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Ole-Kristian HOPE
University of Toronto

Danqi HU
Northwestern University

Hai LU
Singapore Management University, hailu@smu.edu.sg

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Ole-Kristian Hope
Rotman School of Management
University of Toronto
okhope@rotman.utoronto.ca

Danqi Hu
Kellogg School of Management
Northwestern University
danqi.hu@kellogg.northwestern.edu

Hai Lu
Rotman School of Management
University of Toronto
hai.lu@rotman.utoronto.ca

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The benefits of specific risk-factor disclosures

Abstract

Practitioners have long criticized risk-factor disclosures in the 10-K as generic and boilerplate. In response, regulators emphasize the importance of being specific. By using a computing algorithm, this paper establishes a new measure (*Specificity*) to quantify the level of specificity of firms' qualitative risk-factor disclosures. We first examine determinants of variations in *Specificity*, and document that firms with high proprietary costs provide less specific risk-factor disclosures. More importantly, we find that, controlling for numerous determinants, the market reaction to the 10-K filing is positively and significantly associated with *Specificity*. In addition, our results suggest that analysts are better able to assess fundamental risk when firms' risk-factor disclosures are more specific. Together, these findings suggest that more specific risk-factor disclosures benefit users of financial statements.

Key words: Risk-Factor disclosure, Specificity, Specificity, Market reactions, Trading volume, Analyst risk assessments, Scenario analysis

G30, G31, G34, M41, M1, L20

The benefits of specific risk-factor disclosures

1. Introduction

This paper provides unique evidence on the benefits of more specific risk-factor disclosures. While extensive prior research has examined how capital markets react to earnings information to form expectations about stock returns (see Kothari 2001 for an overview of such research), less is known about how investors incorporate risk information. The market-wide underestimation of risk reflected in the 2007–2009 financial crisis has increased the demand for improved risk reporting (Singleton-Green and Hodgkinson 2011). Risk-factor disclosure (Item 1A in the 10-K report), which has been criticized by practitioners as boilerplate, has received considerable attention from the Securities and Exchange Commission (SEC) during and after the financial crisis. Many SEC comment letters are issued to those firms whose risk-factor disclosures are deemed to be generic (Johnson 2010). Despite the SEC's call for *more specific* risk disclosure, there is limited evidence concerning the benefits of such practice.

In this paper, by introducing a computing algorithm to quantify the level of specificity of firms' qualitative risk-factor disclosures on a large-scale sample, we speak to the issue of whether being more specific is a desirable feature of qualitative disclosure.[1] That is, we investigate whether and how investors and analysts benefit from more specific risk-factor disclosure. To address this research question, we first explore potential determinants of the degree of specificity in risk-factor disclosures. Then, after controlling for determinants, we examine whether specificity is positively associated with (1) the stock-market reactions to risk-factor disclosures and (2) analysts' reliability in assessing fundamental risk.

[1] By "specificity" we mean that a higher level of detail is provided conditional on the firm deciding to disclose a particular risk. In other words, given the disclosed risk factors (we control for the proxies for content used in extant research), the construct we are interested in captures the variation in the specificity of the disclosure.

Risk disclosure is potentially valuable when investors are uncertain of the riskiness of the firm's cash flows, which is a reasonable assumption based on prior research (e.g., Beyer 2009; Heinle and Smith 2015). Our study is motivated in part by Heinle and Smith (2015), who provide a model of imperfect risk disclosures. They investigate how stock prices react to noisy signals of the variance of cash flows, and conclude that more precise signals receive greater weights. Our study provides empirical evidence consistent with their theoretical predictions.

To examine the economic consequences of providing more specific risk-factor disclosures, we introduce a new measure, *Specificity*, to quantify the specificity in firms' risk-factor disclosures. Specific entity names such as "Microsoft" or "China" contain more specific information than general words such as "supplier" or "geographic segment." For example, "Our China business heavily relies on Microsoft for supply" represents greater specificity of the disclosing firm than "One of our geographic segments relies heavily on one supplier." Consistent with this concept, we construct *Specificity* as the number of specific entity names, including names of persons, locations, and organizations; quantitative values in percentages; money values in dollars; times; and dates, all scaled by the total number of words in that section.[2] To extract specific entity names, we use the Named Entity Recognition (NER) technique and specifically the Stanford NER tool, which can extract entity names close to human performance (Finkel, Grenager, and Manning 2005). The higher the value of *Specificity*, the more specific the risk-factor disclosures are.

As *Specificity* is new to the literature, we perform validity tests by asking both senior undergraduate accounting students and Ph.D. students in accounting to manually score a random sample of risk-factor disclosures. We compare our NER-based measure with the students' scores and find a high correlation (see Section 3.1 for details), suggesting that our measure has external

[2] Inferences are unaffected if we do not scale by the total number of words.

validity.

In our empirical analyses, we first explore the determinants of *Specificity*. Consistent with the emphasis on competitive concerns by practitioners and academics, we find that firms with high proprietary costs provide less specific risk-factor disclosures. Furthermore, we show that *Specificity* is positively related to the number of risk-related words from Campbell, Chen, Dhaliwal, Lu, and Steele (2014), the 10-K report length, and proxies for firm risk, and negatively associated with total accruals and firm size.

Our primary interest lies in the economic consequences of firms' more specific risk disclosure. For this purpose we conduct short-window market-reaction tests. An established strength of event-study methodology is that it reduces the chances of other variables explaining the documented effects. Nevertheless, our multivariate tests contain numerous controls motivated by prior research. Specifically, we control both for factors prior research has shown to affect market reactions and for all determinants of variations in *Specificity*. We find a strong positive relation between *Specificity* and the absolute value of three-day cumulative abnormal returns around the 10-K filing date, suggesting that a higher level of specificity leads to a stronger market reaction. In additional analyses, we consider abnormal short-window trading volume as an alternative measure of stock-market reaction. We find a positive and significant trading-volume reaction, further corroborating our findings based on stock-price reactions.

To provide further comfort in our primary findings, we implement a *pseudo analysis*. Specifically, in the years from 2001 to 2004 (a period when risk-factor disclosures were *not* required by the SEC), we repeat the market-reaction tests using *Specificity* calculated based on risk-factor disclosures from 10-K reports filed *in 2006* as a pseudo *Specificity* measure. In these pseudo tests we find *no* evidence of *Specificity* being significant, reducing possible concerns that

Specificity may capture omitted firm and firm-report characteristics. Given the importance of proprietary costs as a deterrent to voluntary disclosure in general and to providing specific risk-factor disclosures in particular, we additionally partition our sample and find that both the abnormal returns and abnormal volume results are only present in low proprietary costs subsamples.

Next, we also find that a higher *Specificity* enhances the reliability of analysts' fundamental risk analysis. Specifically, we study the scenario analyses provided by sell-side analysts at Morgan Stanley. Morgan Stanley has required equity analysts to use a "risk-reward framework" since 2007. In addition to providing a traditional base-case valuation, which is derived from a fundamentals-based analysis of the company's intrinsic value and its projected cash flows in the following 12 months, analysts are required to expand their analyses to present both the bull and the bear case-valuation scenarios. Joos, Piotroski, and Srinivasan (2015) document a significant positive relation between the spread between the bull and bear valuations and the absolute value of future 12-month unanticipated stock returns. In other words, the analyst's ex-ante expected range of future price movements is significantly and positively associated with the extent to which the realized price after 12 months differs from the analyst's base case valuation. They regard this positive relation as evidence that analysts reliably assess fundamental risk, because it suggests that through the ex-ante price spread analysts provide a reliable picture of future price movements.

We hand collect analysts' reports from Thomson Investext and manually extract the information on risk-reward analyses. We first replicate the Joos et al. (2015) results in our sample. We then show that analysts *only* reliably assess fundamental risk for the subsample of firms whose risk-factor disclosure exhibits higher *Specificity*. This finding suggests that analysts better assess firms' fundamental risk when risk-factor disclosures are more specific.

This paper makes several contributions. First, it contributes to the textual-analysis literature by introducing a new measure to quantify the level of specificity of qualitative disclosure. Prior work studying management forecasts codes pure qualitative information as the least specific; open-ended and range information as better; and point value as the best (e.g., Francis, Nanda, and Olsson 2008). However, within the category of qualitative disclosure, to date there have been few attempts to quantify and calibrate specificity levels. The *Specificity* measure we develop enables researchers to differentiate the specificity level among qualitative disclosures and captures another quality aspect besides the readability measures used in prior literature (e.g., Li 2008; De Franco, Hope, Vyas, and Zhou 2015).

Second, our study complements the extant risk-disclosure literature, particularly the literature on qualitative risk disclosure. Prior work studies quantitative risk information such as VaR disclosure within the banking industry (Jorion 2002; Perignon, Deng, and Wang 2008) as well as quantitative market-risk disclosures (Rajgopal 1999; Thornton and Welker 2004; Linsmeier, Thornton, Venkatachalam, and Welker 2002). However, qualitative risk disclosure has not been studied until recently, with the advance of textual-analysis techniques. Campbell et al. (2014) quantify the amount of risk disclosed from a firm's risk-factor disclosure by counting the number of risk-related words contained in their predefined dictionary. Similarly, Kravet and Muslu (2013) use the number of sentences containing predefined uncertainty words. While these papers study the amount of risk-related information in qualitative risk-factor disclosures, our study differs from theirs in that it focuses on the quality (or specificity) of risk disclosure. Schrand and Elliott (1998) highlight that it is hard to evaluate the completeness and accuracy of risk disclosure because there is no ex-post settling up. A greater specificity, however, makes the disclosed information more accurate and more verifiable ex post. Thus, by proposing *Specificity* as a quality measure, our paper addresses the challenges in assessing risk-disclosure quality.

Third, this is the first study to demonstrate how analysts' risk assessment is affected by firms' risk-disclosure practices. While extensive research has examined analysts' behaviors in forecasting earnings and recommending stocks (see Bradshaw 2015 for an overview of such research), research on analysts' behavior in assessing fundamental risk is scarce, with only a few exceptions. Lui, Markov, and Tamayo (2007, 2012) document the firm characteristics that contribute to sell-side analysts' risk ratings and the price impact of analysts' risk-ratings changes on the stock market. Joos et al. (2015) examine the reliability of sell-side analysts' risk assessment by evaluating the scenario analyses provided by Morgan Stanley analysts. None of these studies, however, investigates the relation between firms' risk-disclosure practices and analysts' risk assessment.

Finally, from a policy perspective, this paper provides empirical evidence supporting the SEC's call for more specific risk disclosures. The findings suggest that improved corporate risk reporting—especially more specific risk-factor disclosures—benefits investors, and that risk-factor disclosures are likely not "just boilerplate" (as some suggest). We also find that investors seem to appreciate quantitative disclosures more than qualitative ones, and this suggests that regulators could improve the information content of risk disclosures by asking for more quantitative disclosures.

The next section provides background and develops our hypotheses. In Section 3 we describe *Specificity* and explain the empirical design. Data collection and summary statistics are discussed in Section 4. Section 5 presents the empirical results. We conclude the paper in Section 6.

2. Background, literature review, and hypotheses development

2.1 Institutional background and literature review

In 2005 the SEC required firms to extend their risk-factor disclosures to their quarterly and annual reports to describe "the most significant factors that make the company speculative or risky." Previously, such disclosure was only required in S-1 registration statements, which are filed before a firm proceeds with a public offering. Although this risk-factor section (Item 1A in the 10-K report) is mandatory, firms still have a great degree of discretion, because only qualitative description is required. This contributes to practitioners' criticism that risk-factor disclosure is useless as it contains only boilerplate information. After the 2007–2009 financial crisis, the SEC re-emphasized its initial requirement that firms should "avoid generic risk-factor disclosures that can be applied to any firms" (Johnson 2010). For example, the SEC questioned a risk factor in Eagle Materials' 10-K for fiscal year 2009. The reviewer, an SEC accounting branch chief named Rufus Decker, said the building-materials provider's brief note about the possibility of economic and market conditions affecting the fair value of its pension assets was "too broad and generic." Decker further wrote: "It is not readily apparent why such risk would be unique to you and your business" (Johnson 2010).

The first explicit risk-disclosure section in the 10-K was required by the SEC in 1997 with the release of FRR No. 48, which requires firms to include a discussion of "Qualitative and Quantitative Market Risks" (Item 7A) in annual and quarterly reports.[3,4] Previous studies support

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[3] For completeness, accounting academics had sought risk-related information in financial reports even before explicit risk disclosure was required by regulatory authorities. For example, Beaver, Kettler, and Scholes (1970) were the first to study the relation between beta and financial-statement risk measures. They document that market-based beta is positively correlated with a firm's leverage and earnings variability and negatively correlated with a firm's dividend payout ratio (see also Hamada 1972; Lev 1974).

[4] The MD&A also includes discussion about risks but is not explicitly focused on risk. Other accounting rules related to risk disclosures include SFAS No. 140, which requires firms with securitized financial assets to disclose information about key assumptions made in determining fair values of retained interests, and SFAS No. 133, which encourages firms to disclose quantitative information about market risks of derivative instruments and hedging activities.

the efficacy of FRR No. 48 by showing that the disclosed exposures to certain risk factors, such as commodity prices, foreign exchange rates, and interest rates, have incremental power to explain the future stock-return sensitivity to the risk-factors (Rajgopal 1999; Thornton and Welker 2004; Linsmeier et al. 2002). However, these studies examined only market-risk disclosure and its information content.[5] In addition, Sribunnak and Wong (2006) show that the allowed exclusion of nonfinancial positions from the market-risk disclosure hinders the usefulness of the disclosed quantitative information.

"Risk factors," Item 1A of the 10-K required by the SEC in 2005, provides risk information in a broader sense not limited to firms' market risk and financial positions; however, the information contained in this section is descriptive and qualitative. In an early study, Li (2006) counts the frequencies of the words "risk" ("risks" and "risky") and "uncertain" ("uncertainty" and "uncertainties") as proxies for risk sentiment in firms' 10-K reports. The most closely related studies are two recent ones, by Kravet and Muslu (2013) and Campbell et al. (2014), that quantify the amount of risk disclosed in qualitative risk disclosure by establishing predefined dictionaries. The analyses in Kravet and Muslu (2013) and Campbell et al. (2014) show that firms with high leverage discuss more debt-risk factors; firms with low taxes discuss more tax-risk factors; firms with high pre-disclosure betas discuss more systematic risk factors; and firms with high pre-disclosure stock-return volatility discuss more idiosyncratic risk factors. In terms of economic consequences of risk-factor disclosures, Campbell et al. (2014) find a significant positive relation between the number of risk-related words identified in the risk-factor section and future stock-return volatility and market-based beta, after controlling for historical volatility and historical

[5] To be precise, FRR 48 is about market risk (e.g., interest rate risk, foreign currency exchange rate risk, and commodity price risk) inherent in market risk sensitive instruments. In contrast, Item 1A requires the discussion of "the most significant factors that make the company speculative or risky." (Regulation SK, Item 305(c), SEC 2005).

market beta. Kravet and Muslu (2013) demonstrate that the year-to-year change in the number of sentences containing uncertainty words in a company's 10-K file is positively associated with the future stock-return volatility and the three-day abnormal trading volume around the 10-K filing date. We complement these studies by providing further empirical evidence on risk-factor disclosures and in particular address the policy question of whether greater specificity in risk disclosures benefits investors.

To the best of our knowledge, only a few papers study analysts' behaviors in assessing firms' risk. Lui, Markov, and Tamayo (2007) find that firm characteristics commonly viewed as risk proxies, such as idiosyncratic risk, size, leverage, and accounting losses, are positively related to sell-side analysts' risk ratings, and that analysts' risk ratings in turn are positively associated with future stock-return volatility. Lui et al. (2012) further show that changes in analysts' risk ratings are followed by significant changes in Fama-French factor loadings, and that the stock-price impact of risk-rating changes is greater than that of credit-rating changes. Finally, Joos et al. (2015) show that the bull-bear spread in Morgan Stanley analysts' scenario analysis is positively associated with the base-case valuation error, indicating that analysts' ex-ante forecasted price spread reliably pictures future price movement.[6] Based on this evidence, they conclude that analysts have some ability to assess fundamental risk. We add to this stream of literature by examining whether the specificity in disclosed risk factors is relevant for analysts in assessing risk.

2.2 Hypotheses development

The hypotheses examined in this paper are centered on whether the extent to which

[6] Dechow and You (2015) also provide evidence that is at least indirectly relevant. They predict and find that analysts' target-price implied returns are a function of the expected dividend distribution, analysts' private information, and errors with respect to forecasting cash flows and discount rates.

investors and analysts incorporate risk information varies with the level of specificity in risk disclosures. Our hypotheses are developed based on the assumptions that the market possesses a certain degree of efficiency and that analysts make the best use of public information given their time and attention constraints.

Our primary premise is that more precise disclosures imply greater information content of the disclosures and that investors should thus pay more attention to such disclosures. Prior research concludes that information that is more costly to extract from financial reports is less completely incorporated in market prices (Ball 1992; Bloomfield 2002; Hirshleifer and Teoh 2002: Bonsall, Bozanic, and Merkley 2015).[7] Less precise information is likely more difficult for investors to extract, process, evaluate, and verify (Bozanic, Roulstone, and Van Buskirk 2015; Bonsall et al. 2015). Importantly, Heinle and Smith (2015) present a model of the pricing effects of risk disclosures. Unlike prior analytical researchers, they assume that investors are uncertain about the variance of a firm's cash flows, and that the firm releases an imperfect signal regarding this variance. Their primary findings are that this variance uncertainty is priced and that more precise signals receive greater weight. This is consistent with practitioners' demand for more precise disclosures. The model offers a theoretical rationale for the prediction that the market should react more to more precise risk disclosure (i.e., we expect greater specificity to lead to more precise information).[8] Intuitively, the idea is that a firm's risk-factor disclosure should have a greater

[7] Jørgensen and Kirschenheiter (2003) analytically examine how risk disclosures can affect stock returns in a multi-firm setting.

[8] In addition to these economics-based arguments, supporting arguments also exist in the psychology literature. In particular, according to Construal-Level Theory (e.g., Trope and Liberman 2010), concrete or specific information has greater impact on the judgments of events or objects that are psychologically close to the individuals, whereas abstract or general information has greater impact on the judgments of events or objects that are psychologically distant. To the extent that investors (analysts) and a particular firm they are investing in (covering) can be regarded as psychologically close, risk information that is more specific will have a greater impact on investors' and analysts' decisions. In other words, given a certain amount of risk disclosed, a higher level of specificity leads to a greater portion of risk information being processed, enhancing investors' and analysts' risk understanding.

impact on the investors' decisions when it is higher in specificity. We thus predict that higher *Specificity* will lead investors to put more weight on the disclosed risk information, which will facilitate the incorporation of risk information into the stock price. This, in turn, will result in a stronger market reaction to the more specific risk-factor disclosures. However, the direction of stock-price change is unclear because how specific risk-factor disclosures affect investors' perception of the mean of the variance of cash flows is uncertain (although greater specificity in risk-factor disclosure reduces the variance uncertainty premium and thus the expected cost of capital) (Heinle and Smith 2015). The above discussion leads to our first hypothesis (stated in the alternative form):

H1: *The stock-market reaction to the 10-K report is positively associated with the level of specificity in risk-factor disclosures.*

To the extent that more specific risk-factor disclosures have economic benefits, a natural question is why not all firms use specific language in their risk disclosures. The reason is that there are also costs to voluntary disclosure. In our empirical analyses, we first examine determinants of variations in *Specificity*. Perhaps most importantly, we consider the role of *proprietary costs*, the most commonly cited reason for lower-quality disclosure (see Verrecchia 2001 and Beyer et al. 2010 for overviews of such arguments and related literature). Also important is that, for the tests of market reactions (in which we control for determinants), we examine whether investors' responses vary systematically with the firm's proprietary costs.

Analysts' risk assessment is economically important, as such assessment affects the risk perception of investors. We predict that, consistent with investors', analysts' judgments of the covered firms should rely more on specific information than on general information. We thus hypothesize that more specific risk-factor disclosures will provide more information that analysts can use to assess firms' fundamental risk, and therefore that analysts' reliability in assessing fundamental risk increases in *Specificity*.[9,10] The above discussion leads to our second hypothesis (stated in the alternative form):

H2: *The reliability of analysts' fundamental risk assessment is positively associated with the level of specificity in risk-factor disclosures.*[11]

3. Measures and empirical design

3.1 *Specificity* measure and validity tests

Motivated by the SEC's warning that firms should avoid generic risk-factor disclosures that can be applied to *any* firms, we define a new measure, *Specificity*, as *the number of specific words or phrases conveying specific information relevant to the disclosing firm, divided by the number of total words in the risk-factor disclosure section (Item 1A)*. To operationalize the construct "specific words or phrases conveying specific information relevant to the disclosing

[9] The implicit assumption here is that firms can only choose to disclose or to withhold specificity in risk-factor disclosures. They cannot provide misleading or false content. This assumption appears in many analytical works (e.g., Dye 1985; Shin 1994; Kumar, Langberg, and Sivaramakrishman 2013). As a practical matter, we control for numerous determinants of variations in risk disclosure when testing for the economic consequences of variations in these disclosures.

[10] Similar to our hypothesis for investors' market reactions, additional support can also be found from construal-level theory. The firms covered by analysts can be viewed as psychologically close to the analysts because analysts cannot issue any reports without extensive research. Analysts refer to those covered firms as firms in "my/our" coverage (social); analysts are more "confident" about the performance of those firms (hypothetical); analysts' predictions are based on most "current" data and relevant for "near future" (temporal).

[11] However, alternative arguments exist to support the idea that analysts' reliability in assessing fundamental risk is *not* affected by the level of specificity in risk-factor disclosures. To the extent that analysts do not pay attention to risk-factor disclosure by either unintentionally neglecting or intentionally ignoring such information, as is shown in anecdotal evidence, *Specificity* should not affect analysts' risk assessments. As an example, consider the argument that "risk-factors are looked upon as boilerplate. The irony of it is that risk-factors are almost meant not to be read, or relied upon" (Reuters 2005).

firm," we use specific entity names belonging to seven entity categories. Specific entity names such as "Microsoft" contain more idiosyncratic details than general words such as "firm." We include a comprehensive set of categories to make sure the specificity measure is driven by a particular kind of specific words and, more importantly, that it does not simply reflect firms' business model or complexity. These categories include (1) names of persons, (2) names of locations, (3) names of organizations, (4) quantitative values in percentages, (5) money values in dollars, (6) times, and (7) dates.

Our approach is also consistent with the SEC's call that firms' risk-factor disclosures should not be so generic that they can be applied to any firm. In other words, specific entity names tend to be more context-specific. For example, "Our firm has borrowed $100,000 from Microsoft" is more relevant to the disclosing firms than "Our firm has borrowed some amount of money from a supplier." The latter sentence can be applied to many other firms.

To implement this construct on a large-scale sample of risk-factor disclosure documents, we use the Named Entity Recognition (NER) technique to identify and extract specific names belonging to the above seven entity categories. NER refers to a natural language-processing task that seeks to locate and classify atomic elements in text into predefined categories. NER is a key technology by which to understand the semantics of plain text, and has enabled recent advancements in intelligent systems, such as the IOS Siri system (Berry, Gervasio, Peintner, and Yorke-Smith 2011) and Google's Knowledge Graph (Singhal 2012; Waters 2012).[12] In the course of system development, state-of-the-art NER systems for English can produce near-human

[12] The term "Named Entity" was developed in Message-Understanding Conferences (MUC) in 1995, and has been widely used in Information Extraction (IE), Question Answering (QA), and other Natural-Language Processing (NLP) applications. Researchers note the importance of recognizing information units such as names and numeric expressions, thus extracting these entities is recognized as one of the important sub-tasks of Information Extraction. NER systems can now identify more sophisticated categories, such as "Odyssey" as a book title, "Windows" as a product name, and "Empire State Building" as a geographical and political entity, and so on.

performance. In this paper, we use the Stanford NER tool, which is based on the Conditional Random Field model, to predict the Named Entity categories.[13] Appendix A provides examples of risk-factor disclosures with high and low *Specificity*.

We validate *Specificity* by comparing the scores produced by the NER program with those produced by senior accounting students (CPA track) enrolled in a financial accounting theory course as well as accounting doctoral students (including several with professional designations). We randomly extract 95 risk-factor disclosures (i.e., nineteen firms from each quintile as ranked by the NER program) of 1,200–2000 words and ask the students to rate the level of specificity of each document. Appendix B provides the instructions we give to the students. The results, based on 94 responses, suggest that the level assigned by the NER program is highly consistent with the level identified by the student subjects. In untabulated tests, the mean of student ratings changes monotonically from high to low when going from the highest to the lowest quintiles as rated by the NER program. Without averaging student ratings for each quintile, the correlation between the two ratings based on the 94 observations is 0.51, statistically significant at the 0.01 level using a two-sided test. We conclude that the validity test provides further comfort that our approach yields results similar to what the results would be if the scoring of *Specificity* were done by "real" financial statement users.[14]

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[13] We use Stanford NER tool13 version 3.2.0 to identify entities in seven categories including Time, Location, Organization, Person, Money, Percent, and Date. Finkel, Grenager, and Manning (2005) explain the basic idea of the Stanford NER tool. The theory underneath Stanford NER tool is Conditional Random Field (CRF), first introduced by Lafferty, McCallum, and Pereira (2001). In our setting, we feed all Item 1A text into the CRF classifier to obtain extracted entities along with the categories they belong to.

[14] A securities class action filed on September 3, 2015, against Wayfair for its failure to identify its specific competitor, Overstock, when discussing competition risk in the risk-factor section, provides further external validation of the idea of counting specific entity names to measure the specificity level of risk-factor disclosures. The class-action lawsuit suggests that investors regard specific competitor names as material information, and this provides us external validation from the investors' perspective. (The details of the case can be found at the Stanford securities class action database.)

3.2 Empirical design

H1 predicts that *Specificity* is positively associated with the market reaction to the risk-factor disclosure in 10-K report. Our research design follows the extant risk-factor disclosure. However, instead of being interested in whether risk-factor disclosures move prices up or down, we focus on the *specificity level* of such disclosures. Specifically, we are interested in the textual feature of Item 1A and whether greater specificity of that section induces greater market reaction. Therefore, unlike Campbell et al. (2014), who examine the relation between signed three-day abnormal returns around the 10-K filing date and the amount of risk information disclosed, we study the relation between the absolute value of three-day abnormal returns around the 10-K filing date, $|CAR^{10\text{-}K}_{-1,1}|$, and *Specificity,* the main variable of interest.[15] Using unsigned abnormal returns to measure the information content of risk-factor disclosure has both a theoretical rationale in this context and extensive prior empirical support. The model in Heinle and Smith (2015) does not provide a directional prediction on the change of stock price in response to risk disclosure. Risk disclosures reduce the variance-uncertainty premium and thus the expected cost of capital, while also affecting investors' perceptions of the mean of the variance of cash flows. As a result, the total effect on price is unclear. Empirically, there is a long history in research using unsigned, unexpected returns (e.g., Beaver 1968; May 1971; Cready and Mynatt 1991; Griffin 2003; Brown and Tucker 2011) or unexpected trading volume (see the review by Bamber, Barron, and Stevens 2011) to measure information content in financial reports. Dating back to Beaver (1968), the measures are particularly appropriate when a research question is only concerned with the magnitude of the changes in investor expectations rather than the direction of the changes. For example, Brown and Tucker (2011) use unsigned market reactions to examine the usefulness of

[15] Our approach is consistent with Brown and Tucker (2011), who use unsigned market reactions to examine the usefulness of updated MD&A disclosures.

updated MD&A disclosures. In the context of risk-factor disclosure, because we are interested only in the magnitude and not in the direction of the investors' expectation changes, we focus on unsigned market reaction.

By examining returns in a narrow event window, we minimize the chances of problems with correlated omitted variables. Nevertheless, we include numerous controls motivated by prior research.[16] We first control for several alternative 10-K report characteristics such as the specificity of the entire 10-K report excluding risk-factor disclosures (*Specificity 10K*), the number of risk-related words as defined in Campbell et al. (2014) in Item 1A (*Amount*), the number of times "risk" is mentioned in the 10-K as defined in Li (2006) (*RiskWords)*, readability of the 10-K (*Fog*), and 10-K report length (*TotalLength*).

The second set includes firm characteristics as well as risk proxies, performance measures, and firm complexity measures. Most noticeably, we test for the effect of proprietary costs (*ProprietaryCost*) using R&D expense scaled by beginning-of-year total assets (e.g., Albring, Banyi, Dhaliwal, and Pereira 2016; Dambra, Field, and Gustafson 2015; Ellis, Fee, and Thomas 2012; Wang 2007; King, Pownall, and Waymire 1990).). We also control for current performance (Δ*Earnings*), total accruals (*Accrual*), size (*Size*), book-to-market ratio (*BtM*), past performance (*PastLoss*), leverage (*Leverage*), stock-return volatility in the previous year (*ReturnVolatility*), litigation risk (*Litigation*), the number of business segments (*Segments*), the number of 8-Ks, and analysts' forecast errors (*Analyst Forecast Error*; and an indicator for missing values, *ForecastMissing*). As in Brown and Tucker (2011), we additionally control for late filers (*FileDate*), the number of data items in COMPUSTAT (*NumItems*), and market reaction to the

[16] Note that we do not use the same controls for the market-reaction and analyst tests, as we follow prior literature when choosing control variables. However, no inferences are impacted if we impose a constant set of controls for both analyses.

earnings announcement ($|CAR^{EA}_{-1,1}|$). Finally, we include year and industry (Fama-French 17) fixed effects in all regressions.[17] All variables are defined in Appendix C. The standard errors are two-way clustered by firm and filing month.[18] A significant positive α_1 in equation (1) supports H1 that *Specificity* is positively related to the market reaction to the 10K file.

$$
\begin{aligned}
&|CAR^{10,k}_{-1,1}|_{it} \\
&= \alpha_0 + \alpha_1 Specificity\ 1A_{it} + \alpha_2 Specificity\ 10K_{it} + \alpha_3 Amount_{it} + \alpha_4 RiskWords_{it} \\
&+ \alpha_5 Fog_{it} + \alpha_6 TotalLength_{it} + \alpha_7 ProprietaryCost_{it} + \alpha_8 \Delta Earnings_{it} + \alpha_9 Accrual_{it} \\
&+ \alpha_{10} Size_{it} + \alpha_{11} BtM_{it} + \alpha_{12} PastLoss_{it} + \alpha_{13} Leverage_{it} + \alpha_{14} ReturnVolatility_{it} \\
&+ \alpha_{15} Litigation_{it} + \alpha_{16} Segment_{it} + \alpha_{17} Num8K_{it} \\
&+ \alpha_{18} ForecastError_{it} + \alpha_{19} ForecastMissing_{it} + \alpha_{20} Filedate_{it} + \alpha_{21} NumItems_{it} + \alpha_{22} |CAR^{EA}_{-1,1}|_{it} \\
&+ error_{it} \qquad (1)
\end{aligned}
$$

To test our second hypothesis, we follow Joos et al. (2015), who provide initial evidence on the reliability of analysts' fundamental risk assessment by studying the scenario analyses in equity-research reports by analysts at Morgan Stanley. Morgan Stanley has required its equity analysts to use a "risk-reward framework" since 2007. The idea behind this new approach is that most sell-side equity research remains outside the risk-return framework, focusing largely on single-point estimates. As discussed in Weyns, Perez, Hurewitz, and Jenkins (2011), experienced analysts instinctively analyze and weigh the relative importance of risk factors before arriving at a recommendation for a stock. Morgan Stanley's risk-reward approach is a means to encourage

[17] Using the Fama-French 48 industry classification does not change our inferences.
[18] No inferences are affected if we instead cluster by firm or by firm and year.

analysts to think probabilistically about the ranges of uncertainty related to fundamental value drivers. Under this framework, analysts need to provide not only the traditional base-case valuation (*Base*), which is derived from a fundamentals-based analysis of the company's intrinsic value in the following 12 months, but also valuations under both the bull (*Bull*) and bear (*Bear*) scenarios. The bull and bear case scenarios reflect analysts' assessment of future price movements and fundamental risks.

Specifically, Joos et al. (2015) calculate *Spread* as *Bull* minus *Bear* scaled by *Base* to measure analysts' ex-ante expected price uncertainty. Then they use |*UnanticipatedReturn*| to measure the ex-post absolute estimate error. It is calculated as the absolute value of the difference between the realized raw return excluding dividends in the following 12 months, $\frac{Price_{it+365} - Price_{it}}{Price_{it}}$, and the corresponding expected return suggested by the base-case valuation, $\frac{Base_{it} - Price_{it}}{Price_{it}}$. They find a significant positive relation between *Spread* and |*UnanticipatedReturn*|, suggesting that the price spread in analysts' ex-ante scenario analyses reliably reflects the future price movement and thus that analysts reliably assess fundamental risk.

Motivated by their findings, we include the interaction term $Spread \times HighDetail$ in the regression to ascertain whether analysts' ability in assessing fundamental risk (as reflected in the positive relation between *Spread* and |*UnanticipatedReturn*|) is positively associated with the level of specificity in firms' risk-factor disclosures. *HighSpecificity* is an indicator variable which equals one if *Specificity* is in the top quintile and zero if in the bottom quintile (see next section for details).

$$
\begin{aligned}
|Unanticipatedretur|_{it} \\
&= \alpha_0 + \alpha_1 Spread_{it} + \alpha_2 Spread_{it} \times HighSpecificity_{it} \\
&+ \alpha_3 HighSpecificity_{it} + \alpha_4 Leverage_{it} + \alpha_5 BtM_{it} + \alpha_6 Size_{it} \\
&+ \alpha_7 EarningsVolatility_{it} + \alpha_8 NegEarnings_{it} + \alpha_9 ReturnVolatility_{it} \\
&+ \alpha_{10} Specificity\ 10K_{it} + \alpha_{11} Amount_{it} + \alpha_{12} RiskWords_{it} \\
&+ \alpha_{13} Fog_{it} + \alpha_{14} TotalLength_{it} + \alpha_{15} \Delta Earnings_{it} + \alpha_{16} Accrual_{it} \\
&+ \alpha_{17} PastLoss_{it} + \alpha_{18} Litigation_{it} + \alpha_{19} Segment_{it} + error_{it} \qquad (2)
\end{aligned}
$$

A positive α_2 in regression equation (2) suggests that the positive relation between |*UnanticipatedReturn* | and *Spread* is increasing in *Specificity*, which indicates that a higher level of specificity enhances analysts' reliability in assessing fundamental risk. Again, we control for year and industry fixed effects.

4. Data, sample selection, and descriptive statistics

We obtain our sample in the following steps. First, we download all available 10-Ks from 2006 to 2011 from SEC EDGAR.[19] We then extract risk-factor disclosures from Item 1A in each 10-K report. We clean up all HTML marks and use the section title to identify the scope of a section. For example, a non-empty text between one appearance of "Item 1A Risk-factor" and a follow-up appearance of "Item 2" is considered as the content of Item 1A in this report. Second, we match the CIK used as identifier in EDGAR with GVKEY (from COMPUSTAT) and PERMNO (from CRSP). Firms that cannot be matched with COMPUSTAT and CRSP are dropped from the sample. Third, observations with missing data on controls are excluded from the sample.

[19] Risk-factor disclosure was mandated from December 2005. For completeness, we also download 10-Ks filed in EDGAR in 2005, but few of those files contain risk-factor disclosure sections.

This yields a sample of 14,865 firm-year observations for our full sample (market-reaction analyses).[20]

Panel A of Table 1 provides the sample composition by year. The table shows that our sample is distributed evenly across years. It also indicates that, responding to the SEC's call for more specific risk disclosure, firms increase their risk disclosures (i.e., more words) and disclose more specific information, but the increase in specific words or phrases is slower than the increase in the length of the risk-factor section. In other words, although firms are providing longer risk-factor disclosure sections, they do not increase the specificity proportionally.

Table 1, Panel B provides the sample composition by Fama-French 17 industry classification. There is some concentration in "other" (30.67%), banking and insurance (21.43%), and machinery and business equipment (12.97%); otherwise the sample is not dominated by any industry.[21] Among all the industries, utilities, mining and minerals, and transportation are the top three in terms of *Specificity*. The table also shows that the ranking of *Specificity* is not only driven by the length of Item 1A (the denominator). For example, although firms in mining and minerals provide the second-longest risk-factor disclosures (Item 1A), the length does not drive down their level of specificity. The average *Specificity* of mining and minerals firms still ranks second among all industries.

To carry out the empirical analysis of analysts' risk assessment, we hand-collect analysts' reports from Investext and manually extract the scenario-analysis parts of the reports. Because of the high cost of hand-collecting data, we choose to study the sample firms' risk-factor disclosures

[20] We use a different method from Campbell et al. (2014) to extract Item 1A from 10-K reports. However, the size of our extracted sample is comparable to theirs.

[21] For the smaller sample with available scenario analyses from Morgan Stanley analysts, untabulated statistics show that the sample covers a variety of industries.

only with the level of specificity ranking in the top and bottom quintiles.[22] In addition to lowering (the already high) data collection costs, focusing on the group indicator (top versus bottom quintile) instead of a continuous measure makes the results easier to interpret. Our sample is from 2007 to 2011 because Morgan Stanley only requires the scenario risk analysis since 2007. We then manually match the available scenario-analysis information from Investext with the selected firms. Two hundred sixty firm-year observations (142 firms) from the top quintile and 367 firm-year observations (189 firms) from the bottom quintile are matched. This yields a final sample of 627 observations.[23] Although focusing on only Morgan Stanley analysts limits the generalization of our inferences, examining analysts' reports from one brokerage firm is an advantage due to internal consistency across the reports and the fact that we do not need to control for brokerage-firm characteristics.

Panel A of Table 2 presents descriptive statistics for the variables used in our empirical analyses about market reactions to specific risk-factor disclosures. The mean for *Specificity* is 0.054, suggesting that, on average, firms include five words describing specific entities per 100 words used in the risk-factor disclosures. The mean for the absolute value of the three-day abnormal return around 10-K file date is 4%, whereas the absolute value of the three-day abnormal return around earnings announcement is 6%. The mean of *FileDate* indicates that only 4% of the sample firms are late 10-K filers. Finally, the descriptive statistics on *Litigation* suggest that 28% of our sample firms are in industries with high litigation risks.

Panel B of Table 2 presents descriptive statistics for the variables used in our empirical analysis on analysts' fundamental risk assessment. The mean for *Spread* is 0.63, suggesting that

[22] In contrast, for the market reaction tests we are able to utilize the full sample of firms.
[23] This data-collection process shows that analyst coverage is not significantly related to *Specificity*, and that analyst coverage is not concentrated in the high *Specificity* group but rather distributes slightly toward the bottom group.

the average spread between the bull and bear case forecast is 63% of the base case value. The mean for the *HighSpecificity* indicator is 0.41.[24] The mean for the absolute value of unanticipated returns is 20%, indicating that, on average, analysts' base-case forecast for the one-year-ahead stock price is 20 percent higher or lower than the realized price 12 months after.

Panel C of Table 2 shows that *Specificity* has a lower mean for risk-factor disclosures than for the rest of the 10-K and the MD&A section. This finding is consistent with the criticism from practitioners that risk disclosures are often boilerplate (and works against our finding support for our hypotheses). We further observe that the Pearson correlations among different sections in terms of specificity are quite low.

5. Empirical results

5.1 Determinants of *Specificity*

As explained above, we are primarily interested in testing the economic consequences of variations in *Specificity*. However, it is also interesting to explore which factors drive these variations. Also, it is potentially important to consider these in the tests for economic consequences, to control for potential endogeneity of risk-factor specificity. In our empirical analyses, we provide such control by adding the determinants as control variables to the regressions following prior literature on textual analysis of 10-K files (Li 2008). Thus, in this section, we first present results of the determinants of the level of specificity in risk-factor disclosures before we show how *Specificity* affects investors and analysts.

[24] The mean of *HighSpecificity* is not equal to 0.50 because we manually match Morgan Stanley analysts' reports with the top and bottom quintiles extracted from all sample risk-factor disclosures. A greater number of firms in the bottom quintile are matched, which leads to the mean of *HighSpecificity* being smaller than 0.5. As a robustness check, we reclassify the sample into two groups based on *Specificity*. We define *HighSpecificity* as an indicator variable which equals one when *Specificity* is above the sample median and zero otherwise. Conclusions are unaltered with this approach.

Table 3 presents the results of regressing *Specificity* on the potential determinants. Most importantly, we find that firms facing higher proprietary costs are less likely to provide specific risk-factor disclosures. This finding is consistent with prior disclosure literature and provides a rationale for why not all firms choose to provide specific disclosure. Because of the importance of proprietary costs, we further explore their role when examining market reactions in Section 5.2.2. Several other variables are also significant. For example, *Specificity* is positively and significantly related to *Specificity 10K*, *Amount*, *TotalLength*, *ReturnVolatility*, and *Analyst Forecast Error*.[25]

5.2 *Specificity* and stock-market reactions

We start by examining the stock-market consequences of specific risk-factor disclosures using the full sample of firms. Table 4 presents result of regressing $|CAR^{10\text{-}K}_{-1,1}|$ on *Specificity*, controlling for the amount of risk-related information disclosed in Item 1A (*Amount*) and other variables suggested in the literature on short-window market reactions. We additionally control for all determinants included in Table 3.[26]

The coefficient on *Specificity* is positive (0.0267) and significant at the 0.05 level using a two-sided test (Column 1). This result supports H1 that a higher level of specificity in firms' risk-factor disclosures leads to stronger market reactions to 10-K reports (i.e., that the information content increases with *Specificity*).[27] The coefficients on *Size* and $|CAR^{EA}_{-1,1}|$ are significant and consistent with findings in the prior literature.[28] *Specificity 10-K* and *TotalLength* are also

[25] In untabulated analyses we consider institutional ownership and the Herfindahl Index as additional determinants of *Specificity*. Including these variables does not increase the explanatory power of the model (and reduces the sample size by 11%). More importantly, their inclusion does not affect any inferences for our market-reaction and risk-assessment analyses.
[26] No inferences are affected if we exclude any of the control variables.
[27] In terms of economic significance, if *Specificity* is increased by one standard deviation (and other variables are held unchanged), the market reaction increases by 8 basis points. This effect is similar to that of *Specificity-10K* and *Amount*, greater than that of *Fog* and *RiskWords*, and smaller than that of *TotalLength*.
[28] The earnings announcement precedes the 10-K filing date, and we control for any earnings-announcement effect

positively and significantly related to market reactions. The signs of coefficients on most other control variables are consistent with prior literature, but not all estimates are significant.[29,30]

In untabulated analyses we explore which components of *Specificity* contribute most to the information content of risk-factor disclosures. First, if we separate the seven individual items into quantitative (Money, Percentage, Date, and Time) and qualitative groups (Organization, Person, and Location), we find that the specificity of quantitative (qualitative) disclosure is highly significant (directionally consistent but not statistically significant). Second, when we consider the components individually, *Money* and *Dates* are the most significant.

As an alternative widely used measure of the information content of *Specificity* we consider trading volume. While stock-price reactions are determined by the average investor's belief about a specific event, trading-volume reactions are induced by the different beliefs about the future price among individual investors (e.g., Beaver 1968; Bamber and Cheon 1995). As a result, trading-volume reactions can exist without the price reaction, and vice versa. Following the event-study literature (e.g., MacKinlay 1997), we define the 10-K file date as day 0 (event date), and we measure abnormal trading volume as the average daily trading volume in the three-day event window [-1, +1] minus the average daily trading volume in the [-60, -11] window, scaled by the trading volume in the [-60, -11] period.[31] We find that *Specificity* is positively associated with

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($|CAR^{EA}_{-1,1}|$) following prior literature.

[29] Because year 2006 is the first year after risk-factor disclosures are required, the effects that year could either be weaker due to the transition period's weaker regulatory enforcement or stronger due to more attention being paid to the new section of information. Excluding year 2006 from the full sample does not affect any conclusions. Further, the negative coefficient for *NumItems* likely relates to its correlation (0.5) with *Segment*s. If we exclude *Segments*, the estimated coefficient on *NumItems* is positive and our other inferences do not change.

[30] It is important to note that even if the *Specificity* score does not change from one risk disclosure to the next, this does not imply that there is no new information provided in the risk disclosures. Specifically, the risk disclosures could contain completely new information while the specificity level remains the same; thus our setting is different from the typical disclosure setting in the accounting literature. Nevertheless, as an untabulated sensitivity analysis we implement a changes specification in which we use the first difference of both the dependent and all the independent variables. The estimated coefficients on the change in *Specificity* are positive and statistically significant for both returns and volume, providing further support to our primary analyses.

[31] If the [-60, -11] window includes earnings announcements, the trading volume data in three-day windows around

abnormal trading volume. Specifically, Column 2 of Table 4 shows that the coefficient on *Specificity* is positive (0.710) and significant at the 0.10 level (two-tailed test).[32] This finding corroborates the primary analysis based on stock-price reactions.[33,34]

5.2.1 Pseudo analysis

Our multivariate analyses contain numerous variables motivated by extant research. These variables control for factors known to affect short-window stock-market reactions and for determinants of variations in risk-factor specificity. However, in order to further mitigate the possibility that *Specificity* measures some unobservable firm or firm-report characteristics that are significantly correlated with stock-market reactions, we design and implement a *pseudo analysis*. Specifically, in the years from 2001 to 2004, when risk-factor disclosures were *not* required by the SEC, we repeat the market-reaction test using *Specificity* calculated based on risk-factor disclosures from 10-K reports filed *in 2006* as a pseudo *Specificity* measure. If this *Specificity* captures some unknown stable features significantly explaining the market reaction, then the pseudo *Specificity* should be significantly related to the market reaction even when the real *Specificity* is not available. The result in Table 5 (first column) shows that this is not the case. Using the same specification as the market-reaction test, the coefficient of *Specificity* from the

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the announcements are excluded in calculation.

[32] An increase in *Specificity* of one standard deviation is associated with an increase in abnormal trading volume of 2%. This is similar to the effect for *Amount* and *TotalLength* and greater than the effect for *Specificity-10K*, *Fog*, and *RiskWords*.

[33] In untabulated analysis, we alternatively use the number of shares outstanding at the most recent fiscal quarter end as scalar. For *Specificity*, the estimated coefficient continues to be positive and significant at the 0.05 level. In another untabulated test we reestimate *Specificity* without removing filler words. Using this measure, both the abnormal returns and volume effects are significant at the 0.05 level.

[34] As explained, in this study we are interested in the textual feature of Item IA and whether greater specificity of disclosure induces greater market reaction. However, to compare with prior research by Campbell et al. (2014) and Kravet and Muslu (2013), we reestimate using *signed* returns as the dependent variable. Specifically, we test whether the effect documented by Campbell et al. (2014) is amplified for high-*Specificity* firms. In untabulated analyses we find that this is indeed the case (i.e., the interaction term is negative with a t-value of 1.96).

pseudo test is not significant (t = 0.569). This finding suggests that our previously documented significant and positive relation between *Specificity* and market reaction is not driven by *Specificity* being a proxy for unknown features related to market reaction. We also perform this pseudo analysis using abnormal trading volume, and similarly find no significant effect of the pseudo *Specificity* measure (second column).

5.2.2. Cross-sectional effects of proprietary costs

In Table 3 we observe that firms with high proprietary costs are less likely to provide specific risk disclosures. In this section, we partition our sample based on the level of proprietary costs and test whether the information content for the firms that provide more generic disclosure is lower. Table 6 shows that, both for returns and volume tests, *Specificity* is only significant in the low-proprietary-costs subsamples, consistent with the information content of risk disclosures only being discernible among firms that have sufficient (net) incentives to provide specific disclosure in the first place.[35]

5.3 *Specificity* and analysts' risk assessment

We now turn to our tests of analysts' risk assessments. Table 7 presents the results of examining H2. In the first column, we replicate the result in Joos et al. (2015) in our hand-collected sample. Joos et al. (2015) find a significantly positive coefficient on *Spread*. Our result is consistent with theirs. The coefficient on *Spread*, 0.11, is positive and statistically significant (t = 1.954). This result is in line with what Joos et al. (2015) find and suggests that analysts reliably assess

[35] We partition based on whether the sample firms have non-zero R&D costs or not (zero R&D is also the median for the sample). Whereas the difference in coefficient estimates across partitions is significant for the volume test it is insignificant for the returns test.

fundamental risks.

In the second column, we add the interaction term *Spread×HighSpecificity* and the main effect *HighSpecificity* to examine whether the level of specificity in risk-factor disclosures affects analysts' reliability in assessing fundamental risk (as reflected in the significant relation between the ex-post base-case forecast error and the ex-ante price spread that is forecasted in scenario analyses). The coefficient on *Spread* is no longer significant. In contrast, the coefficient on the interaction term *Spread×HighSpecificity*, 0.112, is significantly positive ($p<0.05$, using a two-sided test). These results indicate that high specificity helps analysts make better estimations (and that analysts' reliability in assessing fundamental risk mainly comes from firms that disclose risk factors with greater specificity). In addition, the coefficient on *HighSpecificity* is significantly negative, suggesting that a higher level of specificity associates with a lower ex-post analyst forecast error. Adding interactions of spread with all other qualitative disclosure features (*Specificity 10-K*, *Fog*, *RiskWords*, and *Amount*) into the regression does not change our conclusions (untabulated).

While the above results support H2 that analysts' reliability in assessing risks is increased with the level of specificity in risk-factor disclosure, they do not show a direct relation between specificity and analysts' risk assessment. Table 8 presents the result of regressing *Spread* on *HighSpecificity*, *Amount*, and other firm characteristics. The coefficient on *HighSpecificity*, −0.0338, is significantly negative, indicating that for the higher *Specificity* group, the *Spread* is smaller. This result further suggests that for firms with a higher *Specificity*, analysts are less uncertain about future price movement, and the spreads in their forecasts are narrower.

6. Concluding remarks

We develop a new measure of the degree of specificity in firms' risk-factor disclosures (Item 1A in the 10-K report), and we investigate whether specificity is positively associated with stock-market reactions to the 10-K file and whether more specific risk-factor disclosures enhance analysts' reliability in assessing firms' fundamental risk.

We document that the short-window market reaction to the 10-K file increases in *Specificity*. This finding is robust to the inclusion of numerous controls and to various robustness tests, and is consistent with the idea that investors find specific risk disclosures incrementally valuable in assessing firms' accounting information. We find consistent evidence when using abnormal trading volume as an alternative measure of information content. Further, we show that the information content of *Specificity* is a function of firms' proprietary costs.

Moreover, employing a sample of Morgan Stanley analysts' scenario analyses, we find that analysts' ex-ante bull-bear price spread is significantly positively correlated with the ex-post base case forecast error when *Specificity* is high, suggesting that analysts' forecasted spread reliably pictures future price movement; however, such a relation does not exist for risk-factor disclosure with low *Specificity*. These results indicate that more specific risk-factor disclosures enhance analysts' risk understanding. A caveat associated with these findings is that they are based on a relatively small, hand-collected sample of firms, covered by analysts from one financial institution. However, the strengths of this approach include internal consistency across firms and not having to control for brokerage-firm characteristics.

This study is the first to introduce a measure of the risk-factor specificity level, and to relate firms' risk-disclosure practices to investor reactions and to analysts' ability to assess risk. The results support the SEC's call for more specific risk disclosures by showing that investors respond to the information contained in risk-factor disclosures, consistent with investors benefiting from more specific disclosures. Our empirical findings provide support for the theory predictions in Heinle and Smith (2015) and suggest that the level of specificity in risk disclosures does affect investors' and analysts' evaluations. Finally, by introducing a novel level of specificity measure from the machine-learning domain (and validating this measure through the use of human subjects), we open the possibility for future research to continue our work in assessing disclosure quality in different fields.[36]

[36] There are many opportunities to apply *Specificity* in accounting research. As but two examples, segment reporting and major customer identification seem fertile grounds in which to employ this new measure.

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Appendix A: Examples of risk-factor disclosure with high and low *Specificity*

Example with high *Specificity*: risk-factor disclosures from Williams Controls (December 2007)

ITEM 1A. RISK FACTORS

An investment in our common stock involves a high degree of risk. You should carefully consider the risks discussed below and the other information in this report on Form 10-K before deciding whether to invest in our common stock.

Risks related to our business:

A significant portion of our sales are derived from a limited number of customers, and results of operations could be adversely affected and stockholder value harmed if we lose any of these customers.

A significant portion of our revenues historically have been derived from a limited number of customers. For the years ended September 30, 2007, 2006 and 2005, The Volvo Group accounted for 17%, 16% and 18%, Paccar, Inc. accounted for 14%, 17% and 17%, Freightliner, LLC accounted for 13%, 17% and 18%, Navistar International Corporation accounted for 6%, 8% and 7% and Caterpillar, Inc. accounted for 6%, 5% and 5%, of net sales from continuing operations, respectively. The loss of any significant customer would adversely affect our revenues and stockholder value.

Demand for equipment on which our products are installed may decrease, which could adversely affect our revenues and stockholder value.

We sell our products primarily to manufacturers of heavy trucks, transit busses and off-road equipment. If demand for our customers' vehicles or equipment decreases, demand for our products would decrease as well. This decrease in demand would adversely impact our revenues and stockholder value.

Our products could be recalled, which could increase our costs and decrease our revenues.

Our vehicle component products must comply with the National Traffic and Motor Vehicle Safety Act of 1966, as amended, and regulations promulgated thereunder, which are administered by the National Highway Traffic Safety Administration ("NHTSA"). If NHTSA finds that we are not in compliance with its standards or regulations, it may, among other things, require that we recall products found not to be in compliance, and repair or replace such products. Such a recall could increase our costs and adversely impact our reputation in our industry, both of which would adversely affect our revenues, profit margins, results of operations and stockholder value. We experienced such a recall with respect to certain of our products in fiscal 2001.

We purchase raw materials and component parts from suppliers and changes in the relationships with such suppliers, as well as increases in the costs of such raw materials and/or component parts, would adversely affect our ability to produce and market our products, which would adversely affect our profit margins, results from operations and stockholder value.

We purchase raw materials and component parts from suppliers to be used in the manufacturing of our products. If a supplier is unable or unwilling to provide us with such raw materials and/or component parts, we may be unable to produce certain products, which could result in a decrease in revenue and adversely impact our reputation in our industry. Also, if prices of such raw materials and/or component parts increase and we are not able to pass on such increase to our customers, our profit margins would decrease. The occurrence of either of these would adversely affect our results from operations and stockholder value.

Our products could be subject to product liability claims by customers and/or consumers, which would adversely affect our profit margins, results from operations and stockholder value.

A significant portion of our products are used on heavy trucks and transit busses. If our products are not properly designed or built and/or personal injuries are sustained as a result of our equipment, we could be subject to claims for damages based on theories of product liability and other legal theories. We maintain liability insurance for these risks; however, the costs and resources to defend such claims could be substantial, and if such claims are successful, we could be responsible for paying some or all of the damages. Also, our reputation could be adversely affected, regardless of whether such claims are successful. Any of these results would adversely affect our profit margins, results from operations and stockholder value. We are currently named as a co-defendant in a product liability case that seeks class action. Refer to **ITEM 3 – LEGAL PROCEEDINGS**.

Work stoppages or other changes in the relationships with our employees could make it difficult for us to produce and effectively market our products, which would adversely affect our profit margins, results from operations and stockholder value.

If we experience significant work stoppages, as we did in fiscal 2003, we likely would have difficulty manufacturing our products. Also, our labor costs could increase and we may not be able to pass such increase on to our customers. The occurrence of either of the foregoing would adversely affect profit margins, results from operations and stockholder value.

Our defined benefit pension plans are under-funded and, therefore, we may be required to increase our contributions to the plans, which would adversely affect our cash flows.

We maintain two defined benefit pension plans among the retirement plans we sponsor. No new employees are being admitted to participate in these two plans. Participants in these two plans are entitled to a fixed formula benefit upon retirement. Although we make regular contributions to these two plans in accordance with minimum ERISA funding requirements, investment earnings may be less than expected, and we may be required to increase contributions to the under-funded plan(s), which would adversely affect our cash flows.

Risks related to environmental laws:

The soil and groundwater at our Portland, Oregon facility contains certain contaminants that may require us to incur substantial expense to investigate and remediate, which would adversely affect our profit margins, results from operations and stockholder value.

The soil and groundwater at our Portland, Oregon facility contain certain contaminants. Some of this contamination has migrated offsite to neighboring properties and potentially to other properties. We have retained an environmental consulting firm to investigate the extent of the contamination and to determine what, if any, remediation will be required and the associated costs. During the third quarter of fiscal 2004, we entered the Oregon Department of Environmental Quality's voluntary clean-up program and during fiscal 2004 we established a liability of $950 for this matter. At September 30, 2007, we recorded an additional liability of $546 and as of September 30, 2007, this liability totaled $1,046. Our overall costs could exceed this liability, which could adversely affect our profit margins, results from operations and stockholder value.

We are required to comply with federal and state environmental laws, which could become increasingly expensive and could result in substantial liability if we do not comply.

We produce small quantities of hazardous waste in our operations and are subject to federal and state air, water and land pollution control laws and regulations. Compliance with such laws and regulations could become increasingly costly and the failure to comply could result in substantial liability. Either of these results could increase expenses, thereby adversely affecting our profit margins and stockholder value.

Risks related to foreign operations:

Fluctuations in the value of currencies could adversely affect our international sales, which would result in reduced revenues and stockholder value.

We sell products in Canada, Belgium, Sweden, Mexico, South America, the Pacific Rim nations, Australia, China and certain European nations, purchase components from suppliers in China and Europe, have a manufacturing and sales operation in China, and a sales and technical center in Germany. For the years ended September 30, 2007, 2006 and 2005, foreign sales were approximately 41%, 36%, and 35% of net sales, respectively. Although currently virtually all of our sales and purchases are made in U.S. dollars, we anticipate that over time more of our purchases of component parts and sales of our products will be denominated in foreign currencies. We do not presently engage in any hedging of foreign currency risk. In the future, our operations in the foreign markets will likely become subject to fluctuations in currency values between the U.S. dollar and the currency of the foreign markets. Our results from operations and stockholder value could be adversely affected if currency of any of the foreign markets increases in value relative to the U.S. dollar.

Complying with the laws applicable to foreign markets may become more difficult and expensive in the future, which could adversely affect our results from operations and stockholder value.

Our operations in foreign markets are subject to the laws of such markets. Compliance with these laws may become more difficult and costly in the future. In addition, these laws may change and such change may require us to change our operations. Any of these results could adversely affect our results from operations and stockholder value by increasing expenses and reducing revenues, thereby reducing profits.

Political and economic instability in the foreign markets may make doing business there more difficult and costly, which could adversely affect our results from operations and stockholder value.

Economic and political instability may increase in the future in foreign markets. Such instability may make it more difficult to do business in those countries, may make it more expensive to do so and could disrupt supplies of components into our Portland or Suzhou facilities. If our operations were nationalized by the government of China, this could cause us to write off the value of our operations in such foreign markets and eliminate revenues generated by such operations. Any of these results could result in onetime charges or increased expenses as well as lower revenues, which would adversely affect our results of operations and harm stockholder value.

Risks Related to our Capital Structure:

The market price of our stock has been and may continue to be volatile, which could result in losses for stockholders.

Our common stock is currently listed on the NASDAQ Capital Market and is thinly traded. Prior to October 9, 2006 our stock was traded on the OTC Bulletin Board. Volatility of thinly traded stocks is typically higher than the volatility of more liquid stocks with higher trading volumes. The market price of our common stock has been and, in the future, could be subject to significant fluctuations as a result of the foregoing, as well as variations in our operating results, announcements of technological innovations or new products by us or our competitors, announcements of new strategic relationships by us or our competitors, general conditions in our industries or market conditions unrelated to our business and operating results. Any of these results could adversely impact stockholder value.

Example with low *Specificity*: risk-factor disclosures from Tennant Company (March 2010)

We may encounter additional financial difficulties if the United States or other global economies continue to experience a significant long-term economic downturn, decreasing the demand for our products.

To the extent that the U.S. and other global economies experience a continued significant long-term economic downturn, our revenues could decline to the point that we may have to take additional cost saving measures to reduce our fixed costs to a level that is in line with a lower level of sales in order to stay in business long-term in a depressed economic environment. Our product sales are sensitive to declines in capital spending by our customers. Decreased demand for our products could result in decreased revenues, profitability and cash flows and may impair our ability to maintain our operations and fund our obligations to others.

We may not be able to effectively manage organizational changes which could negatively impact our operating results or financial condition.

We are continuing to integrate acquired companies into our business and adjust to reduced staffing levels as a result of our workforce reduction. This consolidation and reallocation of resources is part of our ongoing efforts to optimize our cost structure in the current economy. Our operating results may be negatively impacted if we are unable to manage these organizational changes either by failing to incorporate new employees from acquired businesses or failing to assimilate the work of the positions that are eliminated as part of our actions to reduce headcount. In addition, if we do not effectively manage the transition of our reduced headcount, we may not fully realize the anticipated savings of these actions or they may negatively impact our ability to serve our customers or meet our strategic objectives.

We may not be able to effectively optimize the allocation of Company resources to our strategic objectives, which could adversely affect our operating results.

The decline in the global economy has constrained resources that are available to allocate among strategic business objectives. If we are not able to appropriately prioritize our objectives, we risk allocating our resources to projects that do not accomplish our strategic objectives most effectively, which could result in increased costs and could adversely impact our operating results.

We are subject to competitive risks associated with developing innovative products and technologies, which generally cost more than our competitors' products.

Our products are sold in competitive markets throughout the world. Competition is based on product features and design, brand recognition, reliability, durability, technology, breadth of product offerings, price, customer relationships, and after-sale service. Although we believe that the performance and price characteristics of our products will provide competitive solutions for our customers' needs, because of our dedication to innovation and continued investments in research and development, our products generally cost more than our competitor's products. We believe that customers will pay for the innovation and quality in our products; however, in the current economic environment, it may be difficult for us to compete with lower cost products offered by our competitors and there can be no assurance that our customers will continue to choose our products over products offered by our competitors. If our products, markets and services are not competitive, we may experience a decline in sales, pricing, and market share, which adversely impacts revenues, margin, and the success of our operations.

We may not be able to adequately acquire, retain and protect our proprietary intellectual property rights which could put us at a competitive disadvantage.

We rely on trade secret, copyright, trademark and patent laws and contractual protections to protect our proprietary technology and other proprietary rights. Our competitors may attempt to copy our products or gain access to our trade secrets. Our efforts to secure patent protection on our inventions may be unsuccessful. Notwithstanding the precautions we take to protect our intellectual property rights, it is possible that third parties may illegally copy or otherwise obtain and use our proprietary technology without our consent. Any litigation concerning infringement could result in substantial cost to us and diversions of our resources, either of which could adversely affect our business. In some cases, there may be no effective legal recourse against duplication of products or services by competitors. Intellectual property rights in foreign jurisdictions may be limited or unavailable. Patents of third parties also have an important bearing on our ability to offer some of our products and services. Our competitors may obtain patents related to the types of products and services we offer or plan to offer. Any infringement by us on intellectual property rights of others could result in litigation and adversely affect our ability to continue to provide, or could increase the cost of providing, our products and services.

We may encounter difficulties as we invest in changes to our processes and computer systems that are foundational to our ability to maintain and manage our systems data.

We rely on our computer systems to effectively manage our business, serve our customers and report financial data. Our current systems are adequate for our current business operations; however, we are in the process of standardizing our processes and the way we utilize our computer systems with the objective that we will improve our ability to effectively maintain and manage our systems data so that as our business grows, our processes will be able to more efficiently handle this growth. There are inherent risks in changing processes and systems data and if we are not successful in our attempts to improve our data and system processes, we may experience higher costs or an interruption in our business which could adversely impact our ability to serve our customers and our operating results.

We may be unable to conduct business if we experience a significant business interruption in our computer systems, manufacturing plants or distribution facilities for a significant period of time.

We rely on our computer systems, manufacturing plants and distribution facilities to efficiently operate our business. If we experience an interruption in the functionality in any of these items for a significant period of time, we may not have adequate business continuity planning contingencies in place to allow us to continue our normal business operations on a long-term basis. Significant long-term interruption in our business could cause a decline in sales, an increase in expenses and could adversely impact our operating results.

We are subject to product liability claims and product quality issues that could adversely affect our operating results or financial condition.

Our business exposes us to potential product liability risks that are inherent in the design, manufacturing and distribution of our products. If products are used incorrectly by our customers, injury may result leading to product liability claims against us. Some of our products or product improvements may have defects or risks that we have not yet identified that may give rise to product quality issues, liability and warranty claims. If product liability claims are brought against us for damages that are in excess of our insurance coverage or for uninsured liabilities and it is determined we are liable, our business could be adversely impacted. Any losses we suffer from any liability claims, and the effect that any product liability litigation may have upon the reputation and marketability of our products, may have a negative impact on our business and operating results. We could experience a material design or manufacturing failure in our products, a quality system failure, other safety issues, or heightened regulatory scrutiny that could warrant a recall of some of our products. Any unforeseen product quality problems could result in loss of market share, reduced sales, and higher warranty expense.

We may encounter difficulties obtaining raw materials or component parts needed to manufacture our products and the prices of these materials are subject to fluctuation.

Raw materials and commodity-based components. As a manufacturer, our sales and profitability are dependent upon availability and cost of raw materials, which are subject to price fluctuations, and the ability to control or pass on an increase in costs of raw materials to our customers. We purchase raw materials, such as steel, rubber, lead and petroleum-based resins and components containing these commodities for use in our manufacturing operations. The availability of these raw materials is subject to market forces beyond our control. Under normal circumstances, these materials are generally available on the open market from a variety of sources. From time to time, however, the prices and availability of these raw materials and components fluctuate due to global market demands, which could impair our ability to procure necessary materials, or increase the cost of such materials. Inflationary and other increases in the costs of these raw materials and components have occurred in the past and may recur from time to time, and our financial performance depends in part on our ability to incorporate changes in costs into the selling prices for our products. Freight costs associated with shipping and receiving product and sales and service vehicle fuel costs are impacted by fluctuations in the cost of oil and gas. We do not use derivative commodity instruments to manage our exposure to changes in commodity prices such as steel, oil, gas and lead. Any fluctuations in the supply or prices for any of these commodities could have a material adverse effect on our profit margins and financial condition.

Single-source supply. We depend on many suppliers for the necessary parts to manufacture our products. However, there are some components that are purchased from a single supplier due to price, quality, technology or other business constraints. These components cannot be quickly or inexpensively re-sourced to another supplier. If we are unable to purchase on acceptable terms or experience significant delays or quality issues in the delivery of these necessary parts or components from a particular vendor and we need to locate a new supplier for these parts and components, shipments for products impacted could be delayed, which could have a material adverse effect on our business, financial condition and results of operations.

We are subject to a number of regulatory and legal risks associated with doing business in the United States and international markets.

Our business and our products are subject to a wide range of international, federal, state and local laws, rules and regulations, including, but not limited to, data privacy laws, anti-trust regulations, employment laws, product labeling and regulatory requirements, and the Foreign Corrupt Practices Act and similar anti-bribery regulations. Many of these requirements are challenging to comply with as there are frequent changes and many inconsistencies across the various jurisdictions. Any violation of these laws or regulations could lead to significant fines and/or penalties could limit our ability to conduct business in those jurisdictions and could cause us to incur additional operating and compliance costs.

We are subject to risks associated with changes in foreign currency exchange rates.

We are exposed to market risks from changes in foreign currency exchange rates. As a result of our increasing international presence, we have experienced an increase in transactions and balances denominated in currencies other than the U.S. dollar. There is a direct financial impact of foreign currency exchange when translating profits from local currencies to U.S. dollars. Our primary exposure is to transactions denominated in the Euro, British pound, Australian and Canadian dollar, Japanese yen, Chinese yuan and Brazilian real. Any significant change in the value of the currencies of the countries in which we do business against the U.S. dollar could affect our ability to sell products competitively and control our cost structure. Because a substantial portion of our products are manufactured in the United States, a stronger U.S. dollar generally has a negative impact on results from operations outside the United States while a weaker dollar generally has a positive effect. Unfavorable changes in exchange rates between the U.S. dollar and these currencies impact the cost of our products sold internationally and could significantly reduce our reported sales and earnings. We periodically enter into contracts, principally forward exchange contracts, to protect the value of certain of our foreign currency-denominated assets and liabilities. The gains and losses on these contracts generally approximate changes in the value of the related assets and liabilities. However, all foreign currency exposures cannot be fully hedged, and there can be no assurances that our future results of operations will not be adversely affected by currency fluctuation.

Appendix B: Validity test instructions

Assignment – Evaluation of the specificity level of risk disclosures

Name ____________________________

You are randomly assigned the risk disclosures from the financial statements of FIVE different companies. You are asked to evaluate the level of specificity of these risk disclosures. The definition of specific risk disclosure is provided below:

A piece of risk disclosure is defined as specific if it contains information that cannot be applied to other firms. In other words, information is considered to be more specific when the disclosure contains more detailed information specifically about the disclosing firm.

Please rate each sample firm into one of the following five levels:

Very specific:	5
Specific:	4
Specific to not very specific:	3
Not very specific:	2
Not specific at all:	1

The following examples with constructed hypothetical sentences are for illustration.

Google's main business in United States Google Search, accounting 30% of the profit, is facing fierce competition from Microsoft's Bing. *(5)*
Google's main business in United States Google Search is facing fierce competition from Microsoft's Bing. *(4)*
Google's main business in United States is facing fierce competition from Microsoft. *(3)*
The firm's main business in United States is facing fierce competition from other firms. *(2)*
The firm's main business is facing fierce competition globally from other firms. *(1)*

Appendix C: Variable definitions

Dependent variables	
$\lvert$*Unanticipated-return*$\rvert$	$\frac{Price_{it+365} - Price_{it}}{Price_{it}} - \frac{Base_{it} - Price_{it}}{Price_{it}}$ The absolute value of the difference between the one-year ahead realized raw return and the *Base*. *Base* is the forecast for the one-year ahead stock price in the first analyst report with scenario analysis issued by Morgan Stanley after the firm files 10-K report for year t.
$\lvert CAR^{10k}_{-1,1}\rvert$	The absolute value of the difference between the three-day stock return starting one trading day before the 10-K release and ending one trading day after and the expected return estimated using the Fama-French three-factor model.
$ABVOL^{10\text{-}K}_{-1,1}$	Average daily trading volume in three-day window around 10-K file date in excess of the mean daily trading volume in the [-60, -11] trading day window (scaled by the [-60, -11] period volume), excluding the trading volume data in three-day window around earnings announcements. Day 0 is defined as the 10-K file date.
Independent variables	
Specificity	The number of specific words identified by the Stanford NER program in Item 1A in the 10-K report divided by the number of total words in Item 1A after stop-words removed. The list of stop words is from Python natural language processing package.
Specificity 10K	The number of specific words identified by the Stanford NER program in the 10-K report divided by the number of total words in 10-K report after stop-words removed. The list of stop words is from Python natural language processing package.
Amount	The log of the number of one plus the risk-related words in Item 1A. The risk-related words are identified using dictionaries developed in Campbell et al. (2014).
RiskWords	The log of one plus the total number of word "risk" and its derivative words defined in Li (2006) in 10-Ks.
Fog	Fog index downloaded from Feng Li's website.
TotalLength	The log of the number of all words in the10-K file.
Spread	$\frac{Bull_{it} - Bear_{it}}{Base_{it}}$ *Bull* and *Bear* are the bull-case and bear-case forecasts for the one-

	year ahead stock price contained in the first analyst report with scenario analysis issued by Morgan Stanley after the firm files 10-K report for year t.
HighSpecificity	An indicator variable that equals one if *Specificity* for firm *i* is in the top quintile among all sample firms in 2010, zero if *Specificity* is in the bottom quintile.
BtM	The ratio of book value of equity to market value of equity.
ReturnVolatility	The standard deviation of daily stock returns in year t-1.
EarningsVolatility	The standard deviation of quarterly earnings in the past 20 quarters scaled by the absolute value of the mean of quarterly earnings in the past 20 quarters.
NegEarnings	An indicator variable that equals one if the sum of the past four quarterly earnings is negative, and zero otherwise.
Δ*Earnings*	The difference between net income in year t and net income in year t-1.
Accrual	The absolute value of accruals calculated using the cash flows statement deflated by average total assets.
PastLoss	An indicator variable that equals one if the firm has one or more loss years over the previous five years, zero otherwise.
Litigation	An indicator variable that equals one for firms in SIC codes 2833-2836, 3570-3577, 3600-3674, 5200-5961, 7370-7374, and 8731-8734, zero otherwise.
$\lvert CAR^{EA}_{-1,1}\rvert$	The same calculation as $\lvert CAR^{10k}_{-1,1}\rvert$ with event date as the annual earnings announcement date.
FileDate	An indicator variable that equals one when the 10-K filing date is at least 90 days after the year end, zero otherwise.
NumItems	The number of non-missing items on COMPUSTAT in a fiscal year.
Size	The natural logarithm of the market value of equity.
Leverage	The ratio of long-term debt to total assets.
Segments	The natural logarithm of one plus the number of segments.
HighInstitution	An indicator variable that equals one if the firm's institutional ownership is above the median institutional ownership of all firms in the same year.
ProprietaryCost	R&D intensity, calculated as the R&D expense divided by total asset at the beginning of the fiscal year. Missing data is replaced by zero.
Num8K	The number of 8-K files in the one-year period before the 10-K filings.
ForecastError	The difference of the mean EPS forecast with the announced EPS standardized by the stock price at the beginning of the fiscal year.

	Missing data is replace by zero.
ForecastMissing	An indicator that equals one if *Forecast Error* is missing and zero otherwise.

Table 1: Sample composition by year and industry

Panel A: By year

Year	*Specificity*	Item 1A # Words	Observations
2006	5.57%	4,193	2,642
2007	5.55%	4,495	2,478
2008	5.43%	4,829	2,733
2009	5.52%	5,447	2,520
2010	5.35%	5,732	2,371
2011	5.22%	6,051	2,121
Total			14,865

Panel B: By industry

Industry	*Specificity* (%)	Item1A	Observations	%
Utilities	7.16	4,558	397	2.67
Mining and minerals	6.4	5,956	123	0.83
Transportation	6.15	4,212	575	3.87
Banks, Insurance Companies, and Other Financials	6.05	5,027	3,186	21.43
Drugs, Soap, Perfumes, and Tobacco	5.99	7,598	609	4.1
Chemicals	5.79	4,395	272	1.83
Fabricated Products	5.62	4,267	108	0.73
Steel Works	5.56	3,807	156	1.05
Automobiles	5.54	3,126	193	1.3
Other	5.41	5,649	4,559	30.67
Food	5.28	3,184	371	2.5
Oil and Petroleum Products	5.1	5,167	563	3.79
Consumer Durables	4.85	3,773	303	2.04
Textiles, Apparel, and Footwear	4.82	4,079	230	1.55
	4.67	5,306	1,928	12.97

Machinery and Business Equipment				
Construction and Construction Materials	4.61	3,743	411	2.77
Retail Stores	4.32	3,871	881	5.93

This table provides data on sample composition for the market-reaction tests. The analyst-related tests rely on a smaller sample, as explained in the text. Item 1A is the length (number of words) of that section.

Table 2: Descriptive statistics

Panel A: Market reaction sample (N = 14,865)

	mean	std	p10	p25	median	p75	p90
$\lvert CAR^{10k}_{-1,1}\rvert$	0.04	0.10	0.00	0.01	0.02	0.05	0.09
Specificity	0.05	0.03	0.02	0.03	0.05	0.07	0.09
*Specificity*10K	0.19	0.04	0.13	0.17	0.19	0.21	0.23
Amount	4.00	0.80	3.05	3.58	4.06	4.53	4.91
$\lvert CAR^{EA}_{-1,1}\rvert$	0.06	0.08	0.01	0.02	0.04	0.08	0.15
FileDate	0.04	0.19	0.00	0.00	0.00	0.00	0.00
NumItems	159.20	22.60	127.00	142.00	161.00	176.00	187.00
Size	6.38	1.92	3.88	5.05	6.36	7.67	8.86
Fog	19.94	1.75	18.33	18.98	19.79	20.71	21.84
TotalLength	10.29	0.79	9.62	10.01	10.34	10.70	11.06
ΔEarnings	0.25	15.35	-0.11	-0.02	0.00	0.03	0.12
Accrual	0.09	0.17	0.01	0.02	0.05	0.09	0.17
BtM	0.65	2.84	0.16	0.31	0.53	0.83	1.29
PastLoss	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Leverage	0.57	0.52	0.20	0.35	0.55	0.76	0.91
ReturnVolatility	0.03	0.02	0.02	0.02	0.03	0.04	0.06
Litigation	0.28	0.45	0.00	0.00	0.00	1.00	1.00
Segments	0.81	0.41	0.00	0.69	0.69	1.10	1.39
Num8K	2.77	0.50	2.20	2.48	2.77	3.09	3.37
ProprietaryCost	0.04	0.09	0.00	0.00	0.00	0.04	0.13
ForecastError	0.03	0.20	-0.01	0.00	0.00	0.00	0.02
ForecastMissing	0.14	0.35	0.00	0.00	0.00	0.00	1.00
RiskWords	4.07	0.64	3.30	3.64	4.01	4.45	4.94

Panel B: Analyst sample (N = 627)

	mean	std	p10	p25	median	p75	p90
|Unanticipated-return|	0.20	0.22	0.03	0.07	0.14	0.24	0.40
Spread	0.63	0.31	0.34	0.42	0.56	0.75	1.00
HighSpecificity	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Specificity 10K	0.16	0.06	0.08	0.11	0.17	0.21	0.23
BtM	0.51	0.40	0.15	0.25	0.41	0.68	0.98
Leverage	0.58	0.21	0.29	0.44	0.60	0.72	0.89
NegEarnings	0.13	0.34	0.00	0.00	0.00	0.00	1.00
EarningsVolatility	2.71	8.53	0.24	0.33	0.54	1.38	5.13
Size	8.96	1.46	7.16	7.93	8.94	9.94	11.01
ReturnVolatility	0.03	0.01	0.01	0.02	0.02	0.03	0.04
Amount	4.08	0.77	3.04	3.66	4.16	4.60	4.97

Fog	19.97	2.12	18.33	19.02	19.83	20.85	22.13
TotalLength	10.62	0.90	9.95	10.32	10.68	11.08	11.41
ΔEarnings	0.01	0.19	-0.07	-0.02	0.00	0.02	0.07
Accrual	0.07	0.06	0.01	0.03	0.05	0.09	0.13
PastLoss	0.30	0.46	0.00	0.00	0.00	1.00	1.00
Litigation	0.38	0.49	0.00	0.00	0.00	1.00	1.00
Segments	0.96	0.44	0.69	0.69	0.69	1.39	1.61
RiskWords	4.47	0.72	3.61	3.99	4.38	4.96	5.37

See Appendix C for variable definitions. The summary statistics presented are before winsorization.

Panel C: *Specificity* by section and Pearson correlations

	Mean	*Std*
Specificity	0.05	0.03
Specificity 10K	0.19	0.04
Specificity MD&A	0.23	0.08
	Specificity 10K	*Specificity MD&A*
Specificity	0.11**	0.08**
Specificity 10K		0.11**

Note: For the pairwise comparison, ** indicates significance at the 5% level (two-sided).

Table 3: Determinants of specificity

	Specificity (×100)
Specificity 10K	7.253***
	(4.017)
Amount	0.189***
	(2.592)
RiskWords	-0.0132
	(-0.113)
Fog	-0.0290
	(-1.201)
TotalLength	0.472**
	(2.248)
Proprietary Cost	-1.201***
	(-2.658)
Δ*Earnings*	0.0634
	(0.983)
Accrual	-0.697*
	(-1.754)
Size	-0.0902***
	(-2.736)
BtM	0.102
	(1.439)
PastLoss	0.114
	(1.264)
Leverage	0.922***
	(4.474)
ReturnVolatility	11.80***
	(4.934)
Litigation	0.124
	(1.123)
Segments	-0.245*
	(-1.747)
Num8K	0.0915
	(0.922)
ForecastError	0.312**
	(2.054)
ForecastMissing	0.464***
	(4.078)
Constant	-1.039
	(-0.526)
Industry FE	Yes
Year FE	Yes
N	14,865
Adjusted R^2	0.098

The table reports coefficient estimates from a regression of *Specificity* on determinants for the full sample. Standard errors are two-way clustered by firm and filing month. t-statistics are in brackets. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively (two-tailed).

Table 4: *Specificity* and stock-market reactions

	$\lvert CAR^{10\text{-}K}_{-1,1}\rvert$	$ABVOL^{10\text{-}K}_{-1,1}$
Specificity	0.0267**	0.710*
	(2.358)	(1.954)
Specificity 10K	0.0200***	0.00828
	(2.613)	(0.0550)
Amount	0.000998	0.0272**
	(1.316)	(2.454)
RiskWords	-0.000127	0.00745
	(-0.187)	(0.352)
Fog	0.000187	0.00353
	(0.794)	(0.895)
TotalLength	0.00255***	0.0296
	(4.142)	(1.384)
ProprietaryCost	0.00111	-0.733***
	(0.250)	(-5.181)
Δ*Earnings*	-0.00190*	0.101***
	(-1.820)	(2.846)
Accrual	0.000992	0.297**
	(0.0990)	(2.100)
Size	-0.00305***	-0.0511***
	(-4.293)	(-2.646)
BtM	0.000171	-0.0734***
	(0.194)	(-4.234)
PastLoss	0.00250***	-0.00830
	(4.811)	(-0.286)
Leverage	0.00716**	0.0721
	(2.539)	(1.321)
ReturnVolatility	0.486***	-4.692***
	(4.611)	(-5.259)
Litigation	0.00265***	0.00586
	(3.143)	(0.225)
Segments	0.00534***	0.0907***
	(3.349)	(3.829)
Num8K	0.00124*	-0.0317*
	(1.892)	(-1.848)
ForecastError	0.0105***	0.0328
	(5.405)	(0.504)
ForecastMissing	-7.37e-05	0.0934**
	(-0.0322)	(2.262)
FileDate	0.00576	0.149**
	(1.613)	(2.037)
NumItems	-4.64e-05**	-4.87e-05
	(-2.475)	(-0.0590)

$\lvert CAR^{EA}_{-1,1}\rvert$	0.270***	3.792***
	(9.483)	(5.579)
Constant	-0.0168**	0.142
	(-2.089)	(0.516)
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	14,865	14,865
Adjusted R^2	0.320	0.067

See Appendix C for variable definitions. The first column reports coefficient estimates from a regression of $\lvert CAR^{10\text{-}K}_{-1,1}\rvert$ *on Specificity* and other controls. The second column reports coefficient estimates from a regression of $ABVOL^{10\text{-}K}_{-1,1}$ *on Specificity* and other controls. Panel A uses levels analyses, and Panel B uses changes analyses. Litigation is suppressed in the changes analyses, as it is based on industry and not changing by year. All continuous variables are winsorized at the top and bottom 1 percent. Standard errors are two-way clustered by firm and filing month. t-statistics are in brackets. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively (two-tailed).

Table 5: Pseudo analysis for *Specificity* and market reactions

	$\lvert CAR^{10\text{-}K}_{-1,1}\rvert$	$ABVOL^{10\text{-}K}_{-1,1}$
Specificity	0.0115	-0.00338
	(0.569)	(-0.566)
Specificity 10K	0.0290	0.00370
	(1.471)	(1.366)
Amount	-0.00110	-2.73e-05
	(-1.108)	(-0.293)
RiskWords	0.000846***	0.000317
	(2.655)	(1.531)
Fog	-0.000634***	2.19e-05
	(-3.130)	(0.397)
TotalLength	0.000485	-0.000182
	(0.413)	(-1.369)
ProprietaryCost	-0.00697	0.000707
	(-0.624)	(0.342)
Δ*Earnings*	0.000412	0.000712***
	(0.237)	(3.993)
Accrual	0.0112***	0.00324
	(3.189)	(1.457)
Size	-0.00103***	-0.000121**
	(-7.572)	(-2.050)
BtM	-0.00160	0.000177
	(-0.924)	(1.219)
PastLoss	0.00256	-0.000140
	(1.135)	(-0.400)
Leverage	-0.00381***	0.000685
	(-9.214)	(1.568)
ReturnVolatility	0.596***	-0.00647
	(12.97)	(-0.895)
Litigation	0.00471***	0.000766**
	(2.727)	(2.526)
Segments	-0.000821	-1.21e-05
	(-0.675)	(-0.0335)
Num8K	0.000957	0.000344**
	(1.304)	(2.216)
ForecastError	0.0196	-0.00203***
	(1.269)	(-4.090)
ForecastMissing	0.00169**	-0.000345
	(2.429)	(-1.095)
Constant	0.0298***	0.00295***
	(4.097)	(3.593)
FileDate	0.00328***	0.000719***
	(3.071)	(4.633)

NumItems	-4.15e-05	-1.46e-05***
	(-1.540)	(-5.001)
$\|CAR^{EA}_{-1,1}\|$	0.111***	0.000138
	(8.791)	(0.0490)
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	4,158	4,156
Adjusted R^2	0.223	0.011

See Appendix C for variable definitions. The table reports pseudo test results. *Specificity* and *Amount* are calculated for the sample firms using data at fiscal year 2006. For each firm's each *Specificity* and *Amount* observation, we calculate dependent variable $|CAR^{10\text{-}K}_{-1,1}|$ and all independent variables other than *Specificity* and *Amount* using the data for the same firm but in the fiscal years from 2001 to 2004. All continuous variables are winsorized at the top and bottom 1 percent. Standard errors are two-way clustered by firm and filing month. t-statistics are in brackets. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively (two-tailed).

Table 6: Cross-sectional tests based on proprietary costs

	$\lvert CAR^{10\text{-}K}_{-1,1}\rvert$		$ABVOL^{10\text{-}K}_{-1,1}$	
	High Proprietary Cost	*Low Proprietary Cost*	*High Proprietary Cost*	*Low Proprietary Cost*
Specificity	-0.00484	0.0375*	-0.0310	1.091**
	(-0.214)	(1.924)	(-0.0514)	(2.230)
Specificity 10K	0.0283	0.00961	-0.219	0.106
	(1.449)	(0.798)	(-0.643)	(0.540)
Amount	-0.000638	0.00216**	0.0177	0.0387**
	(-0.875)	(2.315)	(0.742)	(2.156)
RiskWords	-0.000957	0.000957	-0.0323	0.0399
	(-0.975)	(1.040)	(-0.640)	(1.465)
Fog	0.000170	0.000177	-0.0102	0.0104**
	(0.531)	(0.672)	(-1.202)	(2.108)
TotalLength	0.00293***	0.00216***	0.0214	0.0337
	(3.653)	(2.760)	(0.803)	(0.909)
Δ*Earnings*	-0.00168	-0.00168	0.124	0.0831
	(-0.450)	(-1.246)	(1.127)	(1.217)
Accrual	-0.00153	0.00473	0.263*	0.160
	(-0.167)	(0.447)	(1.925)	(0.538)
Size	-0.00367***	-0.00278***	-0.0563**	-0.0488***
	(-5.504)	(-3.094)	(-2.553)	(-2.634)
BtM	0.000973	-0.000505	0.000864	-0.108***
	(0.677)	(-0.493)	(0.0203)	(-7.014)
PastLoss	0.00226	0.00265***	-0.0112	-0.00485
	(1.509)	(3.676)	(-0.356)	(-0.136)
Leverage	0.00968***	0.00460	0.125	-0.0275
	(4.478)	(1.326)	(1.462)	(-0.466)
ReturnVolatility	0.445***	0.489***	-8.087***	-2.429***
	(4.831)	(4.023)	(-4.161)	(-3.004)
Litigation	0.00264***	0.00267	-0.0214	-0.0117
	(2.703)	(1.085)	(-0.805)	(-0.220)
Segments	0.00543***	0.00376*	0.118***	0.0680**
	(2.843)	(1.860)	(3.752)	(2.384)
Num8K	0.00301**	0.000218	-0.0206	-0.0404**
	(2.149)	(0.408)	(-0.738)	(-2.003)
ForecastError	0.0137***	0.00783**	0.0748	-0.0190
	(3.645)	(2.360)	(0.900)	(-0.216)
ForecastMissing	-0.00222	0.00141	0.0649	0.116
	(-0.589)	(0.696)	(0.726)	(1.563)
FileDate	0.00553	0.00543	0.165	0.137
	(1.532)	(0.789)	(1.488)	(1.196)
NumItems	-0.000115***	2.13e-05	0.000133	0.00103
	(-2.940)	(0.671)	(0.0831)	(1.358)
$\lvert CAR^{EA}_{-1,1}\rvert$	0.247***	0.291***	3.533***	4.072***

	(8.663)	(10.05)	(5.714)	(5.199)
Constant	-0.000632	-0.0276*	0.609***	-0.331
	(-0.120)	(-1.894)	(3.130)	(-0.870)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,045	8,820	6,045	8,820
Adjusted R^2	0.289	0.345	0.063	0.071

See Appendix C for variable definitions. The first two columns report coefficient estimates from a regression of $|CAR^{10\text{-}K}_{-1,1}|$ *on Specificity* and other controls. Columns 3 and 4 report coefficient estimates from a regression of $ABVOL^{10\text{-}K}_{-1,1}$ *on Specificity* and other controls. We partition based on whether the sample firms have non-zero R&D or not. All continuous variables are winsorized at the top and bottom 1 percent. Standard errors are two-way clustered by firm and filing month. t-statistics are in brackets. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively (two-tailed).

Table 7: *Specificity* and analysts' risk assessment

	|*Unanticipated-return*|	|*Unanticipated-return*|
Spread	0.110*	0.0522
	(1.954)	(0.691)
Spread×HighSpecificity		0.112**
		(2.062)
HighSpecificity	-0.0733	-0.0463
	(-1.237)	(-1.386)
Leverage	-0.0709	-0.112*
	(-1.145)	(-1.655)
BtM	0.0419	0.0264
	(0.770)	(0.443)
Size	0.00962	0.00267
	(1.104)	(0.257)
EarningsVolatility	0.000711	0.000950
	(0.439)	(0.603)
NegEarnings	0.0421	0.0166
	(1.403)	(0.567)
ReturnVolatility	3.074***	3.443***
	(2.587)	(2.752)
Specificity 10-K		-0.0171
		(-0.376)
Amount		-0.00184
		(-0.422)
RiskWords		0.0429***
		(2.893)
Fog		0.0120***
		(4.195)
TotalLength		-0.0198***
		(-2.852)
ΔEarnings		-0.103
		(-1.199)
Accrual		0.0113
		(0.0808)
PastLoss		0.00225
		(0.10)
Litigation		-0.0479***
		(-3.041)
Segments		0.000800
		(0.0462)
Constant	-0.0543	-0.119
	(-0.571)	(-0.776)

Industry FE	Yes	Yes
Year FE	Yes	Yes
N	627	627
Adjusted R^2	0.119	0.135

See Appendix C for variable definitions. All continuous variables are winsorized at the top and bottom 1 percent. The first column reports coefficient estimates from a regression of |*Unanticipated-return*| *on Spread* and other controls for the analyst risk assessment sample (i.e., we replicate Joos et al. (2015) and find consistent results). The second column adds interaction term *Spread*×*Specificity*. Note that the second column presents results after controlling for all the determinants of *Specificity* from Table 4 (untabulated). Standard errors are two-way clustered by firm and year. t-statistics are in brackets. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively (two-tailed).

Table 8: *Specificity* and analysts' forecasted spread

	Spread
HighSpecificity	-0.0338*
	(-1.912)
Specificity 10-K	0.432
	(1.464)
Amount	-0.0115
	(-0.764)
RiskWords	0.0269
	(0.953)
Fog	-0.00279
	(-0.449)
TotalLength	0.000794
	(0.0656)
ΔEarnings	-0.0905*
	(-1.873)
Accrual	0.0252**
	(2.145)
PastLoss	0.00292
	(0.0651)
Litigation	-0.00164
	(-0.0402)
Segments	-0.0413
	(-1.147)
Leverage	0.0194
	(0.214)
BtM	0.0836
	(1.559)
Size	-0.0171***
	(-2.734)
EarningsVolatility	-0.000442
	(-0.417)
NegEarnings	0.0480
	(0.640)
ReturnVolatility	9.529***
	(5.428)
Constant	0.360*
	(1.943)
Industry FE	Yes
Year FE	Yes
Observations	627
Adjusted R^2	0.334

See Appendix C for variable definitions. All continuous variables are winsorized at the top and bottom 1 percent. The table reports coefficient estimates from a regression of *Spread* on *HighSpecificity* and other controls for the analysts' risk assessment sample. Standard errors are two-way clustered by firm and year. t-statistics are in brackets. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively (two-tailed).