Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

The Long March

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Abstract

Since the seminal work of March (1991) outlined the importance of balancing exploration and exploitation in organizational learning, an increasing number of studies has analyzed the relationship between this balance and firm performance. While most studies have relied on survey or patent-based indicators to measure firms? exploration and exploitation activities, attention has recently shifted to the use of text based indicators and content analysis, as this holds the promise of generality and universal application. The limited number of studies applying content analysis have used the original terminology and keywords proposed by March to construct indicators of firms? orientation towards exploration or exploitation. In this paper we show 1) that March?s original terminology is unlikely to deliver valid and generally applicable indicators 2) how the construction of representative indicators should be based on a structured series of validity analyses 3) that an inductive approach retrieving keywords from the body of text and based on the validity analyses provides more robust results. Empirically, we analyze more than 100,000 R&D-related press articles

(1996-2003) covering 151 R&D intensive firms based in Europe, Japan and the US. As part of our validity analyses, we confirm an inverted-U shaped relationship between firm performance and exploration orientation ? but only if exploration is measured using an inductive approach that departs substantially from March?s original list of keywords.

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The Long March: The Quest for Valid Text Based Indicators of Exploration and Exploitation

ABSTRACT

Since the seminal work of March (1991) outlined the importance of balancing exploration and exploitation in organizational learning, an increasing number of studies has analyzed the relationship between this balance and firm performance. While most studies have relied on survey or patent-based indicators to measure firms' exploration and exploitation activities, attention has recently shifted to the use of text based indicators and content analysis, as this holds the promise of generality and universal application. The limited number of studies applying content analysis have used the original terminology and keywords proposed by March to construct indicators of firms' orientation towards exploration or exploitation. In this paper we show 1) that March's original terminology is unlikely to deliver valid and generally applicable indicators 2) how the construction of representative indicators should be based on a structured series of validity analyses 3) that an inductive approach retrieving keywords from the body of text and based on the validity analyses provides more robust results. Empirically, we analyze more than 100,000 R&D-related press articles (1996-2003) covering 151 R&D intensive firms based in Europe, Japan and the US. As part of our validity analyses, we confirm an inverted-U shaped relationship between firm performance and exploration orientation – but only if exploration is measured using an inductive approach that departs substantially from March's original list of keywords.

Keywords: exploration, exploitation, content analysis, computer aided text analysis (CATA), firm performance

1. Introduction

Since the seminal work of March (1991) outlined the managerial challenge of balancing exploration and exploitation in organizational learning, an increasing number of studies has analyzed the relationship between this balance and firm performance.[1] Most studies have relied on survey or patent-based indicators to measure firms' exploration and exploitation activities. While these indicators provide detailed information, they are limited in applicability due to limited availability and difficulties to compare the indicators across time (surveys) or limited representativeness for a wide range of sectors (patents). This has given important impetus to the search for alternative indicators of exploration and exploitation. Attention has recently shifted to the use of text based indicators and content analysis (Uotila, 2009; Vagnani, 2012), as this holds the promise of generality and universal application.

Content analysis is particularly suited when dealing with concepts that are difficult to measure (Duriau, Reger, & Pfarrer, 2007; Morris, 1994). It has been applied in management research to assess concepts such as CEO behavior and performance (e.g. Short & Palmer, 2003), organizational sense-making (e.g.Gioia & Chittipeddi, 1991), and entrepreneurship (e.g. Doucet & Jehn, 1997; Ferrier, 2001). Analysis is generally performed on organizationally produced texts such as CEO shareholder letters, annual reports, mission statements and press release articles (Jauch, Osborn, & Martin, 1980). Two prior studies have applied content analysis techniques to measure exploration and exploitation (Uotila et al., 2009; Vagnani, 2012).These studies relied on the keywords describing exploration and exploitation behavior provided in March's (1991) original contribution and applied computer-aided text analysis (CATA)to a large set of press release documents (Uotila et al., 2009) and statements in annual reports (Vagnani, 2012).However, these papers did not apply the range of structured validity analyses recommended by the literature on text based analysis(e.g. Short et al., 2010)and it is yet unclear to what extent the original keywords deduced from March's conceptual framework have a valid application in various empirical contexts.

Against this background the objectives of this paper are to 1) show how the construction of representative indicators should be based on a structured series of validity analyses 2) examine whether March's original lexicon can deliver valid and generally applicable indicators 3) examine whether an inductive approach retrieving keywords from the body of

[1] A non-exhaustive list is: Uotila et al., 2009; Vagnani, 2012; He & Wong, 2004; Jansen et al., 2006, 2009; Belderbos et al., 2010;Rothaermel & Alexandre, 2009; Tamayo-Torres, Ruiz-Moreno & Llorens-Montes, 2011; Yang & Li, 2011; Eisenhardt, Furr, & Bingham, 2010; Posen & Levinthal, 2012.

text analyzed and based on validity analyses provides robust results. Empirically, we analyze more than 100,000 R&D-related press articles (1996-2003) covering 151 R&D intensive US, European and Japanese firms from five different industries. Our analysis confirms an inverted-U shaped relationship between firm performance and exploration orientation (suggesting the importance of balancing both activities), but only if exploration is measured using an inductive approach that departs substantially from March's original list of keywords. The set of March's original keywords, in contrast, does not empirically comprise two distinct factors, while constructs based on the keywords do not relate systematically to firm performance in the context of our empirical setting.

This paper will proceed as follows. In the next section we review prior work on exploitation and exploration in the context of the use of different indicators. In Section 3 we introduce the recommended procedures for validating constructs based on content analysis and we discuss the concepts content validity, discriminant validity, external validity, and predictive validity. In Section 4 we apply these concepts in the empirical setting of the 151 firms, using the set of March keywords as well as an alternative set of keywords determined inductively from the body of text. The predictive validity test involves the estimation of a dynamic firm performance model, relating firms' market valuation (Tobin's q) to firms' relative orientation towards exploration.

2. Background

Since March's (1991) seminal study on "Exploration and Exploitation in Organizational Learning", the terms exploration and exploitation have dominated debates on organizational learning (e.g. Levinthal & March, 1993), strategic management (e.g. He & Wong, 2004; Uotila et al., 2009) and innovation management (e.g. Jansen, van den Bosch, & Volberda, 2006). Exploitation refers to the improvement and extension of existing capabilities by means of activities such as standardization, up-scaling and refinement, leading to predictable returns that are proximate in time. Exploration refers to the creation of new capabilities by means of activities such as fundamental research, experimentation, and search, implying uncertain returns that are more distant in time (March, 1991; Levinthal and March, 1993).[2] March

[2]Other studies have used different terminologies, such as the distinction between effectiveness and short term efficiency (Levinthal & March, 1993), search depth vs. search scope (Katila & Ahuja, 2002), alignment vs. adaptability (Gibson & Birkinshaw, 2004) and fluidity vs. stability (Schreyogg & Sydow, 2010).

defined exploration and exploitation as two ends of a continuum and suggests that resource constraints create a trade-off between the two types of activities. Firms need to maintain an appropriate balance between exploitation and exploration activities in order to prosper in both the short and long run (Levinthal & March, 1993). Organizations that engage only in exploration activities are likely to end up with too many undeveloped ideas and too little distinctive competences. Conversely, firms that focus exclusively on exploitation might end up in competency traps (Levitt and March, 1988) and might experience that core capabilities (Prahalad & Hamel, 1990) turn into core rigidities over time (Leonard-Barton, 1992).

Empirical research has supported March's view of balancing exploration and exploitation activities by showing that firms that engage in both exploration and exploitation financially outperform firms that focus more exclusively on one of both activities(He & Wong, 2004; Jansen et al., 2006; Lavie et al., 2009, Uotila et al., 2009; Venkatraman et al., 2007; Belderbos et al., 2010). However, balancing exploitation and exploration is not straightforward as both activities require different mindsets and organizational routines, with flexible, organic, organizational structures being preferable for exploration purposes, and efficiency-oriented, mechanistic organizational practices and processes being better suited for exploitation purposes (Abernathy, 1991; Ghemawat, 1991; Benner and Tushman, 2003; Jansen et al., 2005 & 2006, Burns and Stalker, 1961). There is still an ongoing discussion in the literature concerning how the balance between exploration and exploitation can be achieved, what the optimal balance between exploration and exploitation is, and what factors influence the nature of this balance (Radner & Rothschild, 1975; Gupta et al., 2006; March, 1991; Tushman & O'Reilly,1996; Van Looy et al., 2005; Raisch et al., 2009). These issues present a rich research agenda and future research will benefit from progress in the determination of accurate indicators of exploration and exploitation.

The existing literature mainly relies on survey-based and patent-based exploration and exploitation indicators. Survey based indicators (e.g. He and Wong, 2004; Jansen et al., 2005, 2006, 2009) cover detailed information about innovation processes but they are characterized by low comparability across industries and countries, and they may suffer from biases as a result of subjective judgments, potential heterogeneity, and endogeneity problems (Kleinknecht, Van Montfort & Bouwer, 2002; Visser et al., 2010; Mohnen-Roller, 2005). Patent-based indicators are an alternative since patent data are easy to collect and include detailed information on the prior art and technology classes of patents, which can be used to classify inventions as explorative or exploitative (e.g. Ahuja & Lampert, 2001; Belderbos et al., 2010; Rosenkopf & Nerkar, 2001; Katila & Ahuja, 2002). However, patent indicators also have some important limitations. Only a fraction of inventions are patented and patent propensities differ across industries and firms (Mansfield, 1986; Arundel & Kabla, 1998), such that patent-based indicators have little applicability across a variety of industries. In addition, it is unclear to what extent patent based indicators are consistent with the conceptual definitions of exploration and exploitation (Gupta et al., 2006).

Recently, Uotila et al. (2009) and Vagnani (2009) applied content analysis to measure exploration and exploitation. Content analysis is defined as a systematic, replicable technique for compressing words of a text into fewer content categories based on explicit rules of coding (Weber, 1990). In the management literature, content analysis is generally performed on archival narratives such as CEO shareholder letters, annual reports, press release articles and mission statements (Duriau et al., 2007). In content analysis, (sets of) single words are used to measure concepts (Pennebaker, Mehl, & Niederhoffer, 2003). Recent advances in computer technologies have enable researchers to perform content analyses of large amounts of text via computer aided text analysis (CATA). CATA is preferred by researchers since it has a higher reliability than human coding with lower cost and greater speed (Neuendorf, 2002).

Uotila et al. (2009) performed a CATA analysis on a set of news articles on firms' business activities using March's (1991) original keywords to measure firms' orientation towards exploration and exploitation. Vagnani (2012) followed a similar approach to measure the exploration orientation of firms via an automated content analysis of corporate annual reports. Both studies followed a 'deductive' approach in selecting the keywords to measure exploration and exploitation in the sense that they relied on March's original terminology and keywords to define exploration and exploitation. The question can be raised whether these theoretically derived keywords have general applicability in multiple empirical settings and result in valid indicators. Both studies appear not to have applied a structured set of validity checks and, for instance, do not report whether the empirical constructs exploitation and exploration are distinct from each other. Uotila et al. (2009, 259) did compare the result of CATA-based counts of the number of exploration and exploitation keywords in a number of texts with a manual classification by expert raters, but only obtained a moderate correlation between the two approaches (0.52).

Against this background, the primary objective of this paper is to examine the validity of CATA-based indicators of exploitation and exploration activities, by following a structured set of recommended validity procedures for content analysis (Short et al., 2010). We compare the validity of two approaches. The first approach, used in prior work, follows the deductively determined list of keywords provided by March (1991) to create the constructs exploration and exploitation (the 'March approach' hereafter). The second approach departs from the body of text under consideration and creates a new and validated dictionary of keywords for exploration and exploitation to create indicators of these constructs. The validation procedures are explained in the following section and the empirical application is described in Section 4.

3. Validity Steps in Content Analysis

Validity concerns the extent to which a measure accurately represents focal concepts (Cronbach,1971). Before empirical work can safely rely on content analysis indicators of exploration and exploitation, the demonstration of the validity of these indicators is a crucial step (Kerlinger & Lee, 2000). Different empirical techniques have been proposed in the literature (Cronbach & Meehl, 1955; Krippendorff, 1980 & 2004; Messick, 1989 & 1995). A recent study of Short et al. (2010) suggests a structured set of procedures for validating constructs using content analysis in organizational research. In this section, we introduce the different proposed validity checks.

Content validity is the degree to which a measure demonstrates the behavior or phenomenon for which it is intended (Nunnally & Bernstein, 1994). In content analysis, the adequacy of the words to represent a certain construct is critical. When selecting keywords, two techniques can be distinguished: deductive and inductive (Doucet & John, 1997; Kabanoff, Waldersee & Cohen, 1995). The deductive approach starts from theoretical definitions and uses critical keywords to define the construct of interest. The content validation will be enhanced by opinions of experts who are familiar with the constructs. In the inductive approach the word list is derived from the body of text to be analyzed. Commonly used words of interest are examined as potential keyword candidates. Selected words are evaluated by multiple expert raters and the inter-rater ratio is used to assess the content validity.

Most content analyses use single words as the unit of analysis. This single-word approach originates from the field of psychology and has the underlying assumption that the words people use in their narrative texts are the reflection of their thoughts (Pennebaker, Mehl, & Niederhoffer, 2003). Following this assumption, the words use in narrative texts about firms' activities (e.g. press releases, annual reports, etc.) provides valuable information. However, this ‘paper trail’ contains documents written for various purposes and by different people who may differ in various respects (internal/external to the firm, vocabulary, etc.). An approach that solely relies on keywords deduced from theory may face limitations to applicability as the assumption of universal interpretation and use of these keywords across different settings may not be justified. Conversely, an inductive method that acknowledges the vast diversity in sources and styles of reporting and that starts from the data analyzed - but is still informed by theory in its selection of keywords –may be more appropriate to identify keywords in the context of a large and varied text dataset.

Discriminant validity measures the extent to which a construct is distinct from other constructs (Campbell & Fiske, 1959). It can be assessed by means of a correlation analysis, such as exploratory or confirmatory factor analysis (Hair et al., 1998). In the current context, the keyword-based constructs exploration and exploitation should be sufficiently distinct from each other (cf. March, 1991), and the correlations between keywords pertaining to the same construct should be higher than the correlations between keywords across constructs.

External validity can be defined as the ability to generalize findings across multiple settings (Cook & Campbell, 1979). In order to evaluate the external validity of an indicator, the consistency of an indicator should be compared across multiple settings. The simplest way to assess external validity is to randomly split the sample in two subsets and compare the consistency of the indicator across both subsets.

Predictive validity is the degree to which an indicator or construct behaves in a manner predicted by theory (Krippendorff, 1980). It can be assessed using regression analysis, structural equation modeling or other accepted empirical methods associated within a particular research stream (Short et al., 2010). In the strategic management literature, organizational performance has been the focal variable of interest in relationship with exploration and exploitation activities (e.g. He & Wong, 2004; Uotila et al., 2009; Belderbos et al, 2010). The consensus prediction is that a balanced strategy outperforms a focused exploration or exploitation strategy, such that the degree to which a firm focuses on exploration rather than exploitation has an inverted-U shaped relationship with firm performance.

4. Empirical Analysis

To illustrate the application of these four validity steps we constructed a panel dataset (1996-2003) on 151 R&D intensive US, European and Japanese innovative firms that are active in five different industries including Chemicals, Pharmaceuticals and Biotechnology, Electronics and Electrical Engineering, IT Hardware (computers and communication equipment), and Non-Electrical Machinery.[3] The firms are drawn from the '2004 EU industrial R&D investment scoreboard', which provides listings of the 500 most R&D intensive European and the 500 most R&D intensive US and Japanese firms. The sample firms are roughly equally distributed across the five main industries and home regions and represent the firms with the largest R&D budgets in their industry and region.

The dataset is created by drawing on several data sources: Lexis-Nexis, Worldscope, Compustat and corporate annual reports. Worldscope and Compustat contain information on firms' financial performance (Tobin's Q), R&D expenses and firm size (assets). Exploration and exploitation indicators are constructed drawing on more than 100,000 news articles covering the sample firms' research and development related activities. These articles are retrieved from the Lexis-Nexis database, which includes a wide range of information sources.[4] Prior studies relied solely on organizationally produced text, such as corporate press releases (Uotila et al.,2009) and annual reports (Vagnani, 2012). However, using only organizationally produced texts raises questions about objectivity and credibility since organizationally produced texts may also serve as a public relations tool rather than solely reflecting firm's actual practices (Morris, 1994).

In order to get a broader picture on firms' exploration and exploitation activities, we collected the news articles at the consolidated firm level, using all name variations of the 151 parent firms and their majority-owned subsidiaries. For this purpose, we constructed yearly lists (to account for changes in the group structure of firms over time) of firm subsidiaries included in corporate annual reports, 10-K reports filed with the SEC in the US and, for Japanese firms,

[3]Our original sample consists of 184 firms. By limiting analyses to firms that have a sufficient coverage in the text database and which have information on Tobin's q, the sample is reduced to 151 firms in this paper.

[4]Key sources include major disseminators of news releases like *Business Wire*, *PR Newswire Association, Information Bank Abstracts(by The New York Times*), *Information Access Company* (*Thomson Corp.*), etc. as well as more specialized information brokers like *Reuters Health Medical News*, *Intellectual Property Today*, *Espicom Business Intelligence* (focused on the pharmaceutical sector), and so on. It is fair to assume our data offers an exhaustive coverage of all publicly known and codified information about corporate R&D activities of our sample firms in the considered time period.

information on foreign subsidiaries published by Toyo Keizai in the yearly 'Directories of Japanese Overseas Investments'.

4.1. Content Validity

The content validity of a text based indicator is assessed via the accuracy of the keywords used to construct this indicator. As explained earlier, two techniques are available to create the keywords' 'dictionary': deductive vs. inductive. Prior work (Uotila et al., 2009; Vagnani, 2012) followed the deductive approach and used the list of keywords of March (1991) for exploration and exploitation. Exploration is captured by the terms *search, variation, risk taking, experimentation, play, flexibility, discovery and innovation*. Exploitation is measured by the terms *refinement, choice, production, efficiency, selection, implementation and execution*. Prior work has assumed these keywords to be valid indicators to construct measures of exploration and exploitation (Uotila et al., 2009).

In this study, we compare the deductive approach with an inductive approach deriving keywords from the body of text analyzed. We randomly selected (across firms and years) news articles and had an expert rater to classify these as either exploration or exploitation. The rater based his classification on the original definitions of exploration and exploitation by March (1991) suggesting that "the essence of exploitation is the refinement and extension of existing competencies, technologies and paradigms" while "the essence of exploration is experimentation with new alternatives" (March, 1991: p.85). The rater continued to draw articles until a set of 100 exploitation and 100 exploration articles was established. A second and independent rater (an independent scholar who is not involved in the project) classified the same set of articles. The inter-rater reliability (Cohen's kappa) was equal to 0.73, which is commonly considered a sign of substantial agreement across raters (Viera & Garrett, 2005).

We subsequently selected the most frequently occurring keywords in each of the two sets of articles, restricting the data to the 146 articles (out of 200) for which there was inter-rater agreement.[5] This list was reduced by removing non-relevant (the, 1998, and, this…), generic (year, ceo, sector…) and sector-specific (cancer, semiconductor, automotive…) keywords. Furthermore, in order to determine keywords that may distinctly represent exploration or exploitation, we restricted the list of keywords to those that exhibited a significantly higher

[5] We employed NVIVO software to calculate keyword frequencies. Keywords hits were determined by examining the 'root' of keywords, e.g. for the keyword *innovate* we examine the root 'innovat', producing hits for words such as 'innovation', 'innovate', 'innovating' and 'innovative'.

frequency of appearance in one or the other category. This resulted in a list of 69 potential exploration and exploitation keywords, shown in Table 1.

Insert Table 1 about here

This set of keywords was further reduced by examining the actual meaning of keywords as they are used in their specific contexts. First, four independent raters determined whether keywords could be judged to be associated with the definitions of exploration or exploitation. A Keyword-In-Context (KWIC) analysis (Manning & Schütze, 1999) was then used to check whether keywords had an unambiguous meaning across contexts. If a keyword was often used in ambiguous or unrelated contexts, or was highly dependent on its context, it was dropped. For example, *process* was used in the context of exploration if it was used as "new process" but it was also used in an exploitative context if it was used as "current process". The result of this procedure is a reduced list of 19 potential keywords, presented in Table 2.

Insert Table 2 about here

The final step in the content validity analysis consisted of a factor analysis to identify those keywords that are associated with the two underlying constructs of exploration and exploitation.[6]The resulting set of content-validated keywords ensures discriminant validity. Table 2 shows that the 19 keywords load into 5 different factors. The first factor explains a large portion of total variance (eigenvalue of 3.11) and contains exploitation keywords only. Since our objective is to establish a dictionary of keywords in which each keyword is unambiguously linked to either exploration or exploitation, we employed an iterative procedure to remove non-descript keywords and reduce the factor solution to two meaningful dimensions (Table 3). We first dropped the keywords with a factor loading below accepted thresholds (<0.4): *detect* and *implement*. We then dropped the keywords of factors with the smallest number of loading keywords and lowest eigenvalues. This resulted in two remaining

[6]The Kaiser-Meyer-Olkin measure of sampling adequacy (0.8, well above the commonly used benchmark value of 0.5) indicates that our sample lends itself to a factor analysis (Field, 2009). We used principal components analysis as the factoring method, and applied a varimax rotation to the results.

factors: the first factor consists of six keywords indicating exploitation; the second factor contains four keywords indicating exploration. We confirmed that we could not improve on these sets of keywords: adding a keyword not included in the final list of 10 did not maintain the two factor solution. Hence the list of 10 keywords constitutes the most exhaustive dictionary of keywords that are unambiguously associated with either exploration or exploitation activities, in the context of our sample of more than 100,000 R&D-related articles, ensuring its content validity. In the appendix, we provide examples of sentences showing the context of the occurrence of these keywords to confirm their face validity.

Insert Table 3 about here

Finally, we examined the accuracy and sensitivity of the text based indicator, using the set of articles (n=146) which were classified identically by both raters. We classified an article as "exploration" when it contained more exploration than exploitation keywords. The accuracy ratio is defined as the share of articles that are classified correctly (in agreement with the two raters) as exploration by our text-based classification. The sensitivity ratio is defined as the share of articles rated as exploration that are also identified as explorative articles with the text based indicator. The resulting values for accuracy (80%) and sensitivity (67%), while not fully satisfactory, improve substantially on the accuracy (73%) and sensitivity (52%) ratios obtained for the set of March keywords.

4.2. Discriminant Validity

Discriminant validity measures the extent to which constructs are distinct from each other. Discriminant validity for the set of 6+4 keywords determined through our inductive approach is established by design. To test the discriminant validity of the 17 keywords suggested by March (1991), we performed the same factor analysis that we applied in section 4.1. The factor solution is shown in Table 4 and indicates that March's keywords load into six different factors. Most underlying factors combine both exploration and exploitation keywords. For example, factor 1 (which captures most of the variation in the data) includes the exploration keywords *exploration*, *play* and *search* and the exploitation keywords *exploitation and choice*. To allow for a comparison with our inductive method, we also calculated the two-factor solution using the same iterative approach as explained above, which is shown in Table 5.

Several of March's keywords do not meaningfully explain either of the two factors (*execute, experiment, exploit, refine, select* and *variation* judging from the factor loadings smaller than 0.4 (shown as blanks in the table).The keywords that do load on one of both factors have relatively low loadings compared with the inductive 10-keyword solution. Finally, and perhaps most importantly, the two factors in Table 5 include both exploration and exploitation keywords and therefore do not properly align with March's constructs of exploration and exploitation. Hence, while the new inductive keywords can identify two different concepts, exploration and exploitation, discriminately, this is not the case for the March (1991) keywords in the context of our large database on texts covering R&D related articles.

Insert Tables 4 and 5 about here

4.3. External Validity

To test the external validity of both the March keywords and the new inductive set of keywords, we split our dataset into two random subsamples of articles (clustered by firm and without replacement).For each subsample, we counted the number of occurrences per article for the exploration keywords and the exploitation keywords, respectively, and tested for statistical differences using two-sample t-tests. If the keywords apply similarly in different contexts, the mean number of hits per article should not statistically differ between the subsamples. Table 6 shows that the new exploration and exploitation keywords produce a similar number of hits per article in the two subsamples, although there are slight differences. The difference for exploitation is marginally significant at the 10 percent level. For the set of March exploitation keywords the difference for exploitation is significant at the 5 percent level. If we calculate exploration orientation – the ratio of exploration keywords over the total number of keywords for each article – we find a similar pattern, with a marginally significant difference for the inductive set of keywords and a 5 percent significant difference for the March keywords.

Insert Table 6 about here

4.4. Predictive Validity

In this section we ascertained how the newly identified keywords, and the indicator derived from them, behave in the type of analysis that has received considerable attention in prior work i.e. the relation between exploration orientation and firm performance. To measure exploration orientation, we alternately use March's keywords (1991) and our new set of keywords. We follow the operationalization of exploration orientation in Uotila et al. (2009) and divide the number of exploration keywords by the total number of exploration and exploitation keywords per firm-year. Following Uotila at al. (2009) and Vagnani (2012) we measure firm performance through Tobin's q, which captures both short-term performance and long-term prospects (Lavie et al., 2011; Lubatkin & Shrieves, 1986; Allen, 1993). Tobin's q is measured as the market value of the firm divided by the book value of assets (Belderbos et al., 2010; Brown & Caylor, 2006; Bebchuk & Cohen, 2005). The models of firm performance include the following control variables: the one-period lagged value of Tobin's q, firm size (logarithm of assets), R&D intensity, and a set of sector and year dummies. R&D intensity is calculated as R&D expense divided by total sales.

We estimated a system-GMM model to relate firm performance to exploration orientation and past performance (Blundell& Bond, 1998). This approach is suitable for "small T, large N" panel data that includes lagged values of the dependent variable (Arellano, 2003).Further, this dynamic panel data estimation can handle the endogeneity of regressors, unobserved firm and industry specific effects and autocorrelation by using multiple instrumental variables (Roodman, 2009; Richard et al., 2009; March & Sutton, 1997).We treat sector and year dummies as exogenous variables. Lagged Tobins'q, exploration orientation, R&D intensity and firm size are treated as variables to be instrumented. To avoid instrument proliferation we limit the number of lags for the instruments to three years. For comparison, we also include the results of pooled ordinary least square regressions with firm-clustered error terms. While this method is known to exhibit coefficient bias for the lagged dependent variable, it provides a further robustness check on the empirical regularities. Table 8 below shows the empirical results. We restrict the discussion to the estimated coefficients of the variable of interest, *Exploration Orientation*.

Insert Table 7 about here

The results confirm a curvilinear relationship between exploration orientation and firm performance if we measure exploration orientation with the inductively defined set of keywords: both in model 2 (OLS) and model 5 (GMM) the linear term is positive and significant while the square term is negative and significant. The GMM diagnostics confirm the validity of the sets of instruments (the Hansen J test) and the absence of second order autocorrelation (the AR(2) test). The estimated coefficients suggest that an optimal balance between exploration and exploitation is achieved at a ratio of approximately 53%. This finding is consistent with previous studies on the relationship between exploration orientation and firm performance (He & Wong, 2004; Belderbos et al., 2010). In contrast, when using the indicator based on the March keywords we find no significant relationship between exploration orientation and firm performance (models 3 and 6), and we cannot replicate the results of Uotila et al. (2009).

5. Conclusions and Discussion

In this study we aimed to validate content analysis indicators of exploration and exploitation activities of firms based on March's original contribution, and to develop valid indicators using an inductive approach drawing on a large body of text articles. We have shown 1) that March's original terminology and keyword lists pertaining to exploration and exploitation do not necessarily deliver valid and generally applicable indicators 2) that the construction of representative indicators should be based on a structured series of validity analyses 3) that an inductive approach retrieving keywords from the body of text based on the validity analyses provides the most robust results. We find that using March-based keywords in characterizing exploitation and exploration does not yield indicators that pass validity tests, such as discriminant and predictive validity. In particular, we were unable to replicate the inverted-U relationship found in prior empirical work between firm performance (Tobin's q) and relative exploration orientation. In contrast, when developing a new set of indicators based on the occurrence of keywords and a series of validity tests, a new inductive indicator of exploration orientation did show the predicted non-linear relationship with firm performance.

Based on our findings, we recommend that future research utilizing content analysis indicators follows a structured set of validity tests to arrive at valid and better interpretable indicators of exploration and exploitation. Our results indicate that a fixed set of keywords derived from theory is unlikely to generate accurate indicators across different contexts of large text databases, such that an inductive approach departing from keywords in the body of text is likely to give more robust results. Greater validity of content analysis and text based indicators for exploration and exploitation will encourage future research on innovation and exploitation and exploration. This will help to exploit the full advantages of text based indicators related to their accessibility and availability across sector, firms, and time.

Venturing into new data sources and developing novel techniques and indicators always spawns ideas for further robustness checking and refinement. We highlight here what we believe to be the main caveats of our indicator, and how further research might address them. First, a key data limitation is that we do not observe whether an article was authored by someone inside the firm versus an external observer such as journalists, analysts, etc. This distinction is of interest since there may be a structural difference in their objectivity or more generally the way of reporting about firm activities. A study that is able to control for the origin of the text might provide valuable insights in this respect.

Second, our series of validity checks could be further refined and extended. For example, to measure external validity we restricted analysis to within-sample comparisons. A study that compares truly distinct types of data would provide an additional form of empirical generalization. For example, news articles could be compared to patent documents (abstracts and/or full body of text) as an alternative data source to characterize firms' exploration and exploitation activities (Katila & Ahuja, 2002; Belderbos et al., 2010).

Third, while we follow the dominant approach for content analysis in the management literature in the sense that we counted single keywords (Uotila et al., 2009; Vagnani, 2012; Bligh, Kohles, & Meindl, 2004; Lyon, Lumpkin & Dess, 2000), the text analysis literature offers several ways for refinement. For example, the trade-off between precision and recall in automatic text classification has led to the use of weights that contain both recall- and precision-enhancing components, such as term-frequencies and inverse document frequencies (Salton & Buckley, 1988; Liu et al., 2009). We also note that we relied on human judgment at several points in the inductive procedure for identifying keywords, for example to assess accuracy and sensitivity and to reduce the initially identified list of keywords using a basic Keyword-in-Context analysis. The search for relevant contexts could be extended by using word concordance software to retrieve all keyword contexts that occur in the dataset, or the contexts for a given keyword could be drawn from an existing collection, as done in corpus linguistics (Manning, 2003).

Finally, while we regressed Tobin's q on exploration orientation primarily to demonstrate the predictive validity of the new indicator, rather than to make this relation the focal topic of our research, the strategic management literature has identified a range of moderators. For example, it could be examined to what extent analyses using the new indicator would concur with prior work if industry technological dynamism, inter-organizational knowledge flows, absorptive capacity or environmental dynamism were included (Uotila et al., 2009; Rothaermel & Alexandre, 2009; Tamayo-Torres, Ruiz-Moreno & Llorens-Montes, 2011; Yang & Li, 2011; Eisenhardt, Furr & Bingham, 2010; Posen & Levinthal, 2012).

To conclude, we comment on the contribution of our research to the broader discussion on the need for novel innovation indicators. In particular, our analysis ties into the active scholarly and policy debate on better measuring firms' investments in intangible assets in order to understand how companies contribute to economic growth (e.g. Bernanke, 2011; Corrado et al., 2012). However, since systems of company accounts are still very much geared towards tangible assets and the cost of intangibles is typically registered as an expense, getting an accurate view of firms' investments in knowledge creation remains a challenge. We believe that the unlocking of unstructured text data can help to address the problem, not - or not in the first place - by directly supplying innovation input or output indicators, but by capturing in greater detail the type of innovative activities that lead to the build-up of firms' intangible assets. This way, text-based indicators can be a valuable complement to existing indicators. In particular, while offering clear benefits such as detail of information and broad availability, the nature of patent data has undeniably steered many scholars' empirical research agendas towards sectors with high patenting propensities. The more general availability of the data studied in this paper may help to move less technology-driven sectors into the scholarly limelight. This paper has attempted to show that it is indeed possible to build valid indicators from such unstructured big data. At the same time, it has tried to convey the message that in order to permit their usage in rigorous research, these indicators require careful construction and validity analysis in order to leave behind their origins in 'messy' data.

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Table 1: List of Potential Keywords Identifying Exploration and Exploitation

Dimensions	Keywords
Exploration	Access, acquisition, advanced, alliance, alternative, award, challenge, collaboration, core, creative, detect, discover, embedded, enhance, establish, exclusive, extend, forward, idea, implement, improve, initiate, innovate, integrate, invent, know, network, new, outstanding, patent, quest, recycle, research, seek, unique, university, update
Exploitation	Accelerate, additional, assembly, combination, continue, contract, conventional, cost, design, effective, emerging, enhance, exist, expand, experience, feature, flexible, grow, leading, license, maintain, operate, optimize, origin, partner, process, renew, reveal, significant, system, time, venture

Table 2: Factor Analysis: Rotated Loadings for 19 New Keywords

Eigenvalues	**(3.11) Factor1**	**(1.37) Factor2**	**(1.30) Factor3**	**(1.12) Factor4**	**(1.02) Factor5**
Exploitation					
ADDITIONAL	0.5054				
CONTINUE	0.7588				
EXPAND	0.4686				
EXIST					0.6590
GROW	0.7034				
IMPLEMENT					
MAINTAIN					0.5723
OPERAT	0.6480				
OPTIMIZE					0.6034
UPDATE	0.4550				
Exploration					
ADVANCED			0.6302		
CREATIVE				0.7656	
DETECT					
DISCOVER		0.5385			
EXCLUSIVE		0.6423			
INITIATE		0.6260			
INNOVATE				0.7445	
RESEARCH			0.5669		
UNIQUE			0.4278		

Remarks: blanks represent loadings lower than the 0.4 threshold; varimax rotation applied.

Table 3: Factor Analysis: Rotated Loadings for the Final Selection of New Keywords

	Exploitation	Exploration
Eigenvalues	**(2.65)** **Factor 1**	**(1.22)** **Factor2**
Exploitation		
ADDITIONAL	0.5587	
CONTINUE	0.7585	
EXPAND	0.4840	
GROW	0.7074	
UPDATE	0.4997	
OPERAT	0.6433	
Exploration		
ADVANCED		0.4424
DISCOVER		0.6667
RESEARCH		0.7032
UNIQUE		0.5119

Remarks: blanks represent loadings lower than the 0.4 threshold; varimax rotation applied.

Table 4: Factor Analysis: Loadings for March's Keywords

Eigenvalues	**(1.83)** **Factor 1**	**(1.18)** **Factor 2**	**(1.11)** **Factor 3**	**(1.03)** **Factor 4**	**(1.02)** **Factor 5**	**(1.01)** **Factor6**
<u>Exploitation</u>						
CHOICE	0.5534					
EFFICIEN		0.4856				
EXECUTE					0.6732	
EXPLOIT	0.4673					
IMPLEMENT			0.6870			
PRODUCTION		0.6523				
REFINE		0.4754				
SELECT				0.6769		
<u>Exploration</u>						
DISCOVER				0.7960		
EXPERIMENT						0.7415
EXPLOR	0.4095					
FLEXIBLE			0.5597			
INNOVATE			0.6273			
PLAY	0.4036					0.7469
RISK					0.4896	
SEARCH	0.4048					
VARIATION						0.7024

Remarks: blanks represent loadings lower than the 0.4 threshold; varimax rotation applied.

Table 5: Factor Analysis: Two-Factor Loadings for March's Keywords

Eigenvalues	**(1.74)** **Factor 1**	**(1.27)** **Factor 2**
Exploitation		
CHOICE	0.4150	
EFFICIENT	0.4960	
EXECUTE		
EXPLOIT		
IMPLEMENT		0.6303
PRODUCTION	0.4815	
REFINE		
SELECT		
Exploration		
DISCOVER		0.4236
EXPERIMENT		
EXPLOR	0.4286	
FLEXIBLE		0.4163
INNOVATE		0.5785
PLAY	0.4410	
RISK	0.4250	
SEARCH		
VARIATION		

Remarks: blanks represent loadings lower than the 0.4 threshold. Varimax rotation applied.

Table 6: Comparison of average number of keyword occurrences per article and exploration orientation for two random subsamples of articles

	Group 1			Group 2			
	N	**Mean**	**SD**	**N**	**Mean**	**SD**	**t Test**
Exploration –New	56362	1.85	3.99	58227	1.86	4.08	-0.12
Exploitation-New	56362	2.74	5.65	58227	2.81	5.82	-1.93*
Exploration-March	56362	1.28	2.97	58227	1.28	3.20	-0.48
Exploitation-March	56362	0.64	1.74	58227	0.67	1.79	-1.96**
Exploration Orientation -New	33296	0.44	0.35	34569	0.44	0.35	1.86*
Exploration Orientation -March	31300	0.64	0.40	32356	0.63	0.40	2.07**

Remarks: Ho: diff = 0,∗p <0.1 level; ∗∗p <0.05 level; ∗∗∗p <0.01 level

Table 7: Exploration Orientation and Firm Performance

	OLS Results			GMM Results		
	Model 1	*Model 2* Exploration Orientation NEW	*Model 3* Exploration Orientation MARCH	*Model 1*	*Model 2* Exploration Orientation NEW	*Model 3* Exploration Orientation MARCH
Exploration Orientation		0.418**	0.133		1.115***	0.012
		(0.201)	(0.151)		(0.298)	(0.280)
Exploration Orientation ^{2}		-0.448**	-0.080		-1.193***	0.037
		(0.205)	(0.143)		(0.305)	(0.243)
Log Tobin's q_{t-1}	0.824***	0.824***	0.823***	0.737***	0.734***	0.740***
	(0.017)	(0.017)	(0.017)	(0.048)	(0.041)	(0.042)
R&D Intensity	0.757***	0.684**	0.708**	1.104	1.605**	1.990***
	(0.279)	(0.274)	(0.281)	(1.030)	(0.678)	(0.730)
Log Total Assets	-0.023***	-0.027***	-0.026***	-0.136**	-0.087*	-0.087*
	(0.008)	(0.008)	(0.009)	(0.070)	(0.047)	(0.051)
Year dummies	included	Included	Included	Included	Included	Included
Sector dummies	Included	Included	Included	Included	Included	included
Constant	0.403***	0.386***	0.424***	2.371**	1.306*	1.472*
	(0.139)	(0.145)	(0.142)	(1.210)	(0.815)	(0.893)
Missing exploration orientation dummy			-0.044			-0.142
			(0.898)			(0.138)
Observations	998	998	998	998	998	998
F test	419***	367***	349***	-	-	-
Wald $\chi2(df)$	-	-	-	1323	1828***	1759***
AR2	-	-	-	0.374	0.569	0.423
No. of instruments	-	-	-	66	122	123
Hansen J-test	-	-	-	0.02	0.288	0.327

Robust standard errors clustered at the firm level in parentheses. ∗= p <0.1 level; ∗∗=p <0.05 level; ∗∗∗= p <0.01 level; The AR2 values are for the Arellano-Bond AR(2) test for autocorrelation. The missing exploration orientation dummy takes value 1 for a small number of observations for which there is missing information on exploration orientation (the number of exploitation keywords equals to zero for some firms and years).

Appendix. Examples of the Context of Keywords

Additional

Larry Downey, president and CEO of TMP and the new Teva Neuroscience, said, "We remain committed to enhancing the management of multiple sclerosis and we are excited by these additional product opportunities".

Source: Business Wire, February 14, 2001; Teva Concludes Strategic Agreements With Aventis to Acquire TMP, and With Lundbeck to Extend the Existing Cooperation to Oral Copaxone.

Continue

Neurobiological Technologies Inc., of Richmond, Calif., was awarded a $ 100,000 Small Business Innovation Research Grant by the National Institutes of Health, to continue development of its anti-edema agent, Xerecept, for treating peritumoral brain edema. The money will be used to continue patient enrollment and treatment in a Phase II trial.

Source: BIOWORLD Today;February 1, 1999; OTHER NEWS TO NOTE.

Expand

Anglo-Swedish pharmaceutical company AstraZeneca has announced plans to make an additional investment of $37.5m in the next five years to expand its production capacity and upgrade production technology in China.

Source: Financial Times Limited; June 1, 2006. Foreign Direct Investment (fDI) News: Sectors.

Grow

Our relationship with SMS continues to help us better meet the specific industry needs of our small-business customers, while also focusing product innovation, growth and advancements in other areas to better meet the needs of small businesses everywhere.

Source: Business Wire, November 27, 2001. QuickSell Commerce Provides Data Integration With QuickBooks 2002 Products.

Operate

*Compressors are indispensable equipment for any frozen food plant orcold storage warehouse. The RC12 reciprocating compressor is new from Grasso*KAB. Its welded steel design is built to operate with zero ozone depleting ammonia, as well as R22, R134a, R404A and other refrigerants.*

Source: E.W. Williams Publications, Inc.;Quick Frozen Foods International, January 1, 1996. Developing markets in Asia and elsewhere beckon Benelux equipment manufacturers

Update

For Direct Metal Deposition for tooling construction, reconfiguration and restoration; This tool repair technology updates existing metal tooling by using an industrial laser beam and a stream of powdered metal. It reduces time to market by eliminating prototype tooling.

Source: Crain Communications Inc. Automotive News, October 29, 2001. Correction Appended 18 suppliers selected for their innovations.

Advanced

WA, Corixa applies its advanced immunological expertise and proprietary technology platforms to rapidly discover and optimize vaccines and other antigen based products.

Source: Chemical Business Newsbase, June 22, 1999.Corixa partners with Japan Tobacco to research lung cancer vaccines in Japan and North America

Discover

Karo Bio AB and Abbott Laboratories announce that they have determined the three dimensional structure of the Glucocorticoid Receptor (GR), an important target protein for pharmaceutical development. The receptor mediates the anti-inflammatory effects of steroids and regulates glucose metabolism. This is a discovery that the pharmaceutical industry has been trying to uncover for several years.

Source: PR Newswire, April 5, 2001. Scientific Breakthrough in the Karo Bio and Abbott Collaboration.

Research

Advanced RISC Machines Ltd. (ARM) and the University of Manchester have announced a collaborative research initiative leading to the development of the industry's first ""clockless"" asynchronous microprocessor.

Source: Business Wire, December 12, 1994. Advanced RISC Machines and the University of Manchester team to develop asynchronous microprocessors based on ARM core.

Unique

"We are very excited to be moving forward with this development program,"stated Dinesh C. Patel, Ph.D., TheraTech's chairman, president and chief executive officer. ""Astra's preliminary studies confirmed that TheraTech's OTM system provides a uniquely effective dosage form for rapid delivery of a peptide pain medication. Their studies also demonstrated wide-spread consumer acceptance of our patient-friendly OTM system."

Source: Business Wire, May 11, 1998. Theratech And Astra Announce Worldwide Oral Transmucosal Agreement.