - 0.03$ The explicit forecast horizon is set to 5 years, beyond which forecasted residual earnings grow at the expected inflation rate. The dividend payout is assumed to be constant at 50%.	As above
r_avg	Average of r_gls, r_es, and r_ct.	As above

Variable	Description/Calculation	Source
r_ojn	Implied cost of capital estimated using the Ohlson and Juettner-Nauroth (2005) model for each quarter. Winsorized at the 1st and 99th percentiles. $r\_ojn = A + \sqrt{A^2 + \frac{FEPS_{t+1}}{P_t}(g_2 - (\gamma - 1))}$ where $A = \frac{1}{2}(\gamma - 1) + \frac{DPS_{t+1}}{P_t}$ $g_2 = \frac{STG + LTG}{2}$ $STG = \frac{FEPS_{t+2} - FEPS_{t+1}}{FEPS_{t+1}}$ $(\gamma - 1) = r_f - 0.03$ The explicit forecast horizon is set to 1 year, beyond which forecasted earnings grow at a near-term rate that converges to a perpetuity. The near-term rate is the average of the short-term growth rate (STG) and the long-term growth rate (LTG). r_f is the rate on a 10-year Treasury note, and DPS is the dividend per share. The dividends per share are assumed to be constant.	As above
r_avg_alt	Average of *r_gls*, *r_es*, *r_ct*, and *r_ojn*.	As above

Appendix B: Data Sources and Variable Definitions: Other Variables

Variable	Description/Calculation	Data source
Independent variable		
Balanced information composition (BIC)	The Gini coefficient of the frequency counts from each balanced scorecard perspective. The perspectives being: finance, customer, internal processes, and learning and growth. Next, we calculate the z-score of the Gini coefficient and standardize the scale from 0 to 1. Furthermore, we reverse the scale to turn the inequality into an equality (balance) measure, so that it is more intuitive to the reader.	Conference call transcripts from Thomson StreetEvents
Balanced information composition alternative (BIC_alt)	The Theil entropy measure of the frequency counts from each balanced scorecard perspective. The perspectives being: finance, customer, internal processes, and learning and growth. Next, we calculate the z-score of the Theil entropy measure and standardize the scale from 0 to 1. Furthermore, we reverse the scale to turn the inequality into an equality (balance) measure, so that it is more intuitive to the reader.	As above
Control variables		
Beta	Market beta measured over the last 36 months. Winsorized at the 1st and 99th percentiles.	Datastream
Size	Natural log of the firm's market value. Winsorized at the 1st and 99th percentiles.	As above
Book to market	Book value of equity divided by market value of equity. Winsorized at the 1st and 99th percentiles.	As above
Leverage	Short-term debt and current portion of long-term debt divided by total assets. Winsorized at the 1st and 99th percentiles.	As above
Analyst forecast dispersion	The standard deviation of the analysts' one-quarter ahead earnings per share scaled by the stock price at the beginning of the quarter and multiplied by 100. Winsorized at the 1st and 99th percentiles.	As above
Long-term growth rate	The mean of analysts' forecasts for long-term growth. Winsorized at the 1st and 99th percentiles.	As above
Capital intensity	Net property, plant and equipment scaled by total assets.	As above
R&D intensity	Research and development expenditures scaled by net sales in percent.	As above
Operating margin	EBITDA scaled by net sales.	As above
Management tone	The difference between positive and negative words divided by the sum of negative and positive words spoken by managers, following the Loughran and McDonald (2011) word list.	Conference call transcripts from Thomson StreetEvents
Analyst tone	The difference between positive and negative words divided by the sum of negative and positive words spoken by analysts, following the Loughran and McDonald (2011) word list.	As above
Coverage	Natural log of the analysts present in the conference call, adjusted by the number of analysts issuing forecasts for the firm.	As above

Variable	Description/Calculation	Data source
Call structure	The ratio of the words spoken in the MD session to the words spoken in the Q&A session.	As above
Length	Natural log of the total number of words in the MD.	As above
BSC volume	The accumulated word counts of the four balanced scorecard perspectives scaled by all words in the MD.	As above
Industry effects	17 dummy variables classifying firms into industry sectors, using data from Kenneth R. French's data library, which is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html	Website of Kenneth French
Additional Tests		
Forward-looking to backward-looking	Based on the word list for forward-looking words by Matsumoto et al. (2011) we counted the occurrences of forward-looking words in the MD session and subtracted the frequency count from the total word count in the MD session, to obtain a measure for backward-looking words. Next, we standardized and normalized the values and created the ratio of forward-looking to backward-looking words.	Conference call transcripts from Thomson StreetEvents
Long-term to short-term	Based on the word lists by Brochet et al. (2015) we counted the occurrences of short-term and long-term words in the MD session. Next, we standardized and normalized the values and created the ratio of long-term to short-term words.	As above
Non-financial to financial	Based on the word list for financially oriented words by Matsumoto et al. (2011) we counted the occurrences of financial words in the MD session and subtracted the frequency count from the total word count in the MD session, to obtain a measure for non-financial words. Next, we standardized and normalized the values and created the ratio of non-financial to financial words.	As above
Non-quantitative to quantitative	Based on the word lists for numbers and quantifiers from LIWC we counted the occurrences of quantitative words in the MD session and subtracted the frequency count from the total word count in the MD session, to obtain a measure for non-quantitative words. Next, we standardized and normalized the values and created the ratio of non-quantitative to quantitative words.	As above
CSR to other	Based on the word lists for CSR by Pencle and Mălăescu (2016) we counted the occurrences of CSR words in the MD session and subtracted the frequency count from the total word count in the MD session, to obtain a measure for non-CSR words. Next, we standardized and normalized the values and created the ratio of CSR to other words.	As above

Variable	Description/Calculation	Data source
Information composition measure Model 1	Calculated as all words spoken by the management in the MD session minus all finance words spoken by the management in the MD session divided by all words spoken by the management in the MD session.	As above
Information composition measure Model 2	Calculated as the sum of all customer, internal processes, and learning & growth words spoken by the management in the MD session divided by all words spoken by the management in the MD session.	As above
Information composition measure Model 3	Calculated as the Gini coefficient of the customer, internal processes, and learning & growth words spoken by the management in the MD session.	As above
Information composition measure Model 4	Calculated as the Gini coefficient of the finance, customer, internal processes, and learning & growth words spoken by the management in the MD session.	As above
Bid-ask spreads	Bid-ask spread from daily high, low and closing prices as proposed by Corwin and Schultz (2012), calculated as the annualized average spread in the quarter.	Datastream
Amihud illiquidity	Amihud illiquidity measure estimated according to Amihud (2002) as the daily absolute return divided by the daily trading volume calculated as the average in the quarter.	CRSP
Idiosyncratic firm volatility	Annualized standard deviation of daily residuals from the Fama and French (1993) three-factor model. For each firm, the model is estimated quarterly using data from Kenneth R. French's data library, which is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html	Datastream, French's data library
Cumulative abnormal returns	Two-day cumulative abnormal return around the conference call date. The abnormal return is calculated as the stock return minus the return on the S&*P* 500 equally-weighted index over the two-day window $(0, +1)$.	Datastream
Firm volatility	Firm-specific stock volatility. The stock volatility is calculated as the annualized standard deviation of daily stock returns during the previous period.	As above
Industry volatility	Industry-aggregated stock volatility. The stock volatility is calculated as the annualized standard deviation of daily stock returns during the previous period.	As above
Index volatility	Index-aggregated stock volatility. The stock volatility is calculated as the annualized standard deviation of daily stock returns during the previous period.	As above

Appendix C: Development of the Balanced Information Composition Measure

This appendix presents the steps leading to our balanced information composition measure. First, we briefly describe the development of the word lists. Second, we present the final word lists. Third, we illustrate the computation of our balanced information composition measure based on the Gini coefficient using numerical examples. Fourth, we report an additional external assessment of the content validity of our balanced information composition measure. For a more detailed explanation of the whole development process see the supplementary online Appendix S1.

a) Development of the Word Lists

For the development of the word lists, we followed the construct validation procedure proposed by Short et al. (2010). According to the procedure, we first conducted a *deductive approach* to provide a theory-based word list followed by an *inductive approach* based on the management's word choices in conference calls.

In the *deductive approach,* we built on the balanced scorecard literature by Kaplan and Norton as the foundation for developing our initial word lists. First, we created the following working definition for our construct: 'Balanced information composition in a manuscript implies that the text equally covers each of the four perspectives of the balanced scorecard (i.e. finance, customer, internal processes, and learning and growth) by providing related information and attaching the same degree of importance to each perspective.' Second, we assessed the construct dimensionality and applied the categorization of the four perspectives introduced by Kaplan and Norton (1992) distinguishing between finance, customer, internal processes, and learning and growth. Third, we created word lists based on an extensive literature review for each perspective. Thereby, we introduced multiple main words for each perspective, for which we created discrete word lists that helped us to cover the entire scope of the perspectives. Fourth, we assessed the validity of these word lists by using external management consultants who were experts in the field of the balanced scorecard. The experts confirmed 95% of the proposed words and also suggested further words for inclusion in the word lists, which further helped to improve the word lists. This process resulted in deductive word lists for the four balanced scorecard perspectives.

In the *inductive approach,* we used the conference call transcripts as the relevant research object to extract related words and to enrich the initial word lists derived from the deductive approach. First, we identified a list of commonly used words by requiring Wordstat to list all words that occurred in a minimum of three cases in a random subsample of 200 conference calls. Second, from this list, two of the authors independently identified words for the four perspectives that went beyond the deductive word lists. Third, for the identified words, we checked the agreement between the two authors by calculating the level of conformity. This enabled us to assess and establish initial interrater reliability as the calculated value lay above critical thresholds. Fourth, we included all identified words that the two authors had agreed on and discussed the words that only one of the authors had identified. If this discussion led to an agreement, we additionally included the identified word in our word lists. Moreover, we also made extensive use of Wordstat's 'keyword in context' (KWIC) tool to verify that all identified words captured the intended meaning. If this was not the case, we either excluded the words or imposed specific rules regarding how these words had to appear.

In a final step, we united the word lists from the *deductive* and the *inductive approach* to obtain our final word lists for the four perspectives of the balanced scorecard.

b) The Final Word Lists

For the sake of brevity, we simplified the presentation of the final word lists and only included the root word instead of various forms of the searched-for words. For example, the term 'create value' includes creates value, created value, etc. (see the notes to the table for a more detailed description of the variations of words). The following table presents the final word lists including all root words.

PERSPECTIVE	DICTIONARY
Finance	amortization, business value added, BVA, CAPEX, capital cost, cash flow, cash value added, CF, CFROI, charge, COC, COGS, company value, cost of capital, create value, CVA, deliver value, depletion, depreciation, disbursement, earnings, EBIT, EBT, economic profit, economic rate of return, economic value added, enhance value, enterprise value, EP, EPS, ERR, EVA, expand value, expenditure, expense, FCF, firm value, G&A, improve value, income, increase value, internal rate of return, IRR, liquidity, loss, margin, market capitalization, NCF, net present value, NOPAT, NPV, OCF, OPEX, outlay, overhead, profit, return on asset, return on capital, return on equity, return on investment, return on revenue, return on sales, return on shareholder, revenue, ROA, ROAC, ROACE, ROC, ROCE, ROCI, ROE, ROI, ROIC, RONA, ROR, ROS, ROTI, sales, SG&A, share price, shareholder return, shareholder value, spending, stock price, TSR, unlock value, value delivery, value enhancement, value expansion, value improvement, value increase, value of the company, value of the enterprise, value of the firm, value unlock, WACC
Customer	brand, buyer, client, clientele, consumer, cross-selling, guest, image, market acceptance, market demand, market penetration, market position, market power, market relation, market satisfaction, marketing, patient, position in the market, purchaser, share in the market, share of the market, shopper, subscriber, trademark, user
Internal processes	automation, consumption of resources, cycle time, design, device, digital, distribution, economies of scale, economies of scope, effectively, effectiveness, efficacy, efficiency, efficient, fabrication, goods, lean, life cycle, logistic, manufact, merchandise, operation, optimization, output, procurement, productive, productivity, resource consumption, resources used, SCM, service, sourcing, supply, synergy, time to market
Learning and growth	ability, competence, culture, development pipeline, expertise, headcount, human capital, human resource, innovate, invent, knowledge, leadership, learn, modernization, novelty, patent, personnel, potential, qualification, R&D, research, skill, staff, talent, team, training, worker, workforce

Notes: The presented words cover several variations of each word. First, we also counted words if words were inserted in between the searched-for words (e.g. return on assets covers return on net assets, return on net operating assets, etc.). Second, we also counted words that only differed in their suffix (e.g. manufact covers manufacture, manufacturing, etc.). Third, we included separate and conjoint forms of the listed words (e.g. trademark also covers trade mark and trade-mark). Thus, the complete word lists that were applied are even more extensive. The complete developed word lists for use in QDA (or other CATA software) including all relevant variations are available from the authors upon request.

c) Numerical Examples of the Computation of our Balanced Information Composition Measure

Based on the word lists, we counted the occurrences of the four perspectives in each conference call MD session using Wordstat. In order to transform the four individual counts of the balanced scorecard perspectives into one score, we used the following formula to compute the Gini coefficient and to represent the balance of the information composition: Gini coefficient $= 1 + \frac{1}{n} - \frac{2}{n^2\bar{z}} \sum_{i=1}^{n}(i * z_i)$, where $n = 4$ is the number of perspectives, z_1, z_2, z_3, and z_4 are the word counts for each of the four perspectives in descending order, and $\bar{z}$ is the mean word count of the perspectives. Following other studies, we normalized and standardized the Gini coefficient on a 0-to-1 scale (Chen & Hambrick, 2012). Finally, we reversed the scale to obtain our balanced information composition equality measure (*BIC)*. The following table presents numerical examples of the computation.

Conference Call	Nike Q3 2012	Ford Q2 2005
Words per perspective		
Finance	133	118
Customer	56	1
Internal processes	50	29
Learning and growth	52	4
Gini coefficient	0.2174	0.6184
Standardized value	– 2.5479	0.8294
Final value	0.9661	0.1815

d) Additional External Assessment of Content Validity

Lastly, after computing the balanced information composition measure with the Gini coefficient based on the self-developed word lists, we sought to validate our newly proposed measure. Therefore, we examined how well our measure captures the perceived equality between the four balanced scorecard perspectives in conference call texts.

We performed this test using graduate students from management accounting courses who were given a random subsample of MD sessions of conference calls. Each student was supposed to read three texts and each text was supposed to be read by two students. We asked the students to rate the balance of each text on a scale from 1 (very low) to 7 (very high). We then assessed the validity of our measure by calculating the correlation between the students' average survey score for each text and the balanced information composition measure. This test yielded correlations ranging from 0.77 to 0.86 (when excluding extreme outliers). We interpreted this finding as support for our measure's content validity. In conclusion, we are confident that we developed a proxy in line with the balanced scorecard literature and Short et al.'s (2010) construct validation procedure that successfully measures the information composition in conference calls in line with the balanced scorecard.