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Voluntary forward-looking disclosures and default risk pricing

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This study examines the effects of textual and numerical information contained in voluntary forward-looking management forecast reports (MFRs) on the pricing of default risk. We find that abnormal changes in credit default swap (CDS) premiums around MFR issuance dates are inversely associated with textual quality and the extent of positive textual news conveyed in the MFR. Furthermore, we find that the negative association of CDS premiums with either textual or numerical news is qualified by the MFR's textual quality. Collectively, our evidence implies that CDS counterparties use textual quality to verify the quality of the information disclosed in both textual and numerical modes before impounding it into the default risk price. These findings suggest that multimodal verification can enhance the overall information quality of incentive-driven disclosures.

Keywords: management forecast reports; multi-modal information; default risk pricing; credit default swap

1. Introduction

The management forecast report (MFR) is an important form of voluntary disclosure and a significant source of forward-looking information for outside investors (e.g. Sengupta 1998, Hutton et al. 2003, Ng et al. 2013, Schivakumar et al. 2011, Lok and Richardson 2011).[1] Beyer et al. (2010) find that the information content in MFR accounts for 55% of the stock return variations when considering all the accounting information disclosed by a firm. This evidence suggests that MFR is remarkably more informative than other forms of firm disclosure. However, the manner

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[1]An MFR typically comprises numerical earnings forecast (numerical information component) and accompanying text running into multiple pages (textual information component). An MFR may be issued along with an earnings announcement report (bundled) or independently on its own (unbundled). Considering that our focus is on the effect of forward-looking MFRs rather than the effect of combining them historical earnings announcements, we examine unbundled MFRs only.

in which market participants verify the information provided by MFRs remains unclear due to the voluntary nature of MFRs and the incentives of management involved. To clarify this, we investigate how the textual and numerical information provided in MFRs affect the pricing of default risk, as measured using credit default swap (CDS) spread.

The CDS spread reflects the market's default risk premium for the underlying debtor firm.[2] A defining feature of a CDS contract is the transfer of default risk from the risk protection buyer to the risk protection seller. CDS lenders (risk protection buyers), typically banks, can transfer the default risk of the underlying private debt to their CDS counterparties (risk protection sellers) by paying a price, known as the CDS spread or premium. These risk protection sellers, such as insurance firms, dealers, or hedge funds, ultimately bear the default risk. However, unlike other debt instruments, CDS contracts do not grant the ultimate counterparties control or monitoring rights over the underlying debt, nor do they provide access to the private information associated with these rights (Marsh 2009, Stulz 2010, Parlour and Winton 2013). That is, CDS counterparties are sophisticated outsiders who lack direct contractual relations with a referenced borrower and cannot directly observe its changing asset quality.[3] Consequently, CDS counterparties can benefit theoretically from firm-level public disclosures of referenced debtor firms when pricing the default risk of such firms (e.g. Lennox 1999, McDonald and Van de Gucht 1999, Duffie and Lando 2001, Shumway 2001, etc.).

Specifically, we examine the impacts of MFR information on default risk pricing from two perspectives. One perspective concerns the relative relevance of textual information within the MFR beyond numerical information (i.e. numerical earnings forecasts). The other perspective concerns whether and how CDS counterparties use the information in textual and numerical modes to verify the quality of disclosed information when pricing default risk.[4] We refer to this as the 'interactive and mutually verifying impacts' of these information modes. While the literature has extensively covered how numerical earnings information (forward-looking and historical) affects CDS default premiums (Callen et al. 2009, Lok and Richardson 2011, Schivakumar et al. 2011, Griffin et al. 2015), the impact of textual information is largely ignored. In a cursory reading of MFRs, textual information is generally more abundant compared to numerical information.[5] Nevertheless, the extent to which the textual information contained in an MFR can be informative and relevant remains unclear. Research on accounting disclosures generally demonstrates that textual attributes (e.g. textual readability and tone) convey relevant information (e.g. Li 2008, Feldman et al. 2010, Loughran and McDonnald 2011, Davis et al. 2012,

[2]CDSs are derivative insurance contracts designed to protect credit suppliers from borrowers' default risk. These instruments are commonly traded on the over-the-counter market among large institutions. A typical CDS contract requires the protection seller (e.g. insurance firms, dealers and hedge funds) to compensate the protection buyer (e.g. credit suppliers such as banks) when a credit event (e.g. bankruptcy, default, restructuring, credit rating downgrade or other pre-specified events affecting credit quality) occurs for a specific company. This is where the CDS contract is written (i.e. a reference entity). In return, the protection seller charges the buyer a fixed CDS premium, commonly known as the CDS spread. We interchangeably use the terms CDS premium and CDS spread. This spread is quoted in terms of basis points of the CDS contract's notional principal (e.g. Callen et al. 2009). The CDS market remains a large and viable market with market risk transfer activity (MRTA) on a four-quarter rolling average basis ranging between \$600 billion and \$700 billion per quarter (ISDA 2019).

[3]Kim et al. (2017) provide evidence that shareholders of CDS debtor firms demand and benefit from increased firm-level public disclosures from the referenced debtor firm because of the reduction in lender's monitoring. Although, it may be argued that CDS counterparties are more sophisticated than retail shareholders, they are no different from the shareholders in that they are all outsiders.

[4]The known information modes include numerical, textual, visual, and audio modes.

[5]Appendix B provides an example of a management earnings forecast report.

Baginski et al. 2016, Ertugrul et al. 2017, Chen et al. 2019). However, the literature provides limited evidence on how textual earnings information influences default risk pricing.

As a form of voluntary disclosure, MFR content is discretionary and unaudited and is not required to follow any generally accepted structure. Moreover, the forward-looking nature of MFRs shields issuing firms from legal liability (e.g. Private Securities Litigation Reform Act 1995, Hirst et al. 2008).[6] Existing studies suggest that although voluntary disclosures are susceptible to manipulation, outside investors in equilibrium penalise firms with lower disclosure quality through a higher default risk premium on the firm's debt (e.g. Verrecchia 1983, Duffie and Lando 2001, Yu 2005, Miller and Skinner 2015).[7] Hence, the logical inquiry revolves around how information users verify disclosure quality, especially for textual information, to determine the extent of distortion.[8] The body of literature addressing this question (e.g. Balakrishnan and Bartov 2010, Chen et al. 2015, Baginski et al. 2016, Chen et al. 2019) reports that interaction across textual and numerical modes can affect their content verification.[9] This reveals that further investigation is needed to ascertain how CDS counterparties verify the textual and numerical quality of an MFR when pricing default risk.

This study investigates whether and how CDS counterparties utilise the contemporaneous textual quality of an MFR to verify the credibility of both textual and numerical information content within the same report when pricing default risk. In doing so, we extend prior research conducted by Baginski et al. (2016) on the multimodal verification of voluntary disclosures. While Baginski et al. (2016) primarily focus on using numerical information quality to verify the credibility of textual information content within the equity market,[10] our study takes a different approach by exploring the intra- and intermodal verification functions of textual information quality in the context of pricing default risk.[11] Furthermore, adopting a multimodal information perspective underscores the significance of employing both inter- and intra-modal verification functions of earnings-relevant information to detect inconsistencies or complementarities across modes when assessing its credibility.[12]

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[6]See also the last paragraph of the sample MFR in Appendix B.

[7]Duffie and Lando (2001) develop an analytical model showing that a firm's default risk premium is negatively associated with the quality (or transparency) of its noisy generic information disclosures in a world with incomplete information. They write the following: 'One might extrapolate to practical settings and anticipate that, other things equal, secondary-market yield spreads are decreasing in the degree of transparency of a firm' (Duffie and Lando 2001, p. 649).

[8]A cursory comparison of the numerical (i.e., the numerical earnings prediction) and textual components (i.e. the self-structured narrative) in the sample MFR in Appendix B would reveal that the room available for manipulation is wider and more nuanced in the narrative than the numerical prediction.

[9]In particular, Baginski et al. (2016) examine the verifying function of numerical information quality and found that equity investors can use numerical information quality in MFRs to verify the credibility of textual information in these MFRs.

[10]The issue with using numerical earnings forecast as the only verifying mechanism of textual information is that the credibility of numerical information cannot be verified until the actual earnings is realised.

[11]'Intra-modal' refers to the interactions among different elements within the same mode of information; that is, how CDS investors use the textual information quality to verify the credibility of textual information content when pricing default risk. Meanwhile, 'Inter-modal' refers to interactions between different modes of information; that is, how CDS investors use the textual information quality to verify the credibility of numerical information content.

[12]The 'multi-modal information perspective' refers to a theory that analyses information from multiple modalities, such as numerical, textual, visual, and audio. This integration allows a more comprehensive understanding. Research in Artificial Intelligence (AI) in recent years has made rapid advances in the fusion of multi-modal information and its applications (e.g., Ramachandram & Taylor, 2017; Baltrusaitis et al., 2019). This line of research aims to use methodologies from natural language processing (NLP), machine leaning (ML) and deep leaning (DL) to process and fuse multi-modal information and thus

To conduct our investigation, we collect the actual texts of MFRs and construct empirical proxies for textual information. Following the literature (e.g. Asquith et al. 2005, Li 2010, Twedt and Rees 2012, Huang et al. 2014, Loughran and McDonnald 2014, Baginski et al. 2016, Chen et al. 2019), we use textual readability to proxy for the textual quality of an MFR. We also use textual news (measured by the change in textual opinion) and numerical news (measured by the change in numerical earnings forecasts) disclosed in an MFR as proxies for textual and numerical information content, respectively. We then conduct an event study on the CDS market reactions to MFR announcements using a sample of 3,055 reports issued by 386 firms and their corresponding CDS contracts with a 5-year maturity. Our empirical results reveal the following: First, we find that abnormal changes in CDS premiums around MFR issuance dates are inversely associated with (1) the textual quality and (2) the extent of positive textual information content. These results indicate that textual information quality and content significantly affect the pricing of default risk beyond numerical information. We also reveal that the impact of forward-looking textual information quality in MFR is greater than that of historical numerical information quality. It is also greater than the combined impacts of textual and numerical information content in the same MFR. In support of our hypotheses, these findings suggest that the quality and content of textual information in MFRs significantly affect default risk pricing.

Second, we find that the textual quality of MFR affects the negative association of CDS premiums with either the textual or numerical information content contained in such MFR. These findings support our hypotheses. In addition, we show that both textual and numerical information content have significant impacts on default risk pricing only in a subsample of higher-readability MFRs. These findings collectively suggest that the information relevance of both textual and numerical information elements in an MFR is contingent upon the textual quality of such MFR.

For robustness checks, we conduct additional cross-sectional analyses of the differential textual information impacts of MFRs on default risk pricing. We show that both textual quality and content have greater impacts on the default risk pricing of firms with lower credit ratings and good numerical news. These findings suggest that CDS counterparties, mindful of potentially manipulative forecasts, rely on textual information when debtor firms are associated with low creditworthiness or when they disclose good (numerical) news. We also find that both textual quality and content generate stronger default risk-pricing effects among firms with larger analyst followings. This finding suggests that analyst following can increase the production of textually informative MFRs or enhance the impact of such information.

This study has several contributions. First, our study extends the existing literature on management forecasts that predominantly examines the role of such information in the stock market and supply chain dynamics (Hutton et al. 2003, Ball and Shivakumar 2008, Ng et al. 2013, Chen et al. 2019). Schivakumar et al. (2011) examine the impact of management earnings forecasts on the credit market; however, they explore only the impact of numerical information on default risk pricing. Our study is the first to focus on the impact of textual information quality and content in MFRs on default risk pricing.

Second, our study is the first to use a multimodal information perspective to examine the verification of voluntary disclosures across textual and numerical information modes in the context of default risk pricing. While prior literature has highlighted the use of numerical information by

improve information accuracy. One major function of multi-modal information fusion is to enhance the consistency and complementarity of a specific type of information (e.g. earnings-related information) between information modes.

quality investors to verify the reliability of textual information in MFRs (Baginski et al. 2016), our research emphasises the significance of textual readability as an indicator of disclosure quality. We examine how CDS counterparties use textual readability to verify the quality of textual information content within the same mode and verify the quality of numerical information content across different modes. We extend the literature by identifying an additional mechanism through which incentive-driven information disclosures can be verified both intra-modally and inter-modally. Our findings are consistent with the notion that adopting a multimodal information perspective is crucial when investigating the price relevance of incentive-driven accounting information.[13]

The remainder of this paper is organised as follows. The hypothesis development is presented in Section 2. Section 3 explains the research methodologies, including the measurement of key research variables and model specifications. Section 4 reports and explains the findings. The final section presents the conclusion.

2. Hypothesis development

2.1. *Do CDS counterparties use firm-level public disclosures?*

Stulz (2010) highlights the notion that a CDS contract can easily be understood as an insurance contract for debt against the default risk of the underlying borrower (i.e. the referenced debtor firm). The CDS contract is between the insurance beneficiary (i.e. CDS lender) who owns the debt and the insurance provider (i.e. the CDS counterparty) who does not own the debt. In other words, default risk is transferred for a price from the CDS lender to the CDS counterparty. The latter can transfer the default risk further by selling the CDS contract to other prospective counterparties in an actively traded CDS market. Two implications emerge. First, the trading price of a CDS contract concerns the default risk premium purely because it is not affected by the contractual provisions of the underlying debt, such as covenants, coupons, and maturity (Blanco et al. 2005, Stulz 2010). Second, the ownership, contractual, and monitoring rights of the underlying debt remain with the CDS lender after the default risk is transferred to the CDS counterparty (Stulz 2010, Parlour and Winton 2013, Kim et al. 2017).

Once CDS lenders pay to transfer their default risk, they are unlikely to use their rights and access to monitor the referenced debtor firms actively (Subrahmanyam et al. 2014, Kim et al. 2017). However, the default risk remains. To assess default risk and determine how much CDS premium to charge, both actual and prospective CDS counterparties must use all available firm-level information on the referenced debtor firm. Unlike CDS lenders with contractual or relational links to referenced debtor firms, CDS counterparties lack direct access to private information and are unable to monitor debtor firms (Stulz 2010, Kim et al. 2017). Specifically, CDS counterparties are essentially outsiders and cannot directly observe the changing asset quality of a referenced debtor firm in practice. In this sense, CDS counterparties are not different from the shareholders of the referenced debtor firms (Kim et al. 2017). Consequently, they can benefit from firm-level public information when evaluating changes in default risk (e.g. Lennox 1999, McDonald and Van de Gucht 1999, Duffie and Lando 2001, Shumway 2001, etc.). Given that MFRs are a major form of forward-looking disclosure, they have potential information value for CDS counterparties when assessing the prospects of debtor firms (Beyer et al. 2010, Kim et al. 2017). Empirical evidence indicates that CDS

[13]We believe that the AI advances in the fusion of multi-modal information can be applied to understanding how accounting information is disclosed to great impact.

counterparties use MFR information in the numerical mode for default risk pricing (e.g. Schivakumar et al. 2011).[14]

2.2. *Does textual information affect default risk pricing?*

Existing analyses suggest that although voluntary disclosures are susceptible to strategic manipulation, outside investors in equilibrium penalise a firm with lower disclosure quality by charging a higher interest rate premium on the firm's debt (e.g. Verrecchia 1983, Duffie and Lando 2001, Miller and Skinner 2015). The implication is that the information content (both textual and numerical) in voluntary disclosures is likely to be distorted. However, the extent of the distortion is negatively related to disclosure quality. As the sample in Appendix B shows, textual information in the MFR sample is a significant, if not major, component of the overall information contained in the report. As such, textual information content is unlikely to be ignored by CDS counterparties.[15] Furthermore, when comparing the numerical component (i.e. numerical earnings prediction) with the textual component (i.e. narrative discussion), it becomes apparent that narrative discussion provides more extensive and nuanced room for strategic manipulation by firm insiders than numerical prediction. Therefore, we contend that the textual information quality of MFRs is a likely significant factor contributing to the overall information quality of these reports.

Our first hypothesis concerns the impact and relevance of the textual information quality (measured by textual readability) in a firm's forward-looking discretionary MFRs on the pricing of CDS premiums. Existing research (e.g. Bloomfield 2008, Li 2008, You and Zhang 2009, Loughran and McDonnald 2014, Chen et al. 2019) argues that straightforward and easy-to-read MFRs are textually more transparent and thus more informative than convoluted and difficult-to-understand MFRs. All other things being equal, convoluted reports can result from firm insiders intentionally manipulating information to mislead the public. Stated differently, textually opaque and convoluted disclosures arise from strategic manipulation to hide or obscure negative information and thus generally increase the default risk faced by outside investors in the debt market. Therefore, H1 predicts that CDS counterparties demand a higher CDS premium from reference debtor firms with lower textual information quality in their MFRs.

> Hypothesis H1: The change in credit default swap premium around an MFR issuance is lower for reference debtor firms with more readable MFRs, all other things being equal.

The second hypothesis concerns the impact and relevance of textual information content (measured by textual news) in a firm's MFRs on CDS premium pricing. Existing research (e.g. Asquith et al. 2005, Li 2010, Twedt and Rees 2012, Huang et al. 2014, Baginski et al. 2016) argues that, when considering quality, earnings forecast reports with more positive textual news indicate better earnings prospects for their underlying firms. As better earnings prospects suggest a lower risk of debt default, we predict in H2 that CDS counterparties demand a

[14]CDS counterparties most likely use all information available to them to assess the future default risk of their reference debtor firms. Our view is that as a major form of forward-looking firm-level information disclosure, the MFRs are likely be a relevant and significant source of information to CDS counterparties. This is along with other forms of available information, which needs to be controlled for in empirical analyses.

[15]CDS counterparties are insurance firms, funds, and other sizeable institutions. Unlike small investors, CDS counterparties have the resources, expertise, and scale-advantage to read the textual content of MFRs carefully.

lower CDS premium on reference debtor firms with more positive textual news in their MFRs, controlling for textual quality.

> Hypothesis H2: The change in credit default swap premium around an MFR issuance is lower for reference debtor firms with more positive textual news in their MFRs, other things being equal.

2.3. *Can textual quality be used to verify textual and numerical information content in MFRs?*

Given that textual and numerical content are different information modes, the manner in which information is transmitted through these two modes may not necessarily be parallel. The quality of a numerical earnings prediction can be verified contemporaneously by precision or at realisation by accuracy. However, verifying the quality of textual information content in forecasting disclosures is more difficult (e.g. Crawford and Sobel 1982, Benabou and Laroque 1992, Schrand and Walther 2000, Dye and Sridhar 2004, McVay 2006). Despite these difficulties, the literature documents that textual information content is incrementally relevant to outside shareholders (e.g. Li 2008, Kothari et al. 2009, Feldman et al. 2010, Loughran and McDonnald 2011, Davis et al. 2012, Huang et al. 2014, Baginski et al. 2016, Ertugrul et al. 2017). The documented evidence suggests that when investors are examining forecasting disclosures that inform investment decisions, there are possible unknown methods that they could also be using to evaluate the veracity of the textual content. Therefore, a gap exists in the literature.

To the best of our knowledge, Baginski et al. (2016) are the first to explore intermodal interactions between textual and numerical information in a sample of firms with MFRs. They propose that MFR reports contain two signals: numerical earnings predictions and textual news. Their hypothesis is as follows: as numerical earnings predictions can be verified ex post through actual earnings realisation, this information is considered credible and can be used to assess the quality and credibility of textual content. Their findings indicate that the effects of textual information in MFRs on stock prices are stronger in two scenarios. First, the numerical and textual information in an MFR is consistent in terms of content (e.g. higher-than-expected numerical prediction combined with more positive textual news). Second, numerical earnings forecasts demonstrate high contemporaneous quality (e.g. higher precision).

We argue that using the quality of numerical information as the only signal can be limiting and that other information modes are worth exploring. The quality of numerical forecasts is verified only by actual realised earnings, whereas investors often need to make decisions based on forecast information before actual earnings are realised. Thus, the verification function of numerical information can be enhanced through signals from other information modes. Given the proportion of the textual component in an MFR, such information is likely to be important in signalling the prospects of the referenced debtor firm. Thus, we conjecture that the textual information quality of MFRs can be used to contemporaneously verify the credibility of textual and numerical information contents within the same reports. All else being equal, more opaque and convoluted textual disclosures can signal that the disclosing firm has more to hide from, or mislead, outsiders. By contrast, more straightforward and easy-to-read disclosures can signal that the disclosing firm is generally more transparent in conveying firm-specific information to outsiders. In other words, the textual quality of MFRs indirectly reflects the overall information transparency of disclosing firms.

Accordingly, we hypothesise that CDS investors can directly use the contemporaneous textual information quality of MFRs to assess the credibility of textual and numerical information content within the same reports. Our third hypothesis is as follows:

Hypothesis H3a: The negative association between the change in credit default swap premium around MFR issuance and the extent of positive textual news of an MFR, if any, is weakened by less readable MFRs, all other things being equal.

Hypothesis H3b: The negative association between the change in credit default swap premium around MFR issuance and the extent of positive numerical news in an MFR, if any, is weakened by less readable MFRs, all other things being equal.

3. Research design

3.1. *Data description and sample construction*

3.1.1. *Collecting MFRs*

Given the lack of a readily available database of actual MFRs, we collect these reports by crawling through online textual financial information on Factiva. During processing, frequent changes in Factiva's website structure caused problems. We rely on three different sets of keywords, as suggested by Hutton et al. (2003), Baginski et al. (2004), and Chuk et al. (2013). We search the Wall Street Journal, PR Newswire, Dow Jones News Service, and Business Wire online through Factiva for possible MFRs disclosed for each listed firm in the period 1998–2011. We begin with 1998 as the coverage of management earnings forecasts in the CIG database (from which we locate the forecast release dates) before 1998 is limited (e.g. Chuk et al. 2013). Our sample period ends in 2011 as we encounter difficulties in updating the data beyond that year as Factiva enhanced its preventions against online crawling.[16] After deleting the duplicates, we obtain 199,707 unique MFR candidates. We then identify the actual MFRs from these candidates using the procedure described below.

First, an algorithm is developed to extract company identifiers (e.g. tickers and names) for each MFR candidate. Subsequently, this information is used to identify the company that released the MFR. We assume that all reports are with tickers. We focus only on MFRs from listed firms, deleting reports without tickers. Second, we match company identifiers, names, and ticker symbols to the corresponding *cusip* and *permno* numbers in the CRSP of 152,999 MFR candidates. Third, using *cusip* numbers, we locate the issuance dates of actual MFRs in the First Call's Company Issued Guidance (CIG) database. Candidates that fall within the three-day window of issuance dates are classified as actual MFRs.[17] The *permno* numbers are then used to collect the corresponding accounting information from Compustat.

The above procedures yield 62,093 actual MFRs issued by 4,359 firms. To avoid the confounding effect of earnings announcements, we exclusively analyse 'unbundled' MFRs (MFRs not issued along with earnings announcements). We exclude MFRs from firms that released earnings announcements within a 3-day window surrounding the MFR issuance date. This process yields 13,415 'unbundled' MFRs issued by 2,641 firms from 1998 to 2011. Panel A of Table 1 shows the step-by-step identification of the management earnings forecast reports.

[16]Difficulty in collecting actual MFRs is a common problem in this line of textual research and explains why relatively few textual studies exist on these reports. For example, the analysis of Baginski et al. (2016) is based on a sample of actual MFRs from 1997 to 2006. Davis et al. (2012) and Davis and Tama-Sweet (2012) both use the same earnings press reports from 1998 to 2003. Huang et al. (2014) use a sample of earnings press reports from 1997–2007. Although the impact of financial information quality on default risk pricing is not time specific, we are exploring other means to update our sample.

[17]We select 300 reports randomly and manually check whether they are actual MFRs. We find that all 300 reports are actual MFRs.

Table 1. Sample selection procedures.

Possible reports downloaded from Factiva using three sets of keywords	199,707 unique possible reports issued in the period from 1998 through 2011
After deleting candidates reports without ticker symbols;	152,999 candidates reports issued in the period from 1998 through 2011
Identifying MFRs;	4,359 firms in the period 1998–2011 issued 62,093 actual MFRs.
After deleting MFRs without the information needed to calculate quantitative information *(MF numerical news)* and qualitative information (readability and textual tone);	40813 MFRs issued by 3086 firms in the period from 1998 to 2011.
After deleting the MFR if the issuing firm makes any earnings announcement in the 3-day window surrounding the issuance date of that MFR.	13,415 ‘unbundled’ MFRs issued by 2,641 firms in the period from 1998 through 2011.
After merging the sample of ‘unbundled’ MFRs with CDS premiums of 5-year CDS contracts of senior unsecured debts which starts from year 2001;	3,569 ‘unbundled’ MFRs issued by 430 firms in the period from 2001 through 2011*.
After deleting the MFR if the Mergent FISD bond ratings file records any rating change or credit watch on the reference entity’s bond issues in the 3-day window surrounding the issuance date of that MFR;	3,283 ‘unbundled’ MFRs issued by 417 firms
After deleting the MFRs that miss necessary data to calculate control variables.	3,055 ‘unbundled’ MFRs issued by 386 firms from 2001 through 2011.

* CDS data is available from 2001.

3.1.2. *Sample construction*

As shown in Table 1, our initial sample contains 11,711 ‘unbundled’ MFRs issued by 2,172 firms. The CDS data are obtained from the Markit database, in which the composite CDS premiums are based on the daily closing bid-ask price from the official books of market makers and are recorded at the end of each trading day.[18] We match a Compustat *Gvkey* to each reference entity covered by the Markit CDS database according to multiple criteria such as company name, industry, and time. To maintain the homogeneity of CDS contracts and consistency with previous studies, our sample consists of only the most liquid and commonly used 5-year U.S. dollar-denominated CDS contracts of senior unsecured debts (e.g. Schivakumar et al. 2011). We use Compustat *Gvkey* to match the ‘unbundled’ MFRs with the CDS data. The matched sample consists of 3,569 ‘unbundled’ MFRs issued by 430 firms between 2001 and 2011.

In addition, we collect numerical management earnings forecasts from the CIG database, stock returns data from CRSP, financial data and the S&P senior debt rating from Compustat, analyst forecast data from I/B/E/S, S&P 500 implied volatility index data from the Chicago Board Options Exchange database, and treasury rates data from the Federal Reserve Board database. Furthermore, we drop an MFR if the Mergent FISD bond-rating file records any rating change or credit watch on the reference entity’s bond issues in the 3-day window surrounding the issuance date of the MFR. Data incompleteness among the control variables produces a final sample comprising 3,055 ‘unbundled’ MFRs issued by 386 firms from 2001 to 2011.

[18]As the CDS data are available from 2001, our final sample period is from 2001 to 2011.

3.2. *Key variables*

3.2.1. *Textual quality*

Following the current literature, we use textual readability as a proxy for textual information quality in MFRs (e.g. Li 2008, Loughran and McDonnald 2014, You and Zhang 2009, Chen et al. 2019). Textual readability measures the ease with which one can read a text (Smith and Smith 1971). The extent of readability or the lack of it can be indexed using a Natural Language Processing (NLP) algorithm that assesses textual characteristics such as the size of a text, number of words, length of sentences, proportion of complex words, and number of characters (e.g. Li 2010, Jegadeesh and Wu 2013, Loughran and McDonnald 2014, Bonsall and Miller 2017).

To the best of our knowledge, six different readability indices have been constructed: (i) the Gunning Fog Index (*FOG*), (ii) Flesch-Kincaid Index (*FK*), (iii) Flesch Reading East (*FRE*), (iv) SMOG Grading *(SMOG)*, (v) Coleman-Liau Index (*CLI*), and (vi) Automated Readability Index (*ARI*). These indices calculate the readability of a management forecast report based on the complexity of the words in a document. Complexity typically refers to (i) the number of letters in a word, (ii) the number of syllables in a word, or (iii) the number of words in a sentence.[19] As each index can be argued to capture a different dimension of readability, a consensus has not yet been reached on the most accurate measure of readability. Following Rogers et al. (2011) and using simple principal component factor analysis, we construct a single factor from the above six indices as our first readability measure, *READABILITY-COM.* We also employ the Gunning Fog Index (*FOG*) exclusively as the second measure of readability.

3.2.2. *Textual content (textual news)*

Consistent with prior research (e.g. Asquith et al. 2005, Li 2010, Twedt and Rees 2012, Huang et al. 2014, Baginski et al. 2016), we use textual news disclosed in an MFR report as a proxy for textual information content. Textual news is measured as the change in the textual opinion of each MFR. To measure textual opinion, we classify the words in each MFR into either positive or negative opinion categories and then aggregate both to obtain the overall textual opinion of the report. Different algorithms (or dictionaries) have been used to classify positive and negative words. General Inquirer (*GI*) and Diction Text-Analysis (*Diction*) algorithms are widely used to measure word opinions (e.g. Tetlock et al. 2008, Feldman et al. 2010, Davis et al. 2012). However, they are not designed for financial and business documents. Consequently, Loughran and McDonnald (2011) construct their own dictionary for measuring the textual opinions of financial documents (*LM*). We use the *LM* approach and follow the steps described below.

First, we employ the *LM* approach to categorise words as either positive or negative and calculate the percentage of each in every MFR. These percentages are multiplied by 100, resulting in the positive opinion variable (*POS*) and the negative opinion variable (*NEG*) for each MFR. Second, we take the difference between *POS* and *NEG* variables and arrive at a net positive textual opinion (*NET_POS*) for each MFR issued by debtor firms.[20] Third, we calculate the change in *NET_POS* as the proxy for textual news disclosed in an MFR. Specifically, following the previous approach (e.g. Feldman et al. 2010), we take the difference between the *NET_POS* of a particular MFR and the average *NET_POS* of all MFRs issued by firms in the same industry within the 400 days prior to such MFR's issuance. We then divide this difference by the standard deviation of the *NET_POS* of these MFRs. We denote the textual news in an MFR as the textual information content of the MFR (*MF textual news*).

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[19]A complex word is a word with three or more syllables.
[20]If *POS* is less than *NEG* in a report, the net positive opinion, *NET_POS*, is naturally negative.

3.2.3. *Numerical content (numerical news)*

In line with prior research (e.g. Schivakumar et al. 2011), we use the numerical news disclosed in an MFR as a proxy for its numerical information content. To extract this, we calculate the difference between the earnings forecast provided in the MFR and the most recent consensus analyst earnings forecast, scaled by the absolute value of the latter forecast. This is denoted as *MF numerical news*. Only point and range estimates are used to calculate the *MF numerical news*. If the management earnings forecast provided in the MFRs is a numerical range estimate, we follow Anilowski et al. (2007) and define it by calculating the average of the highest and lowest estimates within the forecast range.

3.3. *Model specification*

Following Schivakumar et al. (2011), we conduct an event study to investigate the short-window CDS premium change in response to the textual information quality (*Unreadability*) and textual information content (*MF textual news*) of management earnings forecast reports. Specifically, we test H1 by estimating the following equation:

$$\Delta\text{CDS premium} = \beta_0 + \beta_1 \mathit{UNReadability} + \beta_2 \mathit{MF\ textual\ news} + \beta_3\, \mathit{MF\ numerical\ news} + \sum_n \beta_n \mathit{Control}, \tag{1}$$

where the dependent variable (*ΔCDS premium*) is the CDS premium change over a 3-day announcement window (–1, +1) of an MFR, subtracted by the average CDS premium change of the matched set of CDS contracts, with the reference firms having the *same* credit rating but not having any MFR issued during the same window. *ΔCDS premium* is conveniently denoted as *abnormal change* in CDS premium. Following Lok and Richardson (2011) and Schivakumar et al. (2011), we calculate two forms of CDS premium changes as our dependent variables: the raw CDS premium change (*ΔCDS_SPREAD_raw*) and the percentage CDS premium change (*ΔCDS_SPREAD_pct*). The raw CDS premium change (*ΔCDS_SPREAD_raw*) is simply the CDS premium change over the 3-day event window. The percentage CDS premium change (*ΔCDS_SPREAD_pct*) is calculated as the raw changes in CDS premium over the 3-day event window divided by the CDS premium on the first day of the event window. The literature shows that the CDS market responds to rating agency announcements (Norden and Weber 2004, Galil and Soffer 2011). To control for confounding effects, we exclude MFR observations if any rating agency announcements are made during the event window. [21]

In Equation (1), two key variables of interest are used to test H1. The first is *UNReadability,* which denotes the *lack* of textual readability of an MFR and measures the textual information quality. The second variable is *MF textual news,* which denotes changes in textual opinions in the MFR and measures the textual information content. As explained in the previous section, we use *READABILITY-COM* and *FOG* as proxies for textual readability in MFRs. The greater the (un)readability measure, the lower the textual quality. H1 is supported if $\beta_1 > 0$ is observed. A positive and significant coefficient on *UNReadability* suggests that a less readable MFR is associated with a higher abnormal CDS premium over the 3-day announcement window (−1,1). H2 is supported if $\beta_2 < 0$ is observed. The negative and significant coefficient of *MF*

[21]We also verify if no other events occur during the event window, e.g. M&A, SEO, restatements, etc.

textual news suggests that CDS investors charge fewer CDS premiums for firms with more positive textual news conveyed in MFRs.

Following prior studies (e.g. Zhang et al. 2009, Schivakumar et al. 2011), our empirical model includes the following set of control variables: (i) the numerical information content of MFRs (*MF numerical news*); (ii) numerical information quality of MFRs (*Precision*); (iii) historical information quality captured by accruals quality (*AQ*); (iv) volatility of prior stock return (*σ[RET]*) over the estimating window [−137, −6] relative to the event day (the MFR announcement day); (v) residual of a cumulative 3-day market adjusted stock returns (*r_RET [−1, +1]*);[22] and (vi) volatility of prior daily CDS premiums (*σ[CDS premium]*) over the estimating window [−137, −6] relative to the event day (i.e. MFRs release day). We also control for a set of macro variables: (i) the proportional change of the S&P 500 implied volatility index (*ΔVIX [−1, +1]*) over the event window; (ii) 3-day cumulative return of S&P 500 index (*S&P_RET [−1, +1]*) and (iii) change in 3-month Treasury rate (*ΔTR3M [−1, +1]*) over the event window.

H3a and H3b test the verifying effect of textual readability on both textual and numerical information content in MFRs. H3a (H3b) is concerned with the role of textual readability in verifying the credibility of textual (numerical) news in MFR. To test H3a and H3b, we add two interaction variables to Equation (1), as follows:

$$\begin{aligned}\Delta CDS\ premium = \beta_0 &+ \beta_1 UNReadability + \beta_2 MF\ textual\ news \\ &+ \beta_3 UNReadability{*}\ MF\ textual\ news + \beta_4\ MF\ numerial\ news \\ &+ \beta_5 UNReadability{*}MF\ numerical\ news + \sum_n \beta_n Control \end{aligned} \quad (2)$$

The key variable of interest for testing H3a in Eq. (2) is the interaction variable *UNReadability *MF textual news.* H3a is supported if we observe $\beta_2 < 0$ and $\beta_3 > 0$, indicating that the effect of textual information content on CDS premiums is verified intra-modally by textual readability, weakened by the lack of textual quality in the MFR. The key variable of interest for testing H3b in Eq. (2) is the interaction variable *UNReadability *MF numerial news*. Hypothesis 3b is supported if we observe $\beta_4 < 0$ and $\beta_5 > 0$, indicating that the effect of numerical news on the CDS premium is verified by textual readability, weakened by the lack of textual quality. The controls used in Eq. (2) are the same as in Eq. (1).

4. Empirical results

4.1. *Descriptive analysis*

Table 2 presents the descriptive statistics of variables used in the study. Notably, the popular Fog index (*FOG*) indicates that readers (native speaker of English) need, on average, 17.54 years of formal education to understand an MFR at their first-time reading. The numerical earnings forecast contained in the MFRs (*MF numerical news*) deviates, on average, from the most recent consensus analyst earnings forecast by only 5%. We interpret this finding as follows: First, MFRs tend to be complex, hindering investors' understanding. Second, the room for incentive-driven manipulation is relatively limited in the numerical information mode of the MFRs. Third, most incentive-driven manipulation lies in the textual information of MFRs.

[22]We use the market adjusted stock return (*RET*) to control for *other* information simultaneously released with MFRs. To mitigate multi-collinearity concerns, we regress the cumulative 3-day market adjusted stock return (*RET*) on other control variables to get the stock return residual (*r_RET)* and use it in the regression models.

Table 2. Descriptive statistics.

variables	N	MEAN	SD	MIN	Q1	MEDIAN	Q3	MAX
ΔCDS_SPREAD_raw	3055	0.01	0.10	−0.34	−0.01	0.00	0.01	0.51
ΔCDS_SPREAD_pct	3055	0.01	0.07	−0.21	−0.02	0.00	0.02	0.32
FK	3055	13.01	3.76	6.88	10.44	12.04	14.91	26.18
FRE	3055	−50.83	17.06	−83.09	−62.78	−54.59	−40.24	−3.67
SMOG	3055	14.51	2.45	10.25	12.83	13.95	15.81	22.17
CLI	3055	12.52	2.60	7.68	10.66	11.94	14.44	20.14
ARI	3055	15.91	4.66	8.99	12.75	14.51	18.09	33.30
FOG	3055	17.54	3.70	11.86	14.98	16.60	19.26	30.08
READABILITY-COM	3055	0.00	0.97	−1.56	−0.68	−0.28	0.56	3.02
MF textual news	3055	−0.06	1.18	−3.48	−0.72	0.07	0.70	2.49
AQ	3055	−0.03	0.02	−0.10	−0.04	−0.03	−0.02	−0.01
r_RET	3055	0.00	0.06	−0.21	−0.03	0.00	0.03	0.19
MF numerical news	3055	−0.05	0.25	−1.00	−0.09	−0.01	0.02	0.96
Precision	3055	0.17	0.38	0	0	0	0	1
σ(RET)	3055	0.02	0.01	0.01	0.01	0.01	0.02	0.05
σ(CDS premium)	3055	0.18	0.31	0.00	0.03	0.08	0.20	2.00
S&P_RET	3055	0.00	0.02	−0.06	−0.01	0.00	0.01	0.05
ΔTR3M_raw	3055	−0.01	0.06	−0.26	−0.02	0.00	0.02	0.14
ΔTR3M_pct	3055	0.00	0.13	−0.62	−0.01	0.00	0.01	0.67
ΔVIX_raw	3055	−0.10	1.91	−5.92	−1.00	−0.17	0.69	7.16
ΔVIX_pct	3055	0.00	0.08	−0.17	−0.05	−0.01	0.04	0.25

This table reports the descriptive statistics of variables used. All variables are defined in Appendix A.

Table 3 presents the correlations among the variables used in the empirical models. The following is apparent. First, *ΔCDS_SPREAD_raw*, representing the abnormal raw change in CDS premium around the 3-day release window of an MFR, is correlated positively and significantly with our (lack of) readability measures: *READABILITY-COM* and *FOG*. This finding suggests that less readable MFRs (or MFRs with lower textual information quality) are associated with greater CDS premiums. Second, *ΔCDS_SPREAD_pct* and *ΔCDS_SPREAD_raw* are both correlated negatively and significantly with the extent of positive textual news (*MF textual news*), suggesting a negative association between the extent of positive textual news in an MFR and the change in CDS premium. Third, *ΔCDS_SPREAD_pct* and *ΔCDS_SPREAD_raw* are both correlated negatively and significantly with the numerical information within MFRs (*MF numerical news).* This is in line with Schivakumar et al. (2011), who find a significantly negative correlation between numerical information in an MFR and CDS premium. Fourth, *ΔCDS_SPREAD_pct* and *ΔCDS_SPREAD_raw* are both correlated negatively and significantly with the accruals quality (*AQ*), suggesting that higher historical accounting information quality in general is significantly associated with lower CDS premium. Fifth, *AQ* (historical accruals quality), *Precision* (numerical information quality), and *MF numerical news* (numerical information content of MFRs) are somewhat correlated with the MFRs' textual quality (*READABILITY-COM* and *FOG*) and textual information (*MF textual news*). However, the actual correlation coefficients are low (less than 14.2% in magnitude) and only some are significant. These findings suggest that: (i) forward-looking disclosures such as MFRs are distinct from historical disclosures such as annual reports, and (ii) textual information is distinct from numerical information in forward-looking disclosures.

Table 3. Pearson pairwise correlations among variables.

	ΔCDS_ SPREAD _raw	*ΔCDS _SPREAD _pct*	*FOG*	*READABILITY-COM*	*MF textual news*	*Precision*	*AQ*	*r_RET*
ΔCDS_SPREAD _pct	0.755***							
FOG	0.046**	0.073***						
READABILITY-COM	0.043**	0.065***	0.970***					
MF textual news	−0.079***	−0.074***	0.041**	0.062***				
Precision	−0.001	−0.003	−0.031*	−0.028	0.022			
AQ	−0.048***	−0.030*	−0.005	−0.009	0.086***	0.035**		
r_RET	−0.273***	−0.247***	−0.041**	−0.031*	0.194***	0.022	−0.014	
MF numerical news	−0.093***	−0.074***	−0.030*	−0.022	0.141***	0.045**	0.062***	0.137***
σ(RET)	0.046**	0.009*	0.038**	0.039**	−0.104***	−0.039**	−0.233***	0.034*
σ(CDS Spread)	−0.016	−0.027	0.078***	0.079***	−0.054***	0.017	−0.145***	0.070***
S&P_RET	0.036	0.012	−0.038**	−0.028	−0.022	−0.019	−0.010	−0.004
ΔTR3M_raw	−0.021	−0.008	−0.061***	−0.051***	−0.007	0.012	−0.018	0.010
ΔTR3M_pct	0.002	−0.005	−0.012	−0.008	0.009	−0.004	0.001	0.017
ΔVIX_raw	0.041**	−0.003	0.003	0.006	0.039**	0.002	−0.017	0.010
ΔVIX_pct	−0.023	0.004	0.004	0.004	0.02	0.001	−0.016	−0.023

Table 3. Pearson pairwise correlations among variables.

	MF numerical news	*σ(RET)*	*σ(CDS Spread)*	*S&P_RET*	*ΔTR3M _raw*	*ΔTR3M _pct*	*ΔVIX _raw*
ΔCDS_SPREAD _pct							
FOG							
READABILITY-COM							
MF textual news							
Precision							
AQ							
r_RET							
MF numerical news							
σ(RET)	−0.124***						
σ(CDS Spread)	−0.094***	0.627***					
S&P_RET	−0.049***	−0.034*	−0.024				
ΔTR3M_raw	−0.013	−0.055***	−0.056***	0.162***			
ΔTR3M_pct	−0.015	−0.014	0.010	0.170***	0.457***		
ΔVIX_raw	0.021	−0.007	−0.002	−0.605***	−0.158***	−0.072***	
ΔVIX_pct	0.013	0.013	0.017	−0.560***	−0.148***	−0.081***	0.924***

This table reports Pearson pairwise correlations among main regression variables. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively. All variables are defined in Appendix A.

4.2. *Multivariate results*

4.2.1. *H1 and H2 results*

Table 4 presents the results of the multivariate regressions in Equation (1). The dependent variable is the abnormal change in CDS premium in raw (*ΔCDS_SPREAD_raw [−1,1]*) in columns (1) and (2) and the dependent variable is the abnormal change in CDS premium in percentage (*ΔCDS_SPREAD_pct [−1,1]*) in columns (3) and (4). We find that (1) the coefficients of both readability measures are significantly positive at the 1% or 5% level and (2) the coefficients of *MF textual news* (with either readability measure) are significantly negative at the 1% or 5% level. Notably, the coefficients of *MF numerical news* are negative and significant at the 1% or 5% level and these results are consistent with those of Schivakumar et al. (2011). Although negative, the coefficient of *Precision* is not statistically significant. These findings indicate two associations. First, the abnormal change in CDS premium over the 3-day window (−1, +1) of an MFR issuance is associated positively with levels of unreadability (which inversely relates to the textual quality). Second, it is negatively associated with the extent of positive textual information content (*MF textual news*) in the issued MFRs. These results are significant beyond the impact of numerical information content (*MF numerical news*) and numerical information quality (*Precision*) in the MFR. These findings support H1 and H2. They suggest that (1) lower textual information quality in an MFR is associated with a higher CDS premium, and (2) higher level of positive textual information content in an MFR is associated with a lower CDS premium.

Regarding the rest of the control variables, the coefficients on *AQ* are all negative and significant (10%) when the dependent variable is measured by *ΔCDS_SPREAD_raw.* This suggests that a higher quality of historical accounting information is significantly associated with a larger decrease in the CDS premium. The coefficients of *r_RET* are negative at the 1% significance level for all specifications. Given that the cumulative market-adjusted stock return can serve as a proxy for residual information released concurrently within the event window of an MFR issuance, this finding implies the presence of additional information that is pertinent to CDS premiums and distinct from the MFR information. Therefore, it is crucial to control for this incremental information in the analysis.

The beta coefficients in Table 4 indicate two effects. First, the impact of textual quality on default risk pricing in the MFR is greater in magnitude than that of historical numerical information quality (measured by accrual quality). Second, the impact of the textual information in MFRs is not materially different from that of the numerical information content in the same reports. In support of H1 and H2, these findings suggest that the textual quality and content of MFRs significantly affect default risk pricing.

4.2.1. *H3 results*

Table 5 presents the results of multivariate regression in Equation (2). The dependent variable is the abnormal change in CDS premium in raw over the 3-day event window (*ΔCDS_SPREAD_raw [−1,1])* in Columns (1) and (2)*;* whereas the dependent variable is the abnormal change in CDS premium in percentage over the 3-day event window (*ΔCDS_SPREAD_pct [−1,1])* in Columns (3) and (4). The coefficients of textual quality (*UNReadability*), textual content (*MF textual news*), numerical quality (*Precision*), and numerical content (*MF numerical news*) remain unchanged, as did those in Table 4.

The coefficients of *UNReadability * MF textual news* are uniformly positive, with significance levels ranging from 10% to 5%. These findings indicate that the negative impact of positive textual news contained in MFR on its CDS premium is weakened by a relative lack of textual credibility (measured by *UNReadability*). In other words, the impact of textual information content within MFRs on abnormal changes in CDS premiums is conditioned or verified by

Table 4. The effects of textual quality of MFRs on abnormal changes in CDS premiums.

Dependent variable=	*CDS_SPREAD_raw[−1,1]*		*CDS_SPREAD_pct[−1,1]*	
	(1) *UNReadability = READABILITY-COM*	(2) *UNReadability = FOG*	(3) *UNReadability = READABILITY-COM*	(4) *UNReadability = FOG*
UNReadability	0.0048**	0.0011**	0.0050***	0.0014***
	(2.3982)	(2.0580)	(3.0938)	(3.2241)
MF textual news	−0.0050**	−0.0050**	−0.0036***	−0.0035***
	(−2.5324)	(−2.5578)	(−2.7323)	(−2.7113)
MF numerical news	−0.0260**	−0.0258**	−0.0177***	−0.0177***
	(−2.5286)	(−2.5070)	(−3.0114)	(−3.0141)
AQ	−0.1929*	−0.1682*	−0.1091	−0.1102
	(−1.7449)	(−1.8912)	(−1.3215)	(−1.3293)
Precision	−0.0020	−0.0021	−0.0012	−0.0013
	(−0.3821)	(−0.4014)	(−0.3035)	(−0.3182)
r_RET[−1,1]	−0.4274***	−0.4283***	−0.2651***	−0.2657***
	(−7.3146)	(−7.3103)	(−7.2415)	(−7.2699)
σ(RET)[−137,−6]	0.7634	0.5056	0.0558	0.0678
	(1.1772)	(0.7680)	(0.1706)	(0.2058)
σ(CDS Spread)[−137,−6]	−0.0276	−0.0251	−0.0149	−0.0141
	(−1.5513)	(−1.4039)	(−1.0676)	(−1.2463)
S&P_RET[−1,1]	0.2370	0.2399	−0.0068	−0.0021
	(1.3970)	(1.4083)	(−0.0646)	(−0.0201)
ΔTR3M [−1,1]	−0.0301	−0.0272	0.0046	0.0051
	(−0.5915)	(−0.5370)	(0.3362)	(0.3730)
ΔVIX [−1,1]	0.0042	0.0054	0.0044	0.0054
	(0.1326)	(0.1687)	(0.1892)	(0.2279)
Constant	−0.0128	−0.0252	−0.0079	−0.0136
	(−0.6738)	(−1.1022)	(−0.6737)	(−1.0057)
Year fix effects	yes	yes	yes	yes
Beta coefficients:				
UNReadability	0.0486	0.0430	0.0687	0.0720
MF textual news	−0.0614	−0.0613	−0.0600	−0.0595
MF numerical news	−0.0689	−0.0683	−0.0638	−0.0638
AQ	−0.0388	−0.0338	−0.0300	−0.0303
Precision	−0.0079	−0.0082	−0.0067	−0.0070
Observations	3,055	3,055	3,055	3,055
Adj.R2	0.0903	0.0908	0.0695	0.0700

This table reports the regression results on the effects of textual quality of MFRs on the abnormal changes in CDS premiums. In columns (1) and (2), the dependent variable is *ΔCDS_SPREAD_raw[−1,1],* defined as the raw CDS premium change around the announcement date of MFR over a 3-day window (−1,1) minus the average CDS premium change of a matched basket of CDS contracts with the same credit rating group but without MFRs during the same 3-day window. In columns (3) and (4), the dependent variable is *ΔCDS_SPREAD_pct[−1,1],* defined as the proportional CDS premium change around the announcement date of MFR over a 3-day window (−1, 1) minus the average proportional CDS premium change of a matched basket of CDS contracts with the same credit rating group but without MFRs during the same 3-day window. In columns (1) and (3), we use *READABILITY-COM* as the proxy for textual information quality (the level of unreadability), whilst in columns (2) and (4), we use *FOG.* The greater value of *READABILITY-COM and FOG* suggests higher level of unreadability, in other words, a lower textual information quality. We use *MF textual news* to proxy for textual information content. *MF numerical news* to proxy for numerical information content of MFR. *Precision* is the proxy for the quality of numerical information contained in MFRs. It is the indicator variable, equals to 1 if the management forecast is a point forecast, and 0, otherwise. All regressions include year fix effects. Standard errors are clustered by firm. All variables are defined in Appendix A. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

Table 5. The verification effect of textual quality of MFRs on the credibility of textual and numerical news conveyed in MFRs.

Dependent variable=	*CDS_SPREAD_raw[−1,1]*		*CDS_SPREAD_pct[−1,1]*	
	(1) *UNReadability = READABILITY-COM*	(2) *UNReadability = FOG*	(3) *UNReadability = READABILITY-COM*	(4) *UNReadability = FOG*
UNReadability	0.0056***	0.0015***	0.0056***	0.0016***
	(2.9259)	(2.9596)	(3.5112)	(4.4883)
MF textual news	−0.0050***	−0.0243**	−0.0038***	−0.0162***
	(−2.6126)	(−2.4458)	(−2.9151)	(−2.9324)
*UNReadability*MF textual news*	0.0040*	0.0011**	0.0022*	0.0007**
	(1.9088)	(2.0634)	(1.9382)	(2.3054)
MF numerical news	−0.0255**	−0.0390***	−0.0172**	−0.0180***
	(−2.0577)	(−2.9323)	(−2.3895)	(−2.8333)
UNReadability MF numerical news*	0.0018*	0.0056*	0.0020*	0.0062*
	(1.8322)	(1.9203)	(1.8207)	(1.9008)
AQ	−0.1941*	−0.2144*	−0.0905	−0.1091*
	(−1.7612)	(−1.9376)	(−1.0976)	(−1.6560)
Precision	−0.0021	−0.0020	−0.0015	−0.0016
	(−0.4060)	(−0.3975)	(−0.3637)	(−0.4762)
r_RET[−1,1]	−0.4175***	−0.4220***	−0.2612***	−0.2624***
	(−7.0177)	(−7.1666)	(−7.0696)	(−12.2971)
σ(RET)[−137,−6]	0.7767	0.5317	0.1453	0.1123
	(1.1905)	(0.8115)	(0.4600)	(0.4819)
σ(CDS Spread)[−137, −6]	−0.0264	−0.0253	−0.0142	−0.0142
	(−1.4741)	(−1.4154)	(−1.0828)	(−1.1318)
S&P_RET[−1,1]	0.2264	0.2240	−0.0053	−0.0020
	(1.3441)	(1.3232)	(−0.0506)	(−0.0263)
ΔTR3M [−1,1]	−0.0290	−0.0273	0.0038	0.0038
	(−0.5730)	(−0.5380)	(0.2726)	(0.3989)
ΔVIX [−1,1]	0.0028	0.0033	0.0044	0.0048
	(0.0886)	(0.1045)	(0.1886)	(0.2478)
Constant	−0.0131	−0.0369*	−0.0016	−0.0289***
	(−0.7004)	(−1.7123)	(−0.2493)	(−3.7359)
Year fix effects	yes	yes	yes	yes
Observations	3,055	3,055	3,055	3,055
Adj.R2	0.0890	0.0898	0.0691	0.0706

This table reports the regression results on the verification effect of textual quality of MFRs on the credibility of textual and numerical news conveyed in MFRs. In columns (1) and (2), the dependent variable is the raw CDS premium change–*ΔCDS_SPREAD_raw[−1,1]* whilst in columns (3) and (4), the dependent variable is the proportional CDS premium change–*ΔCDS_SPREAD_pct[−1,1]*. we add the (1) interaction term between the textual information quality and content, and (2) interaction term between the textual information quality and numerical information content to the model used in Table 4. In columns (1) and (3), we use *READABILITY-COM* as the proxy for textual information quality (the level of unreadability), whilst in columns (2) and (4), we use *FOG*. We use *MF textual news* to proxy for textual information content. *MF numerical news* to proxy for numerical information content of MFR. *Precision* is the proxy for the quality of numerical information contained in MFRs. All regressions include year fix effects. Standard errors are clustered by firm. All variables are defined in Appendix A. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

textual quality. Textual news conveyed in an MFR is positively associated with an abnormal change in the CDS premium, conditional on the textual quality. This strongly indicates that textual information quality can be used to contemporaneously verify the quality of textual content in MFR disclosures by reference debtor firms intra-modally (i.e. within the textual information mode), supporting H3a.

The coefficients of *UNReadability * MF numerical news* (with either readability measure) are uniformly positive at a significance level of 10%. These findings indicate that the relative lack of textual credibility weakens the negative impact of positive numerical news in an MFR on abnormal changes in CDS premium*s*. This evidence indicates that textual information quality can be used to contemporaneously verify the quality of numerical information in MFR disclosures by reference debtor firms inter-modally (i.e. between textual and numerical information modes), supporting H3b.

We conduct further subgroup tests on the interactive and mutual verification functions of MFR textual quality across the information modes. We divide the sample into five subgroups (quintiles) based on textual readability ranking. The Q1 group (bottom 20% based on *UNReadability*) represents the subgroup with the highest textual information quality (easiest to read). The Q5 group (top 20% based on *UNReadability*) represents the subgroup with the lowest textual information quality (the most difficult to read). We then re-estimate Eq. (1) after removing *UNReadability* from the Q1 and Q5 groups only.

Table 6 presents the results. The coefficients of *MF textual news* and *MF numerical news* are uniformly negative and significant at 5% or 1% in the Q1 subgroup. However, neither textual information nor numerical information produces any impact on CDS premiums in the Q5 group. We further test the differences in the coefficients of *MF textual news* and *MF numerical news* between the Q1 and Q5 subgroups (with the highest and lowest textual quality). The results, as shown in the $\chi 2$ statistics at the bottom of each column, indicate that the impact of textual and numerical information content within MFRs on the abnormal changes in CDS premium in Q1 group are significantly greater than those observed in the Q5 group. These findings indicate that the impacts of textual and numerical information contents in an MFR on default risk pricing are conditioned on, and verified by, the textual quality, further supporting H3a and H3b.

Collectively, the results in Tables 5 and 6 suggest that the textual quality of MFRs from reference debtor firms is used by CDS counterparties to contemporaneously intra-modally verify the quality of textual and numerical content. The inter-modal verification effect is bidirectional: while numerical information quality can be used to verify the quality of textual news (Baginski et al. 2016), textual information quality can also be used to verify the quality of numerical news.

4.3. *Additional tests*

We conduct additional cross-sectional analyses of the differential textual information impact of MFRs on default risk pricing. Collectively, these results suggest the robustness of our main findings.

4.3.1. *Credit rating*

The literature shows that the CDS market responds to rating agency announcements (Norden and Weber 2004, Galil and Soffer 2011). Following Schivakumar et al. (2011), we examine credit ratings' effects on the association between abnormal changes in CDS premiums and textual information in MFRs. To convert the rating letters into numerical codes, numbers 1 to 22 are assigned to a rating notch, starting with AAA assigned as 1. Accordingly, a higher rating suggests a lower credit rating and a higher credit risk. We create an indicator variable, *Lowrating,* which equals 1 if the rating number assigned is greater than the sample median and 0 otherwise. We then add *Lowrating* and two interaction variables*: UNReadability * Lowrating and MF textual news * Lowrating to* Equation (1).

Table 7 presents the results. The coefficients of the interaction variable *UNReadability * Lowrating* are positive and significant at 5% or 10% in 3 out of 4 cases (Columns 1–3). The

Table 6. Subsample tests on the verification function of the textual quality of MFRs.

Dependent variable=	*CDS_SPREAD_raw[−1,1]*		*CDS_SPREAD_pct[−1,1]*	
	(1) *UNReadability = READABILITY-COM*	(2) *UNReadability = FOG*	(3) *UNReadability = READABILITY-COM*	(4) *UNReadability = FOG*
High textual information quality (the bottom 20% of unreadability ranking)				
MF textual news	−0.0081**	−0.0075**	−0.0065**	−0.0090***
	(−2.1849)	(−2.2993)	(−2.3552)	(−3.5082)
MF numerical news	−0.0531***	−0.0544***	−0.0391***	−0.0260**
	(−3.1074)	(−3.3223)	(−3.0891)	(−1.9746)
Control Variables	yes	yes	yes	yes
Observations	612	612	612	612
Adj.R2	0.1065	0.1396	0.0709	0.0838
Low textual information quality (the top 20% of unreadability ranking)				
MF textual news	0.0038	0.0043	0.0023	0.0012
	(1.1217)	(1.2319)	(0.8529)	(0.4200)
MF numerical news	−0.0091	−0.0189	−0.0026	−0.0053
	(−0.6688)	(−1.3742)	(−0.2532)	(−0.5108)
Control Variables	yes	yes	yes	yes
Observations	610	610	610	610
Adj.R2	0.2530	0.2730	0.1256	0.1336
Subsample difference tests: High minus Low				
MF textual news	$\chi2 = 4.51$**	$\chi2 = 4.35$**	$\chi2 = 3.92$**	$\chi2 = 3.34$*
	($p = 0.0337$)	($p = 0.0370$)	($p = 0.0476$)	($p = 0.0675$)
MF numerical news	$\chi2 = 3.80$*	$\chi2 = 2.52$*	$\chi2 = 6.88$***	$\chi2 = 2.70$*
	($p = 0.0513$)	($p = 0.0812$)	($p = 0.0087$)	($p = 0.0923$)

This table reports results of the subsample tests on the verification function of the textual quality of MFRs. In column 1 and 3, we use *READABILITY-COM* as the proxy for textual information quality (the level of unreadability), whilst in columns (2) and (4), we use *FOG*. The whole sample are divided into 5 subgroups by ranking the two readability measures into quintile. Q1 group (bottom 20%) represents the subgroup with highest textual information quality, whilst Q5 group (top 20%) represents the subgroup with lowest textual information quality. We use *MF textual news* to proxy for textual information content. *MF numerical news* to proxy for numerical information content of MFR. *Precision* is the proxy for the quality of numerical information contained in MFRs. In columns (1) and (2), the dependent variable is the raw CDS premium change–*ΔCDS_SPREAD_raw[−1,1]* whilst in columns (3) and (4), the dependent variable is the proportional CDS premium change–*ΔCDS_SPREAD_pct[−1,1]*. All control variables in Table 4 are included in regressions. Standard errors are clustered by firm. All variables are defined in Appendix A. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

coefficients of the interaction variable *MF textual news* * *Lowrating* are also negative and significant at 5% or 10% in Columns 1, 2, and 4. These findings indicate that the impacts of both textual information quality and textual information content in MFRs on CDS premium are more pronounced with lower credit rating firms. In other words, textual information (quality and content) in MFRs becomes relatively more important for default risk pricing when the credit risk is higher.

4.3.2. *Analyst following*

Unlike numerical forecasts (numbers), textual information must be read. As specialist information intermediaries in capital markets, analysts possess incentives, expertise, and cost advantages in collecting and processing relevant information on the debtor firms they follow. Thus,

Table 7. The effects of credit rating of the disclosing firm on the relationship between the textual information contained in MFRs and abnormal changes in CDS premiums.

Dependent variable=	*CDS_SPREAD_raw[−1,1]*		*CDS_SPREAD_pct[−1,1]*	
	(1) *UNReadability = READABILITY-COM*	(2) *UNReadability = FOG*	(3) *UNReadability = READABILITY-COM*	(4) *UNReadability = FOG*
UNReadability	0.0058*	0.0017*	0.0048***	0.0015***
	(1.7772)	(1.8866)	(2.6815)	(3.2421)
MF textual news	−0.0067**	−0.0066**	−0.0040**	−0.0038*
	(−2.5392)	(−2.4913)	(−2.0203)	(−1.9209)
*UNReadability*Lowrating*	0.0011**	0.0013*	0.0009**	0.0002
	(2.1211)	(1.7251)	(2.0123)	(1.3236)
*MF textual news*Lowrating*	−0.0014*	−0.0014**	−0.0004	−0.0005*
	(−1.8211)	(−2.1298)	(−1.3327)	(−1.7885)
Lowrating	0.0201**	0.0238**	0.0049*	0.0051*
	(2.1801)	(2.0544)	(1.6608)	(1.7310)
Other controls	yes	yes	yes	yes
Observations	3,055	3,055	3,055	3,055
Adj.R2	0.0888	0.0897	0.0605	0.0621

This table reports the regression results on the effects of the credit rating of the disclosing firm on the relationship between the textual information contained in MFRs and abnormal changes in CDS premiums. rating is the proxy for the credit rating of disclosing firms. To transfer rating letters into numerical codes, numbers from 1 to 22 are assigned to each rating notch starting with AAA assigned as 1. Accordingly, a greater value of rating suggests a lower credit rating and higher credit risk. *Lowrating* is an indicator variable equal to 1 if rating is greater than the sample median, suggesting lower credit rating, zero otherwise, In columns (1) and (2), the dependent variable is the raw CDS premium change–*ΔCDS_SPREAD_raw[−1,1]* whilst in columns (3) and (4), the dependent variable is the proportional CDS premium change–*ΔCDS_SPREAD_pct[−1,1]*. In columns (1) and (3), we use *READABILITY-COM* as the proxy for textual information quality (the level of unreadability), whilst in columns (2) and (4), we use *FOG*. We use *MF textual news* to proxy for textual information content. *MF numerical news* to proxy for numerical information content of MFR. *Precision* is the proxy for the quality of numerical information contained in MFRs. All control variables in Table 4 are included in regressions. Standard errors are clustered by firm. All variables are defined in Appendix A. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

analysts are most likely to read and analyse MFRs.[23] Thus, we expect analyst following to amplify the impact of textual information in MFRs on CDS premiums for two reasons. First, referenced debtor firms with more analyst following (monitoring) produce more textually informative MFRs. Second, the information disclosures of referenced debtor firms with a larger analyst following are transmitted more effectively in the CDS market.

Table 8 presents the results on the effects of analyst following of the disclosing referenced firms. We create an indicator variable, *Dum_analyst,* which equals one if the number of debtor firms' analyst following is greater than the sample median and 0 otherwise. We then add *Dum_analyst* and two interaction variables*: UNReadability * Dum_analyst* and *MF textual news * Dum_analyst to Eq. (1).* The coefficients of the interaction variable *UNReadability * Dum_analyst* are positive and significant at 5% or 10% in all columns. The coefficients of the interaction variable *MF textual news * Dum_analyst* are also negative and significant at 5% or 10% in all columns. The findings indicate that analyst following can amplify the impact of textual information (both quality and content) in MFRs in the CDS market for default risk trading.

[23]CDS counterparties as sophisticated institutions are also likely to read the text of an MFR carefully for the same reason.

Table 8. The effects of analyst following on the relationship between textual information of MFRs and abnormal changes in CDS premiums.

Dependent variable=	*CDS_SPREAD_raw[−1,1]*		*CDS_SPREAD_pct[−1,1]*	
	(1) *UNReadability = READABILITY-COM*	(2) *UNReadability = FOG*	(3) *UNReadability = READABILITY-COM*	(4) *UNReadability = FOG*
UNReadability	0.0087**	0.0024**	0.0063**	0.0017**
	(2.3947)	(2.4905)	(2.2675)	(2.3140)
MF textual news	−0.0066**	−0.0063**	−0.0046**	−0.0046**
	(−2.3990)	(−2.3203)	(−2.2620)	(−2.2411)
*UNReadability*Dum_analyst*	0.0083*	0.0023*	0.0032*	0.0008**
	(1.8142)	(1.9281)	(`1.9127)	(2.0432)
*MF textual news*Dum_analyst*	−0.0009**	−0.0006**	−0.0009**	−0.0009*
	(−2.0121)	(−2.2341)	(−2.1205)	(−1.7671)
Dum_analyst	−0.0090**	−0.0071*	−0.0060*	−0.0090
	(−2.0193)	(−1.7207)	(−1.7561)	(−1.3343)
Other controls	yes	yes	yes	yes
Observations	3,055	3,055	3,055	3,055
Adj.R2	0.0941	0.0944	0.0688	0.0697

This table reports the regression results on the effects of analyst following on the relationship between textual information of MFRs and abnormal changes in CDS premiums. *Dum_analyst* is an indicator variable equal to one if the number of disclosing firm's analysts following is greater than the sample median, zero otherwise. In columns (1) and (2), the dependent variable is the raw CDS premium change–*ΔCDS_SPREAD_raw[−1,1]* whilst in columns (3) and (4), the dependent variable is the proportional CDS premium change–*ΔCDS_SPREAD_pct[−1,1]*. In columns (1) and (3), we use *READABILITY-COM* as the proxy for textual information quality (the level of unreadability), whilst in columns (2) and (4), we use *FOG*. We use *MF textual news* to proxy for textual information content. *MF numerical news* to proxy for numerical information content of MFR. *Precision* is the proxy for the quality of numerical information contained in MFRs. All control variables in Table 4 are included in regressions. Standard errors are clustered by firm. All variables are defined in Appendix A. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

4.3.3. *Good numerical earnings forecast news*

One incentive-driven effect of voluntary disclosures is that firm insiders report good numerical (earnings) news and withhold or delay reporting bad numerical news. Bad news is viewed as credible and good news less so (Kothari et al. 2009). In other words, when CDS counterparties see lower-than-expected numerical earnings predictions (bad numerical news), they are likely to find them more believable. However, if they see a higher-than-expected numerical earnings prediction (good numerical news) in an MFR, they turn to the information in the textual mode for further crosschecking. Given the asymmetric effects of good and bad numerical earnings forecasts, we expect the effect of textual information in MFRs on default risk pricing to be stronger for firms with good numerical news. To study this effect, we create an indicator variable, *Good numerical news*, which equals 1 if *MF numerical news* is good (i.e. higher than the most recent consensus analyst forecast) and 0 otherwise. We then add *Good numerical news* and two interaction variables: *UNReadability* * *Good numerical news* and *MF textual news* * *Good numerical news to Eq. (1).*

Table 9 presents the results. The coefficients of the interaction variables *UNReadability* * *Good numerical news* are positive and significant at 5% or 10% in Columns 1, 3, and 4. The coefficients of the interaction variables *MF textual news* * *Good numerical news* are negative and significant at 10% or 5% in all cases. The findings indicate that the impacts of textual information (quality and content) conveyed in MFRs are stronger when the numerical information is good news.

Table 9. The differential effects of textual information contained in MFRs on abnormal changes in CDS premiums based on the sign of numerical information of an MFR.

Dependent variable=	*CDS_SPREAD_raw[−1,1]*		*CDS_SPREAD_pct[−1,1]*	
	(1) UNReadability = READABILITY-COM	(2) UNReadability = FOG	(1) UNReadability = READABILITY-COM	(2) UNReadability = FOG
UNReadability	0.0047*	0.0013*	0.0043**	0.0012***
	−1.8481	(1.9312)	(2.3452)	(2.6266)
MF textual news	−0.0057**	−0.0057**	−0.0045***	−0.0044***
	(−2.3849)	(−2.3528)	(−3.0058)	(−2.9736)
*UNReadability*Goodnews*	0.0011**	0.0011	0.0026**	0.0023*
	(2.2976)	(1.3086)	(2.1080)	(1.8532)
*MF textual news*Goodnews*	−0.0017**	−0.0017*	−0.0025*	−0.0025*
	(−2.4307)	(−1.8320)	(−1.8831)	(−1.7903)
Goodnews	−0.0092**	−0.0093**	−0.0057**	−0.0058**
	(−2.4273)	(−2.4533)	(−2.1677)	(−2.2056)
Other controls	yes	yes	yes	yes
Observations	3,055	3,055	3,055	3,055
Adj.R2	0.0866	0.0869	0.0690	0.0694

This table reports the regression results on the differential effects of textual information contained in MFRs on abnormal changes in CDS premiums based on the sign of numerical earnings forecast of a MFR. *MF numerical news* is the proxy for the numerical information of MFRs, calculated as management earnings forecast minus the most recent consensus analyst earnings forecast divided by the absolute value of the most recent consensus analyst earnings forecast. *Goodnews* is an indicator variable equal to 1 if *MF numerical news* is greater than 0, suggesting positive numerical information (good news) contained in MFRs, zero otherwise, In columns (1) and (2), the dependent variable is the raw CDS premium change–*ΔCDS_SPREAD_raw[−1,1]* whilst in columns (3) and (4), the dependent variable is the proportional CDS premium change–*ΔCDS_SPREAD_pct[−1,1]*. In columns (1) and (3), we use *READABILITY-COM* as the proxy for textual information quality (the level of unreadability), whilst in columns (2) and (4), we use *FOG*. We use *MF textual news* to proxy for textual information content. *MF numerical news* to proxy for numerical information content of MFR. *Precision* is the proxy for the quality of numerical information contained in MFRs. All control variables in Table 4 are included in regressions. Standard errors are clustered by firm. All variables are defined in Appendix A. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

4.3.4. *Firm complexity*

The readability of MFRs can be affected by insider manipulation as well as firm complexity because the MFRs of firms with more complex characteristics may be less readable. To ensure further that insider manipulation, rather than fundamental complexity, is a significant factor in explaining our baseline results, we conduct an additional analysis using the two-step procedure explained below. We first regress the MFR readability proxies against the determinants of readability suggested by Li (2008) and calculate the residual readability proxies (*Res-Readability-COM* and *Res-FOG*). We then use these residuals as alternative (purged) readability measures and re-estimate the baseline model (Tables 4 and 5). The results (not tabulated) indicate that the effects of the residual measures are qualitatively the same as those shown in Tables 4 and 5. This finding suggests that insider manipulation of textual disclosure quality is a significant factor that affects a debtor firm's default risk premium.

5. Conclusion

The information in voluntary management forecast reports is highly relevant to market participants, but little is known about how this information is verified (e.g. Beyer et al. 2010). In this study, we examined the impact of textual information, specifically, the interactive and mutually verifying impacts of textual and numerical information in MFRs on CDS premiums. We find that a referenced debtor firm's default risk premium is inversely associated with the textual quality (measured by readability) and with the extent of positive textual content (measured by changes in textual opinion) of the MFRs. These findings suggest that CDS counterparties use textual (along with numerical) information in a referenced debtor firm's MFR to price its default risk. We also find that the impacts of both textual and numerical information content in a referenced debtor firm's MFR are conditioned by the MFR textual quality.

This study's findings elucidate how market participants or practitioners (CDS investors, in our case) use and verify the information in voluntary management forecast reports. The main insight is that CDS investors adopt a multimodal informational approach to verify voluntary disclosures. They use contemporaneous textual readability to intra-modally verify the quality of textual disclosures and inter-modally verify the quality of numerical disclosures. Second, MFR information in both the textual mode and the (more traditional) numerical mode can be relevant. Third, capital markets, in general, and the CDS market, in particular, are reasonably robust in processing disclosed forward-looking information. Regulators can help to foster transparency by ensuring that disclosure requirements are robust and encouraging firms to improve the quality and clarity of their disclosures. More generally, our findings are consistent with the argument that multimodal verification of information disclosure can enhance the overall quality of incentive-driven disclosures, such as MFRs.

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Appendices

Appendix A: Variables definition

Dependent Variable-abnormal change in CDS premium	
ΔCDS_SPREAD_raw	Abnormal raw CDS premium change, defined as the raw CDS premium change around the release date of management earnings forecast report (MFR) over a 3-day window (−1,1), subtracted by the average raw CDS premium change of a matched set of CDS contracts of the referenced firms having the same credit rate but not issuing any MFR during the same event window;
ΔCDS_SPREAD_pct	Abnormal proportional CDS premium change, defined as the CDS premium percentage change around the announcement date of MFRs over a 3-day window (−1,1), subtracted by the average CDS premium percentage change of a matched set of CDS contracts of the referenced firms having the same credit rate but not issuing any MFR during the same event window. The percentage measure is computed as the raw CDS premium change (or that of a matched set) over 3-day event window, divided by the CDS premium of the firm (or that of its matched set) on the first day of the window minus 1;
Testing variables:	
Textual quality measures:	
FOG	The fog index of MFRs = (average no. of words per sentence + percent of complex words) * 0.4, where complex words = words of 3 or more syllables;
FK	The flesch-kincaid index of MFRs = (11.8 * syllables per word) + (0.39 * words per sentence)−15.59;
FRE	The flesch reading ease index of MFRs = −1 * (206.8 – (1.015 * words per sentence) – (84.6 * syllables per word));
SMOG	The SMOG of MFRs = $1.0430 * \sqrt{\text{No.of polysyllables} * \frac{30}{\text{No.of sentences}}} + 3.1291$, where polysyllables are the words of 3 or more syllables;
CLI	The coleman–Liau index of MFRs = 0.0588L – 0.296S – 15.8, where L = the average number of letters per 100 words, S = average number of sentences per 100 words;
ARI	The automated Readability Index of MFRs = 4.71 * (characters / words) + 0.5 * (words / sentences) – 21.43, where characters = the number of letters, numbers, and punctuation marks, words = the number of spaces, and sentences = the number of sentences;
READABILITY-COM	The aggregate readability measure = principal component factor from the six indexes–*FOG, FK, FRE, SMOG, CLI, ARI*. The greater is the readability measure, the lower is the readability, the higher is the unreadability;
Textual content measures:	
POS	The fraction of positive words divided by all words in a MFR based on the word list of Loughran and McDonnald (2011) (updated in 2013) then multiplied by 100;
NEG	The fraction negative words divided by all words in a MFR based on the word list of Loughran and McDonnald (2011) (updated in 2013) multiplied by 100;
NET_POS	The (net) positive textual opinion of an MFR, defined as the difference between *POS* and *NEG* in an MFR, *NET_POS* = *POS* – *NEG*;

(*Continued*)

Continued.

Dependent Variable-abnormal change in CDS premium	
MF textual news	The proxy for the *new* textual content in a MFR, defined as the change in textual opinion (i.e. new textual information) between the *NET_POS* of a MFR and the mean of *NET_POS* of all MFRs issued by firms in the same industry in the 400 days before, divided by the standard deviation of *NET_POS* of these MFRs;
Numerical content measures:	
MF numerical news	The proxy for the *new* numerical content in a MFR, measured by taking the difference between numerical management earnings forecast and the most recent consensus analyst forecast, scaled by the absolute value of the latter forecasts (i.e. new numerical information). Only point and range estimates are used in the calculation of *MF numerical news*. For range estimates, the management earnings forecasts are calculated as the average of high and low estimates in the same way of Anilowski et al. (2007);
Control variables:	
Precision	Poxy for the numerical information quality in MFRs. It is an indicator variable, equal to 1 if the numerical management forecast is a point forecast, and 0, otherwise;
AQ	Accruals quality, defined as the standard deviations of the firm-level residuals from the Dechow and Dichev (2002) model, modified by McNichols (2002) and Francis et al. (2005) in the period from year t-5 to t-1. AQ is multiplied by negative one, with a higher *AQ* indicating higher accruals quality;
RET	The cumulative market adjusted stock return over a 3-day announcement window of MFRs ([−1, 1]);
r_RET	The stock return residual, calculated by regressing *RET* on other explanatory variables, and use the residual of this regression instead of *RET*;
σ(RET)	The standard deviation of the firm's market adjusted stock return using the estimating window [−137, – 6] with respect to the MFR release day (day 0);
σ(CDS premium)	The standard deviation of CDS premium using the estimating window [−137, – 6] with respect to the MFR release day (day 0);
S&P_RET	The cumulative S&*P* 500 index returns over a 3-day window around the announcement date of MFR ([−1, 1]);
ΔTR3M_raw	The raw change in three-month treasury rate over a 3-day window around the announcement date of MFR ([−1, 1]);
ΔTR3M_pct	The proportional change in three-month treasury rate over a 3-day window around the announcement date of MFR ([−1, 1]);
ΔVIX_raw	The raw change in S&*P* 500 implied volatility index over a 3-day announcement window (−1,1) of MFR;
ΔVIX_pct	The percentage change in S&*P* 500 implied volatility index over a 3-day announcement window (−1,1) of MFR.

Appendix B: an example of management earnings report

Bellowing is an example of management earnings report we downloaded from Factiva. This report is an annual earnings forecast for 2002, issued by Cummins Inc. on Nov.29th, 2001. Cummins Inc. is one of the identified customers of Pentacon Inc.

Cummins Announces 2002 Outlook; Improvement in Profitability Despite Flat Sales

PD: 29 November 2001 ET: 21:05 SN: Business Wire

COLUMBUS, Ind.–(BUSINESS WIRE)–Nov. 29, 2001–Cummins Inc. (NYSE:CUM) today released its expectation for improved profitability despite essentially flat revenues for 2002. Cummins Chairman and CEO, Tim Solso, said, 'Continuing efforts to reduce costs will enable Cummins to achieve a profitability improvement over 2001 with little to no improvement in revenue.'

During the October 11th teleconference on third quarter earnings Solso noted that rapid market changes in the U.S. and around the world following the September 11th terrorist attacks caused Cummins to revisit its 2002 planning process. Solso stated that, 'a public outlook on 2002 would be delayed until the end of November when market visibility and economic direction may be clearer.'

Based on recently completed plans, the company is forecasting a 2002 PBIT in the range of $155 to $165 million, with net earnings of $35 to $45 million, resulting in diluted earnings per share of approximately $1 per share. Solso stated, 'The completion of our restructuring actions' combined with indirect and direct material cost initiatives and Six Sigma improvement projects will result in a net savings of $75 million.'

'Despite depressed market conditions around the world; Cummins expects to be modestly profitable in the fourth quarter of 2001. We expect to deliver a profit in three out of four quarters during terrible market conditions,' said Solso. 'Cummins will continue to do what it takes to cut costs, improve performance and maintain profitability.'

Power Generation

Power Generation revenues are expected to grow 5 to 10 percent despite weak markets. The growth will come in distributed generation and in selling energy solutions and maintaining a strong market position in standby power applications. Power Generation sales across the world are expected to be level with or slightly above 2001 levels, except India. Sales to consumer markets continue to be weak attributed to declining consumer confidence.

Engine Business

Engine Business revenues for 2002 are anticipated to be near 2001 levels. The North American heavy-duty truck market build is expected to be in the 150,000 unit range. Chrysler volumes for the full year will be similar to 2001, with lower shipments in the first half of 2002, given the mid-year model changeover.

Filtration and Other

Sales in the filtration business are expected to be approximately level with 2001. Given gains in small engine sales for consumer markets a slight increase is expected in North America. A projected drop in sales to European OEM's is expected to be partially offset by sales growth in Latin America and Asia Sales of our international distributors are expected to be up slightly from 2001 attributed to growth in East Asia and Latin America.

First Quarter 2002 Outlook

The company is anticipating revenues for the first quarter of 2002 to be level with the Q1 2001 levels. However, cost reduction efforts will improve PBIT by approximately $25 million over Q1 2001 to a range of $15 to $20 million, resulting in a loss of approximately $.20 per share. The remainder of the year is expected to be profitable.

Cummins, headquartered in Columbus, Ind., is the world's largest producer of commercial diesel engines above 50 horsepower. The company provides products and services for customers in markets worldwide for engines, power generation, and filtration. In 2000, Cummins reported sales of $6.6 billion. Press releases by fax may be requested by calling News on Demand at 888-329-2305. Cummins' home page on the Internet may be found at www.cummins.com.

Information provided and statements made in this release that are not purely historical are forward-looking statements within the meaning of the Private Securities Litigation Reform Act of 1995, including statements regarding the company's expectations, hopes, beliefs and intentions on strategies regarding the future. It is important to note that the company's actual future results could differ materially from those projected in such forward-looking statements because of a number of factors, including but not limited to general economic, business and financing conditions, labour relations, governmental action, competitor pricing activity, expense volatility, and other risks detailed from time to time in Cummins Securities and Exchange Commission filings.

CONTACT: Cummins Inc. Tracy Souza, 812/377-3746 08:05 EST NOVEMBER 29, 2001

AN: bwr0000020011129dxbt0073y