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Content analysis of XBRL filings as an efficient supplement of bankruptcy prediction? Empirical evidence based on US GAAP annual reports

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Klaus Henselmann / Elisabeth Scherr

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Abstract: Most of the bankruptcy prediction models developed so far have in common that they are based on quantitative data or more precisely financial ratios. However, useful information can be lost when disregarding soft information. In this work, we develop an automated content analysis technique to assess the bankruptcy risk of companies using XBRL tags. We develop a list of potential red flags based on the U.S. GAAP taxonomy and assign the elements to 2 categories and 7 subcategories. Then we test our red flag item list based on U.S. GAAP annual reports of 26 companies with Chapter 11 bankruptcy filings and a control group. The empirical results show that in total, the red flag item list has predictive power of bankruptcy risk. Logistic regression results also show that the predictive power increases the nearer the bankruptcy filing date approaches. We furthermore observe that the category 2 red flags (bankruptcy characteristics and influencing factors) have higher discriminatory power than category 1 red flags (earnings management indicators) for one year before the bankruptcy filing date. This difference narrows for two years before the bankruptcy filing date and may turn in favor of category 1 red flags for three years before the bankruptcy filing date.

Titel: Inhaltsanalyse von XBRL Veröffentlichungen als effiziente Ergänzung von Insolvenzprognosen? Empirische Evidenz basierend auf U.S. GAAP Jahresabschlüssen

Schlagwörter: Inhaltsanalyse, Red Flags, XBRL, Insolvenzprognose, Risikobewertung, Bilanzpolitik

JEL Classification: M41, C12, C81

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1 Introduction

Most of the bankruptcy prediction models developed so far have in common that they are based on quantitative data or more precisely financial ratios. Hard information has the advantage that it can easily and objectively be collected. Beaver (1966) applied a univariate discriminant analysis method (UDA) and compared individual ratios for the accuracy of predictability. The Z-Score developed by Altman (1968) is a multivariate discriminant analysis method (MDA) using five accounting ratios. Later developed methodologies are the logit and probit analysis for example Ohlson (1980), who employs a logistic regression model with nine independent variables. The newest development within this field of research is to apply artificial neural networks (NN). Together with MDA they are the most effective bankruptcy prediction methods up to date (Bellovary et al., 2007, p. 10). Other suggested bankruptcy prediction models include the recursive partitioning analysis (e.g., McKee and Greenstein, 2000) and a cash flow simulation model (e.g., Ceccarelli, 2003). Bellovary et al. (2007) provide an overview of bankruptcy prediction studies from 1930 to the present.

However, useful information can be lost when disregarding soft information. Studies in the area of credit risk management show that qualitative information (e.g., credit analyst's judgment of a firm's market position based on the experience gathered from the bank-customer relationship) leads to a more precise assessment of default risk (e.g., Lehmann, 2003; Godbillon-Camus and Godlewski, 2005). Nevertheless Lehmann (2003) is in doubt that the costs of collecting qualitative data exceed the advantages.

With new technologies like the eXtensible Business Reporting Language (XBRL) this may change. XBRL is an internationally acknowledged standard that has been developed for the automatic electronic exchange of business data. In particular, XBRL makes it possible to analyze quantitative and qualitative data of financial statements automatically by using mark-ups (tags) that are associated with specific information items. On January 30, 2009, the Securities and Exchange Commission (SEC) released a rule mandating all SEC filers to file interactive data (or XBRL data) with the EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system over a three year phase-in (SEC, 2009). Therefore, a mass of XBRL filings will be available soon.

In this work, we develop an automated content analysis technique to assess the bankruptcy risk of companies using XBRL tags. The extensive and complex information of annual reports is reduced to the most important red flags for predicting a threatening bankruptcy. We per-

form an empirical investigation of a group of companies that filed for Chapter 11 in the past versus a healthy group of companies to test for the discriminatory power of the proposed method.

This paper proceeds as follows. The next section categorizes our proposed method into the context of content analysis. An initial red flag item list is theoretically derived in the third section. In the fourth section we present an empirical investigation on the discriminatory power of the derived red flag item list. The study concludes with a short summary, explains limitations and gives an outlook to further research opportunities.

2 Content analysis in the area of accounting

Content analysis is a common social science research technique, in which the research object is texts that are analyzed in a special context. It can be defined as “*a research technique for making replicable and valid inferences from texts (...) to the contexts of their use*” (Krippendorff, 2004, p. 18). More precisely, content analysis is a subclass of quantitative textual analysis, albeit being the most common form. In this sense, content analysis “*breaks down the components of a text into units that you can then count.*” (McKee, 2003, p. 127).¹

The main aim of research of studies on content analysis in the area of accounting is to measure the tone of the text by counting for the frequency of occurrence of positive versus negative words. In doing so, Loughran and McDonald (2009) show that subject-specific word lists are more effective in predicting future business outcomes (see also Henry and Leone, 2009). Among others, context-specific word lists avoid problems with polysemy. For example, the term “division” has a negative meaning in the universal General Inquirer (GI) word list, but it is commonly used in financial statements to describe a segment of a firm (Henry and Leone, 2009). Studies that provide and apply word lists for accounting are for example Loughran and McDonald (2009; contains a specific word list for annual reports in the English language) and Henselmann et al. (2010; contains a specific word list for annual reports in the German language).

Instead of positive versus negative words, Humpherys (2009) counts words that represent hedging devices (e.g., profits “will” occur next year versus profits “might” occur next year) in order to detect the degree of fuzziness in the examined text. A logistic regression reveals a correct classification in 69.3% of all cases. And instead of using common dictionaries or self-defined word lists, Purda and Skillicorn (2011) use the Random Forest algorithm, which al-

lows them to conduct the analysis without an ex-ante identification of words. This approach leads them to an overall classification rate of approximately 87% of all cases (Purda and Skillicorn, 2011, p. 32).

Content analysis seems to be important, as it can reduce the complexity of very long documents like annual reports to a minimum. Purda and Skillicorn (2011) compare the correct classification rates of fraudulent reports when qualitative information is used in the traditional approach for fraud detection suggested by Dechow et al. (2011). The results let them conclude that the analysis of qualitative information is a meaningful supplement to traditional quantitative approaches. Besides, Tetlock et al. (2007) show that stock prices include qualitative information that represents otherwise hard to measure aspects of firm's fundamentals, albeit investors apparently underreact to negative information. Therefore, Tetlock et al. (2007) state that "*models in which equilibrium prices induce traders to acquire costly information - e.g., Grossman and Stiglitz (1980) - are broadly consistent with our results*" (Tetlock et al., 2007, p. 33).

This leads us to the first limitation of content analysis: qualitative information is not always easy to capture and often requires higher capital input or costs. Engelberg (2008) empirically examines the role of information processing costs on post earnings announcement drifts and finds that soft information predicts larger changes in future returns. She concludes that the observed underreaction may be due to the fact that qualitative information is more difficult to process than quantitative information. This also may be the reason, why Lehmann (2003) doubts the cost-benefit aspect of additional qualitative information. Other limitations of content analysis are an unavoidable researcher bias (due to which the so called intercoder reliability correlation rate should be as high as possible, see p. 23) and that the assumption that the frequency of occurrence of certain words directly reflects the emphasis that the text assigns to them may not always prove to be true (Smith, 2011, p. 150). Other limitations with automatic content analysis on the basis of word frequency lists are that the search for certain words can lead to distortions due the fact that (1) the searched word is part of another word (e.g., "material" can mean material, but it is also part of the word "materials" and "immaterial") and (2) word combinations may not be encountered (e.g., the search for "reduction" with a positive meaning could also count for the word "reduction of earnings" with a negatively attached meaning).

Some of these limitations can be overcome with another textual analysis method that we include among the content analysis techniques: the *red flag analysis*. Racanelli (2009) introduc-

es several red flag phrases in SEC filings signaling trouble or potentially even fraudulent accounting behavior (e.g., “unbilled receivables”, “change in revenue recognition” or “selling receivables with recourse”). Loughran and McDonald (2011) examine 13 different red flag phrases, especially those suggested by Racanelli (2009), and find that they are significantly related to excess filing period returns, analyst earnings forecast dispersion, subsequent return volatility, and fraud allegations. Therefore, what distinguishes analyses based on red flag item lists from those based on word frequency lists in the first place is that the aim is to examine whether and how many warning signs are spread over the text instead of examining the tone of the text. Therefore, red flags are counted as dummy variables, which means that for each document the dummy variable will be set to one in the case where the red flag phrase occurs in the document and it counts as zero, in the case where it does not occur in the document (see also Loughran and McDonald, 2011, p. 7).

Albeit in our study the focus lies on qualitative red flags, it has to be noted that the term red flags can be very broad. Thus, red flags may be qualitative as well as quantitative warning signs (Grove and Cook, 2004; Bayley and Taylor, 2007; Grove et al., 2010). Lundstrom (2009) defines red flags as: “(...) *a set of circumstances that are unusual in nature or vary from normal activity and raise the auditor’s, internal auditor’s or fraud examiner’s professional senses of suspicion. They are signals that something is not exactly as it should be, and should be further investigated.*” As these warning signs indicate issues that bear risk based on financial statements, red flag analysis is suitable for assessing investment risk.

In theory, red flag analysis mainly is recommended for external auditors as a way to improve fraud detection. For example, Brazel et al. (2010a) suggest that non-financial measures can be a red flag for fraud, when they are used to verify financial measures and there are inconsistencies between the non-financial and financial measures. However, they also find that, in practice, auditors often neglect to use non-financial measures. This is amazing considering the background of SAS No. 99 that contains guidelines on fraud auditing and fraud risk factors including an enumeration of potential red flags (Rezaee and Riley, 2010, p. 245).

The importance of red flag analyses as analytical tools for investors is exemplarily demonstrated by Brazel et al. (2010b). They show that nonprofessional investors may receive higher market returns by considering red flags in their investment decisions. However, Brazel et al. (2011) find that nonprofessional investors do not react to red flag phrases in disclosure environments (like the current situation), where annual reports face a lack of transparency. If this

is the case, they keep on investing and risk losing a lot of money. On the contrary, when there are multiple red flags present and transparent, then investment levels are lower.

With XBRL, an automatic, fast and easy red flag analysis might become possible at low cost also for nonprofessional investors. How this might work and whether the suggested content analysis model is sufficient for bankruptcy prediction shall be explained in the following.

3 Proposed content analysis model

3.1 U.S. GAAP XBRL Taxonomy and its potential use for red flag analysis

In an XBRL environment, for automatic electronic reporting purposes in the field of accounting, each reporting standard (e.g., U.S. GAAP, IFRS GAAP) has to be defined in a standardized hierarchical structure: the so called *XBRL Taxonomy* (e.g., U.S. GAAP Taxonomy, IFRS GAAP Taxonomy). Since 2010, the FASB is responsible for the on-going development and maintenance of the U.S. GAAP Taxonomy (UGT) (FASB, 2011). In the U.S., companies have to use the UGT when they are obligated to prepare their financial statements according to U.S. GAAP and SEC regulations (XBRL US, 2008).²

As XBRL Taxonomies especially contain a predefined list of a business report's possible content, taxonomies are often interpreted as "digital dictionaries" for the transmission of financial statements (Hoffman and Watson, 2010, p. 301). Thus, in the field of accounting, an XBRL Taxonomy can be seen as a "Dictionary of Accounting Terms" for the special GAAP rules it represents. The taxonomy elements that describe the possible contents of a business report (e.g., a financial statement) are so called XBRL tags. A simple approach to automate the extraction of quantitative financial statement information using XBRL and MS Excel is presented by Ditter et al. (2011). But one of the main advantages of XBRL is that it also facilitates the automatic analysis of qualitative data (Hodge et al., 2004, analyze footnotes on stock option compensation). In creating an XBRL report, the different text elements are marked with XBRL tags that add semantic meaning to the textual content. Some of these XBRL tags might represent red flag phrases (e.g., *RelatedPartyTransactionDescriptionOfTransaction*). If sender and receiver use the same list of XBRL tags (e.g., the UGT for the SEC XBRL filing mandate), XBRL provides the opportunity to analyze the technical content of XBRL formatted documents with low costs. One possibility is to use this digital dictionary of the U.S. GAAP

Taxonomy (UGT) for the development of an automatic red flag analysis tool that can be used for bankruptcy prediction.

3.2 Derivation of candidates for the red flag item list

The *UGT 2011* contains approximately 19,000 monetary and non-monetary XBRL tags.³ In order to reduce complexity and to avoid distorting industry effects, we constrict our study to the UGT module “Commercial and Industrial” that is used by most companies.

Our task is to go through the list of XBRL tags and identify XBRL tags that may be red flags for bankruptcy. The general decision criterion in the process is a high discriminatory power for prognosis of financial distress. Therefore, the leading search question is: „Will this respective XBRL tag occur with a higher probability at firms that are relatively near to bankruptcy filing?”

We select the red flag phrases in two consecutive steps: A preliminary list of potential candidates for red flags (3.2) and the final selection of the red flag items, as described in 3.3.

Due to the large amount of XBRL tags that are contained in the UGT (module: Commercial and Industrial), we use the search function of CoreFiling’s online Taxonomy Library (<http://bigfoot.corefiling.com/howto.html>) in the first step, in order to get a first overview. Similar to content analysis with the aim of delivering insights into the tone of the text, we search for words within the XBRL tags that might indicate a poor business situation (e.g., extraordinary, infrequent, unusual, nonrecurring, uncertainty, risk, changes, adjustments, material, unbilled, sale and lease back, off-balance sheet).

Since we want to conduct a qualitative analysis, we primarily choose XBRL tags that are contained within the UGT section “Disclosures”, wherever possible. We generally do not take XBRL tags that are contained within the UGT section “Statements” into account. This has the positive side effect that otherwise possible double counting will be avoided. Double counting may occur, when a disclosure on the face of the financial statements has to be illustrated in detail in the footnotes. However, this approach may lead to distorting results in case there is an accounting choice between recognition and disclosure. Therefore, we set these red flags to one, if they are reported either on the face of the financial statements or in the footnotes. This approach seems to be acceptable, since XBRL technology allows the taxonomy developer to define the XBRL tags so that they work just in this way (for more information, see XBRL International Inc., 2008). Although, in individual cases where it seems appropriate, XBRL tags

that are contained within the UGT section “Statements” are also included into the red flag item list.

Because it is our aim to find a practicable risk analysis tool based on qualitative data, in parts also XBRL technology plays a role in determining the XBRL tags for our red flag item list. For example, we eliminate XBRL tags where the element attribute abstract is true, as these XBRL tags cannot contain any content and therefore are not included in an XBRL report.

In order to assure a high discriminatory power, we choose the lowest reporting level in the hierarchical structure of the UGT where appropriate. The more general an XBRL tag, the higher the probability that the respective XBRL tag occurs for bankrupt as well as for healthy companies.

At the end of this step, we end up with 56 potential candidates for red flags. Mainly guided by the literature, this list still has to be refined.

3.3 Derivation of the red flag item list

In a second step, we go through the list of candidate XBRL tags and analyze them in detail. From the preliminary red flag item list of 56 XBRL tags, we categorize and select 43 XBRL tags that are consistent with reasons discussed in the literature. A detailed overview of the selected red flags together with the respective explanation that is available within the UGT 2011 can be found in Appendix A.

In line with standard literature on content analysis (e.g., Wimmer and Dominick, 2011, p. 166), we assign the XBRL tags to 2 categories and 7 subcategories according to their content before coding. We build the categories according to the guidelines of Tesch (1990): “*A category is comparable to a list of idioms and synonyms, but goes beyond that insofar as the words and phrases in this category are meant to cover all important aspects of the concept represented by the category.*” (Tesch, 1990, p. 186).

Category 1: Indicators for Earnings Management

It can be assumed that there are more incentives for earnings management, when a company gets closer to financial distress or insolvency. Managers will try to avoid bankruptcy filing and try to conceal the critical situation by an accounting behavior that helps to move earnings upward. This expectation is supported by the study of Jaggi and Sun (2006) as well as Leach and Newsom (2007). That managers want to meet analysts’ earnings expectations also plays

an undeniable role (Healy and Wahlen, 1998, p. 12). There is a higher market premium (penalty) for firms that consistently (do not) meet analysts' forecasts (Chevis et al., 2007). Although the results of Barua et al. (2003) suggest that managers of loss-reporting firms might face incentives for big bath accounting, firms that struggle with bankruptcy most likely are in a slightly different situation. We argue that firms, where the financial performance is already very weak, try to avoid bankruptcy and therefore also use income-increasing earnings management measures. In some cases, earnings management will be broadened to an extent that exceeds legal boundaries and managers will enter fraudulent accounting behavior. The transition between legal earnings management and illegal fraud is smooth (see also the illustration in Albrecht et al., 2011, p. 190). Therefore, the red flags within this category should also be based on literature on detecting fraud.

We hypothesize that earnings management will occur a few years before bankruptcy, when managers still see a chance to turn the tide. This hypothesis is supported by Leach and Newsom (2007) that show in a time series analysis of bankrupt firm's earnings management behavior that the companies' financial statements exhibit high earnings management behavior five years prior to the bankruptcy filing date, whereas usually this behavior is reduced the nearer the bankruptcy filing date advances.

1/1 Revenue Recognition

As Turner (2001) puts it: "*The fundamental revenue recognition concept is that revenues should not be recognized by a company until realized or realizable and earned by the company.*". However, there are several possibilities in accounting, where revenues can be recognized at a very early stage, which bears a higher risk for stakeholders.

Under certain conditions, the recognition of revenues is already allowed, when goods are produced and billed but not yet delivered (so called bill and hold transactions) (Sondhi and Taub, 2008, p. 5.21). An example in which such an accounting treatment may occur is when there exists a supply agreement with a customer, but due to a decline of sales the customer faces a lack of inventory storage capacity and requests his supplier to hold the goods until a later point of time (Whitehouse, 2010, p. 25). For a long time, bill and hold transactions were very often reason for SEC fraud allegations (Sondhi and Taub, 2008, p. 5.24). For example, Sunbeam Corp.'s management applied bill and hold sales to brush up earnings, were charged with alleged fraud and initially filed for Chapter 11 bankruptcy. As outlined in the SEC Accounting and Auditing Enforcement Release (AAER) No. 1393: "*Specifically, the Company began*

offering its customers financial incentives to write purchase orders before they needed the goods. Thus, Sunbeam sold goods in the second quarter that it would normally have sold in later periods.” (SEC, 2001). Even if the recognition criteria have been tightened (e.g., the goods that underlie the bill and hold agreement have to be finished, see AAER No. 108), these transactions still bring about a lot of discretionary power or even bear the danger of fraud – especially if they are initiated by the supplier and not the customer. Therefore, Racanelli (2009) suggests “bill and hold” applied to revenue to be a red flag phrase. Loughran and McDonald (2011) find that if phrases like bill and hold appear in 10-K reports, the respective company is more likely to be accused of fraud (Loughran and McDonald, 2011, p. 3). Albeit at the segment level, Hollie et al. (2011) also find that firms with bill and hold transactions have a higher risk of fraudulent financial statements than other firms and conclude that bill and hold practices are a good indicator of fraud. Therefore, we include the XBRL tag *RevenueRecognitionBillAndHoldArrangements* in our red flag item list.

Another warning sign may be that companies display unbilled receivables (Racanelli, 2009). Loughran and McDonald (2011) demonstrate that phrases like unbilled receivables are positively correlated with fraud (Loughran and McDonald, 2011, p. 3). We define unbilled receivables as recognized revenues that are earned in the current period but have not yet been billed (Georgiades, 2008, p. 2.11). There are several XBRL tags relating to this issue in the UGT 2011 that we add to our red flag item list: *UnbilledReceivablesCurrent*, *IncreaseDecreaseInUnbilledReceivables*, *UnbilledContractsReceivable*, *UnbilledReceivablesNotBillableAtBalanceSheetDate* and *GovernmentContractReceivableUnbilledAmounts*.

Further possibilities for earnings management lie in the choice of the revenue recognition method for long-term contracts. One opportunity is to switch between accounting methods. For example, based on the completed contract method revenues cannot be recognized until the goods are produced, whereas based on the percentage of completion method one successively can recognize revenues by the construction process (Carmichael and Graham, 2011, p. 226). Racanelli (2009) claims that it is conspicuous if companies of industries with production times less than one year use the percentage of completion method. Besides, the percentage of completion method itself provides several income increasing opportunities for accounting managers, thereof estimates of completion and progress (Melumad and Nissim, 2009, p. 26). Therefore, we include the XBRL tags *ContractsAccountedForUnderPercentageOfCompletionMember* and *RevenueRecognitionPercentageOfCompletionMethod* to our red flag item list.

1/2 Off-balance-sheet financing

Mills and Newberry (2004) find empirical evidence that firms are more likely to use off-balance-sheet debt, when they exhibit higher credit risk and have higher incentives to polish up their financial performance (e.g., because of a relatively low credit rating). Off-balance-sheet financing means that the raised funds need not be displayed on the face of the balance sheet (Schwarcz, 2003, p. 29). Consistently, Nelson et al. (2003) list off-balance-sheet financing among their examples of common earnings management instruments practiced based on a survey of experienced auditors (Nelson et al., 2003, p. 32). A prominent case of using the earnings management or fraud possibility of sourcing out debt that initially filed for bankruptcy is Enron (Hobson, 2002). Therefore, at first, we add the more general XBRL tag *ReserveForOffBalanceSheetActivitiesMember* to our red flag item list, before changing over to more special XBRL tags on this issue.

Sale and leaseback transactions can be used to manipulate the disclosure of assets and debts (Racanelli, 2009). In a sale and leaseback transaction, “*an asset which was previously purchased is sold and simultaneously contracted to a lease*” (Wells, 2007, p. 2). Because of the selling of the asset, sale and leaseback transactions can be used as an earnings management tool to immediately improve liquidity and earnings. Therefore, Wells (2007) finds that sale and leaseback transactions occur more often for firms that are cash poor and maybe are facing problems with externally acquiring funds (e.g., problems to find a borrower or high capital costs). Wells (2007) also provides a direct linkage to bankruptcy in stating that sale and leaseback transactions may be used to ex ante reduce bankruptcy costs by limiting legal involvement (Wells, 2007, p. 9). He empirically shows that firms with a higher risk of bankruptcy tend to choose sale and leaseback transactions. Therefore, we add the XBRL tag *SaleLeasebackTransactionDescription* to our red flag item list.

Another way of off-balance-sheet financing is securitization (Bhattacharya and Fabozzi, 1996, p. 180). Asset backed securities (ABS) can be defined as “*the set of legal and financial techniques that transforms illiquid assets into tradable financial instruments*” (Banakar, 2010, p. 303). Underlying assets can be, for example, receivables. The advantage from the perspective of the debtor is that firms receive instant cash instead of future cash flows (Lupica, 1998, p. 609). But, the disadvantage from the perspective of the creditor is that, in case of bankruptcy, assets that underlay an ABS transaction are often not part of the lender’s assets any more (Lupica, 1998, p. 597). Thus, under certain conditions, the originator of an ABS transaction can achieve so called bankruptcy remoteness (Ayotte and Gaon, 2005) and therewith reduce

bankruptcy costs (Gorton and Souleles, 2005). This is the case, because accounting and regulatory treatments handle an issue that in fact is a financing construct as true asset sales (Higgins et al., 2009). Higgins et al. (2009) conclude that securitization increases systematic risk (Higgins et al., 2009, p. 25). Therefore, we add the XBRL tags *AssetBackedSecuritiesMember* and *ProceedsFromRepaymentsOfAccountsReceivableSecuritization* to our red flag item list.

1/3 Changes in estimates

It can be assumed that a high frequency of changes of accounting policies is an indicator of a high degree of earnings management and eventually financial distress. Therefore, Racanelli (2009) suggests looking for phrases like “changes in estimated useful life/lives” and “change in the depreciation period”. Stanga and Kelton (2008) empirically underlay this thesis by showing on the basis of the theory of correspondent inferences that accountants and stockholders explain changes in estimates (here: changes as to warranty expenses) with earnings management behavior, when the changes in estimates result in earnings that meet analysts’ forecasts. In an interesting study on investor valuation of accounting changes in the years after the change, Bishop and Eccher (2000) act on the assumption that increases (decreases) in the useful life of long-term assets indicate higher (lower) earnings management, because the consequential changes of earnings are unreal (real). They state that investors act market efficient, as changes in the useful life of long-term assets aiming at increasing earnings are not priced by investors. Therefore, at first we add the XBRL tags *ServiceLifeMember*, *IntangibleAssetsAmortizationPeriodMember* and *ChangeInAccountingEstimateDescription* to our red flag item list.

Besides the estimation of the useful life of assets, accounting managers can manage earnings with the help of discretionary decisions in valuation. There are several red flags that belong to this category of changes in estimating the value of assets that we add to our red flag item list: *SalvageValueMember*, *InventoryValuationAndObsolescenceMember* and *GoodwillImpairedChangeInEstimateDescription*. The same goes for estimating the value of reserves: *WarrantyObligationsMember*, *SalesReturnsAndAllowancesMember* and *ChangeInAssumptionsForPensionPlansMember*.

As we defined red flags as being dummy variables, we do not count the XBRL tag *ChangeInAccountingEstimateFinancialEffect*, although it bears important information for stakeholders. For example, Xerox did not disclose the financial effects of changes in accounting estimates and thus mislead stakeholders (Albrecht et al., 2011, p. 190). We also eliminate the

XBRL tag *GoodwillImpairedAdjustmentToInitialEstimateAmount* from our preliminary red flag item list, as we want to evaluate the current period, whereas the XBRL tag concerns financial effects of a goodwill impaired adjustment on future periods. We also do not count for the XBRL tags *SiteContingencyFactorsChangingEstimate* and *ProductLiabilityContingencyFactorsChangingEstimate* as they list factors that possibly might lead to an adjustment of estimates in future periods.

1/4 Related party transactions

Racanelli (2009) suggests that corporate governance phrases like “related party” or “related party transactions” are important, when screening a document for potential trouble. Related party transactions can be defined as transactions that are “*made with entities that are controlled by the company or that have control over the company, including other businesses, shareholders, directors, lenders, vendors, and customers.*” (Sherman and Young, 2001, p. 134).

Loughran and McDonald (2011) test this hypothesis on a data sample of 10-K reports filed with the SEC EDGAR database and find that the firm’s volatility in the year following the balance sheet date is greater, when the phrase “related party transactions” appears in a company’s annual report. This might relate to a higher uncertainty that is connected with less independent CEOs (Loughran and McDonald, 2011, p. 11). Accordingly, the logistic regression results reveal a significantly higher probability of material accounting misstatements in matters of related party transactions (Loughran and McDonald, 2011, p. 13). However, Loughran and McDonald (2011) also find that a related party transaction is the business activity with the most count within all examined 10-K reports, that is to say independent of whether the respective companies have been subject to shareholder litigation under Rule 10b-5 afterward.

This is consistent to Henry et al. (2007), who state “*that disclosed related party transactions are common while fraudulent financial reporting is relatively uncommon*” (Henry et al., 2007, p. 27). They investigate AAERs including both fraud and related party transactions and find that only a small portion of related party transactions is connected with fraudulent accounting behavior (83 out of 2,500 AAERs, which is approximately 3%). From this they conclude that “*it is reasonable to assume that most related party transactions are not fraudulent*” (Henry et al., 2007, p. 27). This may explain other studies that have found no differences between related party transactions of fraud and non-fraud companies (e.g., Bell and Carcello, 2000).

Thus, empirical findings are ambivalent. However, we fall back on the studies Lin et al. (2010) as well as Jian and Wong (2004) that are led by the assumption that related party transactions are twofold: there may be circumstances in which companies tend to use related party transactions for improving their disclosed firm performance (e.g., an imminent danger of delisting or bankruptcy) and vice versa (e.g., in situations of good firm performance, companies might divert back resources to controlling shareholders).

There are no studies known that explicitly bring related party transactions in conjunction with bankruptcy (risk). But we believe that it is realistic to assume that related party transactions bear a very high potential for earnings management especially in critical situations. This is supported by many real-life examples of bankruptcies in which this was the case and that in the long run even lead to bankruptcy (e.g., Enron). Related parties are closely linked to the company, which probably allows a more open communication connected with a higher probability that the other party is willing to help. Thus, it is most important for this category of red flags to choose XBRL tags depending on their possible discriminatory power. For this reason, we decided to not adding the XBRL tag *RelatedPartyTransactionDescriptionOfTransaction* to the red flag item list as it is too general.

Based on a survey of 253 experienced auditors, Nelson et al. (2003) show examples of how managers attempt to manage earnings that they reference with AAERs in order to illustrate extreme variants of their examples. Among these examples are sales to related parties with recognition of associated profit in order to increase earnings (Nelson et al., 2003, p. 28). For example, Lemout & Hauspie Speech Products N.V., a Belgium based company specialized in speech recognition technology that went bankrupt in 2001, used related party transactions to make 25% of their revenues (Sherman and Young, 2001, p. 134). Thus, covering sales difficulties with the creation of higher revenues through related party transactions may be an easy to use creative accounting instrument that managers tend to use during a financial crisis. Therefore, we consider the XBRL tag *RevenueFromRelatedParties* to be a red flag for a potential troublesome financial situation of the target company and add it to our red flag item list. In order to obviate possible double counting of the same issue, we eliminate the following XBRL tags from our preliminary red flag item list that represent accounts receivables that result from related party transactions: *DueFromRelatedPartiesCurrent*, *DueFromRelatedPartiesNoncurrent*. Whereas we account for upward changes in accounts receivables against related parties in order to consider not only the incidence of sales to related parties, but also the

issue that sales to related parties have increased with the XBRL tag *IncreaseDecreaseInDueFromRelatedParties*.

When a company enters a financial crisis, another possibility to help restructuring and maybe avoiding a bankruptcy filing may be loans from related parties. This especially applies, when the firm's credit rating is that low that the banks refuse to contract new credits. Accordingly, Henry et al. (2007) find that financing activities involving related parties (e.g., loans or borrowings to/from related parties) have a high discriminatory power in predicting fraudulent accounting behavior and thus indicate an excessive creative accounting behavior. Therefore we include the XBRL tags *DueToRelatedPartiesCurrentAndNoncurrent* and *IncreaseDecreaseInDueToRelatedParties* in our analysis. We do not count the XBRL tag *RelatedPartyTransactionExpensesFromTransactionsWithRelatedParty* as it is too general, but instead we use the XBRL tag *DueToRelatedPartiesCurrentAndNoncurrent*. Other possibilities for financing with related party transactions in order to swiftly gain liquidity and to improve the picture of the company may be sale and leaseback transactions with related parties. Therefore we add the XBRL tag *SaleLeasebackTransactionRelatedPartyTransaction* to our red flag item list.

As a general indicator of potentially higher usage of earnings management behavior due to financial distress is the changing of the terms of related party transactions compared to the preceding period (e.g., pricing terms or the duration of a loan). Therefore, we add the XBRL tag *RelatedPartyTransactionEffectsOfAnyChangeInMethodOfEstablishingTerms* to our red flag item list.

For the later analysis that we want to conduct for corporate entities, we eliminate the following XBRL tags from our preliminary red flag item list, as they do not apply for companies with the legal status Corporation or Incorporated: *IntercompanyLoansDescription* and *ManagingMemberOrGeneralPartnerRelatedPartyFeesAndOtherArrangements*.

1/5 Other earnings management methods

There are several other methods of earnings management. One possibility is to use the explicit accounting choices that accounting standards sometimes offer (Abdel-Khalik, 1998, p. 219). Therefore, we add the XBRL tag *ChangeInAccountingMethodAccountedForAsChangeInEstimateMember* to our red flag item list. We also add the XBRL tag *DescriptionOfNatureOfChangesFromPriorPeriodsInMeasurementMethodsUsedToDetermineReportedSegmentProfitOrLossAndEffectOfThoseChangesOnMeasureOfSegmentProfitOrLoss* to our red flag item list.

Another possibility of earnings management is to change the date of financial report or to change the date for impairment test. Therefore, we add the XBRL tag *DisclosureOfChangeOfDateForAnnualGoodwillImpairmentTest* to our red flag item list. As mentioned above, there is a strong capital market incentive for accounting managers to meet analysts' earnings expectations. Maybe against the background of that assumption, Das et al. (2007) examine the hypothesis that in cases where the first quarters of a fiscal year have been characterized by poor performance, managers tend to execute income-increasing measures. They find strong evidence for their expectation. Therefore, we add the XBRL tag *YearEndAdjustmentsEffectOfFourthQuarterEventsDescription* to our red flag item list. Another XBRL tag that we see as a potential red flag is *Reclassifications*. We are doing this in dependence on the study of McVay (2006), who finds that reclassifications between income statement items represent earnings management behavior. Because earnings management during a situation of financial distress may involve real earnings management through unusual business activities, we see the XBRL tag *UnusualOrInfrequentItemGross* as a further warning sign for broadened earnings management due to a danger of bankruptcy and add this XBRL tag to our red flag item list.

Category 2: Characteristics of companies close to insolvency and influencing factors

There are several characteristics that companies in danger of bankruptcy exhibit. We assume that the visibility of these characteristics increases with an approaching need for bankruptcy filing and a decreasing of the possibilities for legal accounting adjustments in favor of the reporting company. We draw the red flags for this category mainly from studies on bankruptcy prognosis and / or analysis.

2/6 Infrequent events that might contribute to insolvency as the case may be

There are infrequent events that, if they occur in connection with an already poor economic situation of a company, they may contribute to insolvency. We add XBRL tags for those infrequent events to our red flag item list that have their cause in business operations and likely are not secured: *BusinessInterruptionLossesNatureOfEvent* and *GainLossOnContractTermination*. We do not incorporate the XBRL tag *LossFromCatastrophes* as we believe that such losses are secured by insurance and are too rare.

2/7 Characteristics of companies potentially filing for bankruptcy

A study of characteristics of companies that filed for bankruptcy reveals three issues that in most cases are the reason for bankruptcy filing: the external business environment (e.g., new competitor), financing (e.g., the inability to get financing) and business operations (e.g., mismanagement of business) (Warren and Westbrook, 2000, p. 75). These results are overall independent from the type of U.S. Bankruptcy Code chapter (e.g., Chapter 7 or Chapter 11) the firms' managers filed for. In the case a bankruptcy filing threatens due to problems in business operations, firm managers might try to counteract by applying restructuring measures. Therefore, we add the following XBRL tags to our red flag item list: *RestructuringCharges* and *SeveranceCosts*. In order to avoid double counting and the counting of events that do not concern the current period, we do not include the XBRL tags *RestructuringAndRelatedCostDescription* and *RestructuringAndRelatedActivitiesDescription* in our analysis.

Vichitsarawong (2007) conducts a cross-sectional analysis and concludes that there is a positive correlation between goodwill impairment and the relative efficiency or economic performance of a firm. His study contributes economic foundation for studies on the connection between goodwill impairments and stock price downturns (see Bens et al. 2007; Li and Meeks, 2006). Hayn and Hughes (2005) find that goodwill write-offs lag behind the economic impairment of goodwill for about three to four years, which may underline the hypothesis, that goodwill impairment is also part of earnings management behavior. Accordingly, we assume that accounting managers of firms with poor performance tend to delay impairment charges that negatively affect net income until a non-reduction of goodwill cannot be justified any more or until the situation of financial distress cannot be hidden from stakeholders any more. Therefore, we add the XBRL tag *GoodwillImpairmentLoss* to our red flag item list.

In correlation to a poor financial performance, there may be substantial doubt about the firm's ability to continue as going concern. This situation has to be disclosed according to Paragraph 948-10-50-4 of the FASB Accounting Standards Codification. Therefore, we add the XBRL tag *LiquidityDisclosureGoingConcernNote* to our red flag item list.

Beaver (1966) defines financial distress as “*incurring huge overdraft, default on payment of preferred stock dividends and corporate bonds, and filing bankruptcy.*” Thus, another indicator of financial distress that indicates liquidity concerns may be that the company is in arrears with dividend payments. Therefore, we add the XBRL tag *PreferredStockAmountOfPreferredDividendsInArrears* to our red flag item list.

We regard debt covenant violations as another important potential red flag for bankruptcy, which exactly is their function within credit contracts: “*Debt covenant violations serve as early indicators of bankruptcy by signaling to creditors potential problems.*” (Bryan et al., 2002, p. 938). Most of the violated covenants appropriately correspond to solvency (e.g., restrictions on leverage or interest coverage), liquidity (e.g., working capital or current ratio) and profitability requirements (Bryan et al., 2002, p. 938; Benish and Press, 1993). Also, most of the covenants that are part of credit contracts are those that have been identified as being effective bankruptcy indicators in studies like Beaver (1966) and Altman (1968) (Bryan et al., 2002, p. 962). Because of their importance as predictors of deterioration of the financial situation of a borrower and concurrently as control mechanism for minimizing default risk, empirical evidence shows that banks are using the information about the probability for financial distress in the determination of debt covenants (Janes, 2003).

When non-professional investors accord fraud risk assessments a high importance during their investment decision-making process, Brazel et al. (2010b) find positive correlation to the use of red flags. They also find that one of these red flags is that investors rely on violations of debt covenants (Brazel et al., 2010b, p. 38). This is consistent with Kim et al. (2010) that show that the probability of earnings management is higher, when the danger of meeting the debt covenants is higher, because managers try to avoid debt covenant default. But independent of that, we are focusing on debt covenants that already have been breached. Therefore, it is irrelevant whether the breach concerns positive or negative debt covenants. Positive debt covenants are financial requirements that delimit certain business actions and negative (or affirmative) debt covenants are non-financial requirements (Janes, 2003, p. 5). We add the following two XBRL tags to our red flag item list: *DebtDefaultShorttermDebtDescriptionOfViolationOrEventOfDefault* and *DefaultLongtermDebtDescriptionOfViolationOrEventOfDefault*.

4 Empirical investigation of the discriminatory power of selected red flags

4.1 Methodology

We want to test the red flag item list for its discriminatory power. Our main research question is whether companies that went insolvent exhibit a higher occurrence of red flags than the control group (RQ#0). If this is the case, we can support the question whether our proposed content analysis model is able to predict bankruptcy. Therefore, the main hypothesis that we test is:

H₀: Companies that went insolvent exhibit a higher occurrence of red flags than the control group.

In order to test this hypothesis, we examine two research questions by applying descriptive statistical analysis as well as a binary logistic regression. First we want to know which red flags have the highest discriminatory power and which red flags prove to be not efficient in predicting bankruptcy (RQ#1). Therefore, we expect to reject the following hypothesis:

H₁: All of the red flags of the red flag item list have the same discriminatory power in predicting bankruptcy.

We believe that the answer to this research question also depends on the time period between the appearance of the red flag and the bankruptcy filing date. Thus, it is our next research question, whether any change in the frequency of red flags can be observed in the lapse of time (RQ#2). Thereby, we expect that the occurrence of red flags of the category 2 is higher the nearer the bankruptcy filing date comes, whereas the occurrence of red flags of the category 1 is lower. In other words, we assume that the category 1 red flags give stronger indication of the failure one year before the bankruptcy filing date than the category 2 red flags. Therefore, the empirical investigation aims at testing the following hypotheses:

H_{2a}: The occurrence of red flags of the category 2 is higher than the occurrence of red flags of the category 1 one year before bankruptcy.

H_{2b}: The occurrence of red flags of the category 2 is lower than the occurrence of red flags of the category 1 two years before bankruptcy.

Besides a simple descriptive statistical analysis, we apply a binary logistic regression, to test the discriminatory power of the red flag model based on our data sample. We apply the following general logit model:

$$B = \beta_0 + \sum_{i=1}^n \beta_i R_i + \varepsilon$$

Where:	B	=	dependent variable that is a dummy variable representing the event of bankruptcy filing (1 = yes, 0 = no)
	β_0	=	regression constant
	β_i	=	regression coefficient
	R_i	=	independent variable that represents a red flag of the red flag item list
	ε	=	error term

We aim at optimizing this logit model through a selection of best discriminant red flags.

4.2 Sample selection

Our final sample consists of 26 US-companies that filed for Chapter 11 bankruptcy between 2006 and 2009 and 26 matched competitor companies that did not file for Chapter 11 in the respective year (see Appendix B). We are not examining US-companies that filed for Chapter 7.

The information of bankruptcy filing comes from the database www.chapter11library.com, which is available for free online. It is “*a concise, confidential database of the most important, most sought-after corporate bankruptcy documents*” and it “*is not designed to be a comprehensive bankruptcy library*” (Nationwide Research & Consulting, 2012). In order to avoid distortive effects of legal status and company size, from our original sample, we eliminate companies that do not have the legal status “Corp.” (Corporation) and “Inc.” (Incorporated) as well as an asset size between \$1.0 and \$5.0 billion. We further eliminate bankrupt companies of the industries Financial Services and Real Estate (classification according to the Chapter 11 database we used), because the red flag item list is based on the “Commercial and Industrial” module of the UGT 2011. From the remaining 44 companies we further eliminate 18 companies due to a lack of information. Afterwards, we derived the control sample for the examinable 26 US-companies that filed for Chapter 11 bankruptcy by a pairwise search for the main competitor via the Hoovers database.

Our study is primarily based on the annual reports (Form 10-K) of the selected 52 companies. We draw the Form 10-K documents from the SEC EDGAR database. In case the Form 10-K

document has been amended ex post, we use the 10-K/A for our study (Form 10-K/A) regardless of whether the respective Form 10-K document is available on EDGAR. For a time series analysis, we analyze the annual report with a fiscal year end directly before the bankruptcy filing year (one year before the bankruptcy filing date) and the year before that (two years before the bankruptcy filing date). Due to a lack of 10-K documents, we reduce our sample to 25 bankrupt companies in the two years before bankruptcy consideration. In total, we analyze 52 Form 10-K or 10-K/A documents for one year before bankruptcy and 50 Form 10-K or 10-K/A documents for two years before bankruptcy.

On January 30, 2009 the SEC released a rule mandating all SEC filers to file interactive data (or XBRL data) with the EDGAR system over a three year phase-in (SEC, 2009). First of all, the SEC XBRL mandate (or Interactive Data Program) still is in its beginning stages. In phase one, the 500 largest issuers (i.e. domestic and foreign large accelerated filers that use U.S. GAAP and have a worldwide public common equity float above \$5.0 billion as of the end of the second fiscal quarter of their most recently completed fiscal year) were required to file XBRL reports beginning with the quarterly report from a fiscal period ending on or after June 15, 2009. All other domestic and foreign filers that use U.S. GAAP were required to file XBRL reports beginning with the quarterly report from a fiscal period ending on or after June 15, 2010. Since the beginning of the SEC XBRL mandate, the number of XBRL filings of listed companies available for analysis online is steadily increasing. However, most of the filers did not file XBRL annual reports until recently. Hence there is not a sufficient number of XBRL filings available for analysis concerning companies that filed for Chapter 11. Additionally, in the case XBRL reports of bankrupt companies are publicly available, they are not yet sufficient for the purpose of our study. For each group of companies (year 1 filer, year 2 filer or year 3 filer) there starts a second requirement - the so called detailed tagging of footnotes - in the second year of XBRL reporting. For example, the requirement includes the tagging of each significant accounting policy. Up to date, blocktext tagging is sufficient, which means that most of the tags in our red flag item list are not contained in the current XBRL reports, because they are from a very detailed hierarchy level in the UGT 2011. Therefore, we decided to draw the complete submission text files (file extension *.txt) from the SEC EDGAR database and to simulate the forthcoming XBRL tagging with the help of the textual analysis software MAXQDA. MAXQDA is “*one of the leading software tools for qualitative data analysis*” (VERBI, 2012). Like in an XBRL environment, once the report contains XBRL tags, an automatic output of the number of XBRL tags defined as being red flags for a threatening bankruptcy that are contained in each examined annual reports is possible.

4.3 Tagging methodology using MAXQDA

In general, content analysis techniques have to fulfill two requirements: reliability and validity (Krippendorff, 2004, p. 18). In order to receive valid results, we develop special coder guidelines, see Table 1. This approach contemporaneously shall ensure so called intercoder reliability, which means that different coders will come to the same coding and finally to the same conclusion (Neuendorf, 2002, p. 142).⁴

Table 1
Coder Guidelines

No.	Guideline	Explanation
1	The relevant paragraphs shall be searched via the search function in the first instance. Afterward, the text shall be read through in detail.	This approach shall ensure valid results and work against threats of reliability. So called coder fatigue can be counteracted (Neuendorf, 2002, p. 145) without losing a thorough coding.
2	The tags shall be coded only once.	We perceive red flags as dummy variables. This means, it is only important, whether the red flags occur or not (yes/no). The reason is that in practice, a single XBRL tag will be used once for the same data content regardless of the number of different locations within a document. This has the advantage that distortions will be avoided. Imagine the case where a company reports about having the variable interest entity (VIE) C at four different locations within the document, whereas company B reports about this fact at only one location. If company A would tag the paragraph with the same issue four times, it would be overvalued as compared to company B.
3	In case there is a conflict between a special tag (e.g., <i>SaleLeasebackRelatedPartyTransaction</i>) and a more general tag (e.g., <i>SaleLeasebackTransactionDescription</i>), then the special case (e.g., sale and lease back related party) has priority.	This approach shall ensure a high discriminatory power. The probability of a high discriminatory power increases with a more specialized tag. Or the other way around, the probability that both groups of companies (i.e. bankrupt companies and healthy companies) exhibit the same tag increases with the generality of the tag.
4	For XBRL tags that begin with „ <i>IncreaseDecrease(...)</i> ” or “ <i>GainLoss(...)</i> ”, dependent on the content of the XBRL tag we only count either an increase or a decrease.	For example, for the XBRL tag <i>IncreaseDecreaseIndueToRelatedParties</i> we only count an increase, as we assume that only an increase is a hint for a deterioration of the financial situation of the business (see also the underlined words in Appendix A).
5	We only count for issues that concern the economic situation of the examined or current fiscal year.	The reason is that we want to assess the likelihood of insolvency to the current point in time on the basis of the business development in the current fiscal year. Thus, for example, we do not count for statements on restructuring measures in previous years or planned restructuring measures.

Notes:

This table presents guidelines for the red flag analysis of the examined annual reports using MAXQDA.

Following Loughran and McDonald (2011), the red flags *ContractsAccountedForUnderPercentageOfCompletionMember* and *RevenueRecognitionPercentageOfCompletionMethod* shall not be counted for companies of construction industries, as the percentage of completion method is common for the industries construction, machinery, aircraft, shipbuilding, and defense.

4.4 Descriptive statistics

First we examine the annual reports with a fiscal year end one year before the bankruptcy filing date. For a time series analysis, we repeat the analysis for the annual reports with a fiscal year end two years before the bankruptcy filing date.

For the further explanations, we do not discuss the XBRL tags 1|BillHold, 1|IncreaseUnbilledRev and 1|ChangesPoC (subcategory REVREC), because they are not disclosed in either of the examined annual reports. The same applies to the XBRL tags 2|VIENonConsolidated (subcategory OFFBALFIN), 3|AmortPeriod and 3|GoodwillImpCh (subcategory CHINEST), 4|SaleLeasebackRelParty and 4|RelPartyChTerms (subcategory RELPARTY), 6|BusInterruption (subcategory EVTS) and 7|ShorttermDebtDefault (subcategory BANKRPTY). Although there were a lot of companies that had transactions with variable interest entities (e.g., in connection with ABS transactions), the companies generally specified that these variable interest entities are consolidated. Naturally, business interruptions are not very common. There were a few companies that reported about business interruptions in former years that mostly were covered by proceeds from insurance. As it often was not clear, whether the underlying credit facility is short-term or long-term, we decided to use the XBRL tag 7|LongtermDebtDefault in case of uncertainty. In summary, the 43 red flags narrow down to a number of 33 red flags for further analysis (see Appendix A).

4.4.1 One year before the bankruptcy filing date

In a broad view, we can support H_0 . When we compare the mean usage rates of all the remaining red flags within the examined annual reports, we name this list of red flags model 1. The results show that in the mean the red flags occur more often in the bankrupt group (23.89%) as compared to the healthy group (15.15%), see Table 2. We calculate the mean usage rate by relating the observed frequency of occurrence of the red flags to the maximum observable frequency of occurrence of red flags. The mean usage rate difference for model 1 is + 8.74%-points in total.

A statistical t-test for comparing means supports our hypothesis with a significance at the 1%-level ($t_{(42)} = -3.790$, p-value = 0.000). Appendix C contains an overview of the red flags and their absolute and relative occurrence in the annual reports for the two groups of companies (bankrupt / healthy). Since there are also red flags included in the list that may be little or not discriminatory, the overall results are very good.

Table 2
Mean usage rates (one year before the bankruptcy filing date)

	Model 1			Model 2		
	Bankrupt (N = 26)	Healthy (N = 26)		Bankrupt (N = 26)	Healthy (N = 26)	
	Mean Usage Rate	Mean Usage Rate	Difference	Mean Usage Rate	Mean Usage Rate	Difference
1 REVREC	3.08%	3.85%	-0.77%	3.08%	3.85%	-0.77%
2 OFFBALFIN	18.27%	12.50%	5.77%	18.27%	12.50%	5.77%
3 CHINEST	28.57%	24.18%	4.40%	14.62%	5.38%	9.23%
4 RELPARTY	23.08%	5.77%	17.31%	23.08%	5.77%	17.31%
5 OTHERS	17.95%	12.18%	5.77%	10.00%	2.31%	7.69%
Category 1	18.79%	12.87%	5.92%	13.21%	5.69%	7.53%
6 EVTS	30.77%	15.38%	15.38%	30.77%	15.38%	15.38%
7 BANKRPTY	44.87%	21.15%	23.72%	38.46%	7.69%	30.77%
Category 2	42.86%	20.33%	22.53%	36.92%	9.23%	27.69%
Total	23.89%	15.15%	8.74%	17.45%	7.14%	10.30%

Notes:

This table presents an overview of the mean usage rates per category and subcategory for model 1 (33 red flags) and model 2 (optimized red flag item list). We calculate the mean usage rate by relating the observed frequency of occurrence of the red flags to the maximum observable frequency of occurrence of red flags. For model 2, we eliminate red flags, that have an absolute occurrence in ten or more examined annual reports for the bankrupt group of companies and the healthy group of companies respectively.

In a detailed analysis of the red flags mean usage rates we have to reject H_1 . There are red flags that seem to be more discriminatory than others. Therefore, the results improve, when the test only includes certain variables of model 1 ($t_{(40)} = -4.991$, p-value = 0.000). We name this optimized red flag item list model 2 and derive the related red flags by eliminating red flags that have an absolute occurrence in ten or more examined annual reports for the bankrupt group of companies and the healthy group of companies respectively. For example, the XBRL tag 3|ChInEstimate seems to be too general as it occurred in the majority of all examined annual reports (the mean usage rate is 61.54% or 80.77%) even with a surplus for the healthy group of companies (see Appendix C). A similar statement can be drawn for the XBRL tag 3|ChPensionPlans (the mean usage rate is 61.54% or 65.38%). We further eliminate the XBRL tags 5|Reclass, 7|RestructuringCharges and 7|SeveranceCosts for model 2. The mean usage rate difference for model 2 is + 10.30%-points in total.

Interestingly, the best discriminant variable is 7|GoingConcern followed by 7|LongtermDebtDefault, that we assumed are predictors of bankruptcy. For example Lear

Corp. reports: “As a result, as of December 31, 2008, we were no longer in compliance with the leverage ratio covenant contained in our primary credit facility.” (Lear Corporation, 2009, p. 5). A categorical analysis reveals the following categories with a mean usage rate difference of higher than 10.00%: 4|RELPARTY, 6|EVTS and 7|BANKRPTY (model 1 and 2).

In contrast, we can approve H_{2a} . For model 1, as expected, the mean usage rate difference of the category 2 red flags (22.53%-points) is higher than the mean usage rate difference of the category 1 red flags (5.92%-points). This may be due to the observance that in a lot of cases the creditors amended the credit facilities, which included restrictive negative covenants that apparently inhibit earnings management behavior. For example, Hayes Lemmerz reports: “The New Credit Facilities contain negative covenants restricting our ability and the ability of our subsidiaries to (...) engage in saleleaseback transactions (...).” (Hayes Lemmerz International Inc., 2009, p. 69). The difference of 16.91%-points even enlarges for model 2 with a mean usage rate difference of the category 2 of 27.69%-points and of the category 1 red flags of 7.53% (i.e., the difference between mean usage rate differences of category 1 vs. category 2 for model 2 is 20.16%-points).

4.4.2 Two years before the bankruptcy filing date

Also for two years before the bankruptcy filing date we can accept H_0 . Again, there is a positive mean usage rate difference between bankrupt and healthy companies for model 1 (3.39%-points) and model 2 (4.00%-points), see Table 3. However, the mean usage rate differences are lower than one year before the bankruptcy filing date, from which we assume that the models are less predictive than one year before the bankruptcy filing date. The lesser discriminatory power of our models for two years before the bankruptcy filing date is supported by results of the t-test for two years before the bankruptcy filing date that are inferior to one year before the bankruptcy filing date. The t-test for examining mean differences does not show significant results for model 1 ($t_{(44)} = -1.567$; p-value = 0.124). The t-test for model 2 shows significant results, albeit the significance is lower than one year before the bankruptcy filing date ($t_{(42)} = -2.489$; p-value = 0.017). Similar to the approach one year before the bankruptcy filing date, for model 2, we eliminate the XBRL tags 3|ChInEstimate, 3|ChPensionPlans, 5|Reclass, 7|RestructuringCharges and 7|SeveranceCosts, because they have an absolute occurrence of ten or higher for the examined annual reports of the bankrupt group of companies and the healthy group of companies respectively. For example, the XBRL tag 3|ChInEstimate

has a mean usage rate of 72.00% or 88.00% and the XBRL tag 3|ChPensionPlans has a mean usage rate of 56.00% or 64.00%.

Again, we have to reject H_1 . Not all of the red flags have a high discriminatory power. The XBRL tag with the best discriminatory power two years before the bankruptcy filing date is 4|RevRelParty. For example, Lear Corp. reports sales to affiliates in the amount of \$82.4 million (Lear Corporation, 2008, p. 122). When defining the best discriminatory categories as such to exhibit a mean usage rate difference of over 10.00% then there is only one category best discriminatory for two years before the bankruptcy filing date: 4|RELPARTY (model 1 and 2).

Table 3
Mean usage rates (two years before the bankruptcy filing date)

	Model 1			Model 2		
	Bankrupt (N = 25)	Healthy (N = 25)		Bankrupt (N = 25)	Healthy (N = 25)	
	Mean Usage Rate	Mean Usage Rate	Difference	Mean Usage Rate	Mean Usage Rate	Difference
1 REVREC	2.40%	2.40%	0.00%	2.40%	2.40%	0.00%
2 OFFBALFIN	16.00%	10.00%	6.00%	16.00%	10.00%	6.00%
3 CHINEST	22.86%	26.86%	-4.00%	6.40%	7.20%	-0.80%
4 RELPARTY	20.00%	5.00%	15.00%	20.00%	5.00%	15.00%
5 OTHERS	25.33%	20.00%	5.33%	14.40%	9.60%	4.80%
Category 1	18.00%	14.62%	3.38%	11.30%	6.78%	4.52%
6 EVTS	12.00%	4.00%	8.00%	12.00%	4.00%	8.00%
7 BANKRPTY	20.67%	14.67%	6.00%	6.00%	1.00%	5.00%
Category 2	19.43%	13.14%	6.29%	7.20%	1.60%	5.60%
Total	18.30%	14.91%	3.39%	10.57%	6.57%	4.00%

Notes:

This table presents an overview of the mean usage rates per category and subcategory for model 1 (33 red flags) and model 2 (optimized red flag item list). We calculate the mean usage rate by relating the observed frequency of occurrence of the red flags to the maximum observable frequency of occurrence of red flags. For model 2, we eliminate red flags, that have an absolute occurrence in ten or more examined annual reports for the bankrupt group of companies and the healthy group of companies respectively.

As expected, the characteristics of an impending bankruptcy are not as obvious as one year before the bankruptcy filing date. There is no indication of a doubtful going concern (the mean usage rate of the XBRL tag 7|GoingConcern is 0.00%) and almost all companies were in compliance with credit facility covenants (the mean usage rate of the XBRL tag 7|LongtermDebtDefault is 0.00% or 4.00%). In conformity with this observation, the mean usage rate difference of category 2 red flags is far less (6.29%-points for model 1) than one year before the bankruptcy filing date (22.53%-points for model 1).

However, for model 1 and model 2, we have to reject our hypothesis H_{2b} . Contrary to our expectation, for model 1, the mean usage rate difference for category 2 red flags (6.29%-points) still is higher than for category 1 red flags (3.38%-points). But, the difference of 2.91%-points

is only about one third of the difference one year before the bankruptcy filing date (8.74%-points). For model 2, the mean usage rate difference for category 1 (4.52%-points) is 1.08%-points lower than the mean usage rate difference for category 2 (5.60%-points). Compared to a mean usage rate difference between the two categories of 20.16 %-points for one year before the bankruptcy filing date, a difference of 1.08%-points is very low and may turn negative (in favor of category 1 red flags) for three years before the bankruptcy filing date.

4.5 Binary logistic regression

In order to investigate the relationship between the number of red flags and the event of bankruptcy filing and especially to test for the predictive ability of our models, we conduct binary logistic regressions with the event of bankruptcy filing as dependent variable. The dependent variable is coded as a dummy variable, which is set to one for companies that filed for bankruptcy and which is set to zero for companies that are included in the healthy group of companies. Pearsons' correlation coefficients were computed in order to test for a possible multicollinearity problem. The tests did not show any abnormalities.

Our logistic model is as follows:

$$B = \beta_0 + \beta_1 \text{SUM} + \varepsilon$$

Where:	B	=	dependent variable that is a dummy variable representing the event of bankruptcy filing (1 = yes, 0 = no)
	β_0	=	constant
	β_1	=	regression estimator
	SUM	=	aggregated independent variable that is computed as the sum of the red flag item results
	ε	=	error term

In order to have a reliable regression model, the sample size has to be a multiple of the amount of predictors (Field and Miles, 2010, p. 197). However, our data sample consists of 50 or 52 observances as compared to 33 variables that could be used as predictor variables. Therefore, we construct an aggregated independent variable SUM that sums up the results of all independent variables in the model. Similar to the descriptive statistics, we compare two models. For model 1 the aggregated independent variable SUM contains all 33 red flags (see Appendix C). For model 2 the variable SUM only contains the 28 red flags of the optimized red flag item list as described in section 4.4 (see also Appendix C).

4.5.1 One year before the bankruptcy filing date

Table 4 reports results of logistic regressions for the two models. The Omnibus-Test shows an overall fit of the two models being very good and significant at the 1%-level (p-value model 1 and model 2 < 0.001). This means that the examined independent variables have a high explanatory power for the event of bankruptcy filing. This is also supported by other statistical measures. Model 1 has a -2LL of 58,539a and model 2 has a -2LL of 50,179a. The smaller the -2LL, the better is the model (Pampel, 2000, p. 65). Also Nagelkerke's R-square indicates a higher explanatory power for model 2 (the dependent variable can be explained to 45.8%) compared to model 1 (30.6%).

Table 4
Binary Logistic Regression Results (one year before the bankruptcy filing date)

	Omnibus-Test			Classification		
	Chi-Square	df	p-value	-2 Log-Likelihood	R-square Nagelkerke	Power of Prediction
Model 1	13.548	1	0.000	58,539a	0.306	69.231
Model 2	21.908	1	0.000	50,179a	0.458	73.077

Notes:

This table presents the results of binary logistic regression for one year before the bankruptcy filing date. Model 1 contains all of the 33 discussed red flag items. For model 2, we eliminate red flags, that have an absolute occurrence in ten or more examined annual reports for the bankrupt group of companies and the healthy group of companies respectively.

As the descriptive statistics already have indicated, the proportion of firms correctly classified is higher for model 2 (73.0772%) compared to model 1 (69.231%). These results affirm our hypothesis that the model 2 red flags have a higher predictive power than model 1 red flags.

4.5.2 Two years before the bankruptcy filing date

In total, the logistic regression results for two years before the bankruptcy filing date are still acceptable, but not as good as one year before the bankruptcy filing date, see Table 5. The Omnibus-Test is significant at the 5%-level for model 2 (p-value < 0.05), but it shows no significance for model 1 (p-value > 0.1). The results for -2LL of 66,835a (model 1) or 63,167a (model 2) as well as Nagelkerke's R-square of 0.065 (model 1) to 0.154 (model 2) are inferior to the results for one year before the bankruptcy filing date.

Table 5
Binary Logistic Regression Results (two years before the bankruptcy filing date)

	Omnibus-Test			Classification		
	Chi-Square	df	p-value	-2 Log-Likelihood	R-square Nagelkerke	Power of Prediction
Model 1	2.480	1	0.115	66,835a	0.065	62.000
Model 2	6.147	1	0.013	63,167a	0.154	62.000

Notes:

This table presents the results of binary logistic regression for two years before the bankruptcy filing date. Model 1 contains all of the 33 discussed red flag items. For model 2, we eliminate red flags, that have an absolute occurrence in ten or more examined annual reports for the bankrupt group of companies and the healthy group of companies respectively.

For two years before the bankruptcy filing date the logistic regression shows a lower power of prediction (the power of prediction is 62.000% for both models) than one year before the bankruptcy filing date (the power of prediction is 69.231% or 73.077%). These results are plausible considering that the event of a later bankruptcy filing is more obvious the closer the annual reporting data is to the bankruptcy filing date and the more inevitable a bankruptcy filing gets.

5 Conclusions, limitations and outlook

There is a lot of qualitative data contained in annual reports that could be analyzed in addition to quantitative data for predicting a later bankruptcy filing. It is the aim of the article to develop an approach of including qualitative data that can be extracted from SEC filings using the XBRL data format.

It is our main hypothesis that XBRL Taxonomies contain XBRL tags that can serve as red flags or warning signs for bankruptcy risk and eventually be used for an automated assessment of investment risk based on the narratives of annual reporting data. We develop a list of potential red flags based on the U.S. GAAP taxonomy and assign the elements to 2 categories and 7 subcategories. In assuming that companies facing a deterioration of business performance have higher incentives to earnings management behavior, Category 1 contains XBRL tags that presumably indicate earnings management (e.g., *RevenueRelatedParty*). Category 2 is comprised of XBRL tags that represent characteristics and influencing factors of companies near bankruptcy filing (e.g., *LongtermDebtDefault*). Then we test our red flags based on U.S. GAAP annual reports of 26 companies with Chapter 11 bankruptcy filings and a control group. The empirical results show that in total, the red flag item list has predictive power of bankruptcy risk. Logistic regression results also show that the predictive power is higher one year before the bankruptcy filing date in comparison with two years before the bankruptcy fil-

ing date. We furthermore observe that the category 2 red flags (bankruptcy characteristics and influencing factors) have higher discriminatory power than category 1 red flags (earnings management indicators) for one year before the bankruptcy filing date. This difference narrows for two years before the bankruptcy filing date and may turn in favor of category 1 red flags for three years before the bankruptcy filing date. The latter expectation would be concordant with Leach and Newsom (2007) that show in a time series analysis of bankrupt firm's earnings management behavior that the companies' financial statements exhibit high earnings management behavior five years prior to the bankruptcy filing date, whereas usually this behavior is reduced the nearer the bankruptcy filing date advances.

In summary, the results of our study contribute to the bankruptcy prediction literature as well as the earnings management detection literature. The red flag analysis based on XBRL filings can serve as an extension of classical credit scoring-approaches. One of the main advantages of using XBRL tags is that otherwise often unused information in the notes gets usable.

For example, Hirschey and Richardson (2003) find empirical evidence that investors still underreact to goodwill write-offs. Our red flag item list contains goodwill impairment charges as a red flag. With this instrument, investors might come to different results. Red flag analysis may also resolve limitations of conventional ratios as financial distress indicators like a possible bias through R&D spending (Franzen et al., 2007).

One first limitation concerns the realization in practice. So far the proposed model cannot be tested on real-life XBRL filings, as stated above. However the ongoing SEC XBRL mandate and especially the introduction of a detailed tagging requirement are positive perspectives. More and more (detailed tagged) XBRL filings will be available soon for analysis online via the SEC EDGAR database. Second, in today's XBRL implementation there still exist errors (Bartley et al., 2010), albeit the errors decrease due to increasing tagging experience (see <https://edgardashboard.xbrlcloud.com/edgar-dashboard/dashboard.do>). It is critical that companies' XBRL tagging is carried out accurately and thoroughly. This could be assured by an (mandatory) audit of XBRL filings (Plumlee and Plumlee, 2008). Third, a further limitation is that XBRL tagging only can be as good as the underlying disclosure. Also, we assumed that companies always use the XBRL tags in favor of taxonomy extensions. Maybe the SEC will decide to release more restrictive taxonomy extension rules. Otherwise some information may be lost due to difficulties in automatic analysis of taxonomy extensions. Also, the proposed analysis model and consequently our empirical study may be distorted by the fact that it can only contain information that is filed within the Form 10-K document. For example, section

G(3) of the SEC's general instructions for Form 10-K (SEC, 2012) allows SEC filers to store information as required by Item 13 of Form 10-K (information about transactions with related persons, promoters and certain control persons as well as information about director independence according to Items 404 and 407(a) of Regulation S-K) in proxy statements, if these are filed no later than 120 days after the fiscal period end of the respective Form 10-K document. If the latter is not the case, then the information must be filed as an amendment to Form 10-K.

Other limitations are inherent to red flag analysis. There are some potential indicators for financial distress for which we do not know that XBRL tags exist (yet) and therefore cannot be included into the red flag analysis. This involves for example, a change of auditors (Kluger and Shields, 1989), the reported doubt of future compliance with debt covenants and a delisting of the company. Examples are The Reader's Digest Association Inc.: "*A decline in our operating results or available cash could cause us to experience difficulties in complying with covenants contained in our financing agreements, which could result in our bankruptcy or liquidation.*" (The Reader's Digest Association Inc., 2008, p. 25) and BearingPoint Inc.: "*On November 13, 2008, the New York Stock Exchange (the "NYSE") notified the Company that it had decided to suspend trading in the Company's common stock prior to market open on November 17, 2008, based on its determination that the trading price of the Company's common stock was "abnormally low".*" (BearingPoint Inc., 2009, p. 2). Additionally, sometimes not only the occurrence of a certain issue is relevant but rather its amount or frequency (e.g., the amount of related party sales) – a problem that dummy variables cannot solve. Also, red flags may not be red flags but rather red herrings (Lundstrom, 2009), which means there is a possibility of "false alarm". For example, related party transactions have a twofold nature and can also be used with the objective to enhance the efficiency of an organization (Lin et al., 2010, p. 83).

Therefore, the red flag analysis should not be the exclusive research method, but rather a supplement to traditional approaches, and the analysis results always should be assessed with caution. However, this is in accordance to the definition of red flags that we have chosen, in which red flags are warning signs that identify issues that need further or deeper investigation.

Future research could broaden the data sample or the time series analysis. Also the search for yet more discriminatory XBRL tags would be interesting. However, the most interesting part of future research will be to analyze real-life XBRL filings. Up to now the SEC's XBRL filing mandate is still in its beginning stages, but this soon will change. Hence, the accessibility

of annual reporting information for investors through improved automatic analysis possibilities and as a result the transparency for investors increases. This is also true for qualitative information, as this study has shown.

Notes

- ¹ We interpret the theme “content analysis” in the sense of Weber (1990) as thematic content analysis. Thus, contrary to Jones and Shoemaker (1994), we are not including readability analysis within the definition scope of the theme “content analysis”.
- ² The taxonomies supported by the SEC XBRL mandate are listed on the Web site <http://www.sec.gov/info/edgar/edgartaxonomies.shtml>.
- ³ A taxonomy viewer is available online at <http://viewer.xbrl.us/yeti2/resources/yeti-gwt/Yeti.jsp>. The UGT also can be downloaded in Excel at <http://xbrl.us/taxonomies/Pages/US-GAAP2011.aspx>.
- ⁴ We see a calculation of intercoder reliability to be not within the scope of this study. For further information about the issue of measuring intercoder reliability see Popping (1988), who points out 39 different agreement indices for coding nominal categories.

Appendix

Appendix A: Red Flag Items List

Table A1

	#	Independent Variables or Red Flags	Variable Definitions (equates to the XBRL names and respective documentations drawn from the UGT 2011)
Category 1: Indicators for Earnings Management I Revenue Recognition (REVREC)	1	I BillHold	<i>RevenueRecognitionBillAndHoldArrangements</i> = Disclosure of accounting policy for revenue recognition under bill and hold arrangements. This disclosure addresses how all criteria and factors used in evaluating bill and hold arrangements are met in order for revenue recognition.
	2	I UnbilledRev	<i>UnbilledReceivablesCurrent</i> = The amount due for services rendered or products shipped, but not yet billed, recognized in conformity with revenue recognition criteria. This element is distinct from unbilled contracts receivables because this is based on noncontract transactions.
	3	I IncreaseUnbilledRev	<i>IncreaseDecreaseInUnbilledReceivables</i> = The increase (decrease) during the reporting period of the amount of revenue for work performed for which billing has not occurred, net of uncollectible accounts.
	4	I UnbilledContractsRev	<i>UnbilledContractsReceivable</i> = Unbilled amounts due for services rendered or to be rendered, actions taken or to be taken, or a promise to refrain from taking certain actions in accordance with the terms of a legally binding agreement between the entity and, at a minimum, one other party. An example would be amounts associated with contracts or programs where the recognized revenue for performance thereunder exceeds the amounts billed under the terms thereof as of the date of the balance sheet.
	5	I UnbilledRevNotBillable	<i>UnbilledReceivablesNotBillableAtBalanceSheetDate</i> = The total amount of unbilled receivables from customers under long-term contracts that have not been billed and were not billable at the balance sheet date.
	6	I GovContractRevUnbilled	<i>GovernmentContractReceivableUnbilledAmounts</i> = Unbilled amounts (net of unliquidated progress payments) of government contract receivables.
	7	I ChangesPoC	<i>ContractsAccountedForUnderPercentageOfCompletion</i> = Modifications to or changes in assumptions surrounding contracts accounted for under the percentage of completion method of accounting. Percentage of completion is a method of accounting whereby profit on a long-term (construction) contracts is recognized based on reliable estimates as to the degree of completion generally based on contractual relationships (costs incurred to total costs anticipated).
	8	I PoC	<i>RevenueRecognitionPercentageOfCompletionMethod</i> = Disclosure of accounting policy for revenue recognition for long-term construction-type contracts accounted for using the percentage-of-completion method. The disclosure would generally be expected to include the method or methods of measuring extent of progress toward completion. If the entity departs from using the percentage-of-completion method for a single contract or a group of contracts for which reasonably dependable estimates cannot be made, such a departure from the basic policy is disclosed. The disclosure may also describe the accounting for significant changes in estimate.

Notes:

This table displays the 43 XBRL tags that we decided to add to the red flag item list consistent with reasons discussed in the literature as well as the respective assigned variable names.

Table A1 (Continued)

	#	Independent Variables or Red Flags	Variable Definitions (equates to the XBRL names and respective documentations drawn from the UGT 2011)	
Category 1: Indicators for Earnings Management	2 Off-balance-sheet financing (OFFBALFIN)	9	2 ReserveOffBal	<i>ReserveForOffBalanceSheetActivitiesMember</i> = Accrued liability to reflect obligations, contingent liabilities, and other exposures relating to off-balance sheet arrangements such as unfunded loan commitments, contractual obligations, recourse from loans securitized, and variable interest entities.
		10	2 SaleLeaseback	<i>SaleLeasebackTransactionDescription</i> = A description of the significant provisions of the transaction involving the sale of property to another party and the lease of the property back to the seller.
		11	2 ABS	<i>AssetBackedSecuritiesMember</i> = This category includes information about securities that are primarily serviced by the cash flows of a discrete pool of receivables or other financial assets (such as mortgage loans or credit-card receivables).
		12	2 ProceedsABS	<i>ProceedsFromRepaymentsOfAccountsReceivableSecuritization</i> = Proceeds from (repayments of) securitizations of receivables treated as collateralized borrowings, which are classified as financing transactions.
		13	2 VIENonConsolidated	<i>VariableInterestEntityNonconsolidatedCarryingAmountAssetsAndLiabilitiesNet</i> = The net carrying amount of the assets and liabilities in the reporting entity's statement of financial position that relate to the reporting entity's variable interest in the Variable Interest Entity (VIE).
	3 Changes in Estimates (CHINEST)	14	3 ServLife	<i>ServiceLifeMember</i> = A revision in the estimated economic useful life of a long-lived tangible asset (the period of time over which the asset is projected to benefit operations).
		15	3 AmortPeriod	<i>IntangibleAssetsAmortizationPeriodMember</i> = A revision in the estimated economic useful life of a finite-lived intangible asset (the period of time over which the asset is projected to benefit operations).
		16	3 ChInEstimate	<i>ChangeInAccountingEstimateDescription</i> = Describes the specific accounting estimate that was revised, including the nature of and justification for the revision.
		17	3 Salv Value	<i>SalvageValueMember</i> = A revision in the estimated value of an asset at the end of its useful life.
		18	3 InventoryVal	<i>InventoryValuationAndObsolescenceMember</i> = A revision in the estimate of excess and obsolete inventory to reduce the carrying amount of inventory to net realizable value.
		19	3 GoodwillImpCh	<i>GoodwillImpairedChangeInEstimateDescription</i> = Description of a change in the estimated amount of a goodwill impairment charge, including the facts and circumstances, including a change in assumptions, underlying the change in estimate.
		20	3 WarrantyCh	<i>WarrantyObligationsMember</i> = A revision in the estimated costs to be incurred to make repairs or fix problems on sold goods or services pursuant to promises or guarantees made as to satisfactory performance.
		21	3>ReturnsCh	<i>SalesReturnsAndAllowancesMember</i> = A revision in the estimated reserve needed for product returns and price or other concessions granted to customers.
22	3 ChPensionPlans	<i>ChangeInAssumptionsForPensionPlansMember</i> = Revisions in the assumptions (for instance, investment yield on plan assets, projected increase in salaries and compensation, forfeitures, discount rate) used in calculating the amount of liability and period expense associated with pension obligations.		

Table A1 (Continued)

	#	Independent Variables or Red Flags	Variable Definitions (equates to the XBRL names and respective documentations drawn from the UGT 2011)	
Category 1: Indicators for Earnings Management	4 Related Party Transactions (RELPARTY)	23	4 RevRelParty	<i>RevenueFromRelatedParties</i> = Revenues arising from transactions between (a) a parent company and its subsidiaries; (b) subsidiaries of a common parent; (c) an entity and trusts for the benefit of employees, such as pension and profit-sharing trusts that are managed by or under the trusteeship of the entity's management; (d) an entity and its principal, owners, management, or members of their immediate families; and (e) affiliates.
		24	4 IncreaseDueFromRelParties	<i>IncreaseDecreaseInDueFromRelatedParties</i> = The increase (decrease) during the reporting period in receivables to be collected from other entities that could exert significant influence over the reporting entity.
		25	4 DueToRelParties	<i>DueToRelatedPartiesCurrentAndNoncurrent</i> = Carrying amount as of the balance sheet date of obligations due all related parties.
		26	4 IncreaseDueToRelParties	<i>IncreaseDecreaseInDueToRelatedParties</i> = The increase (decrease) during the reporting period in the aggregate amount of obligations to be paid to the following types of related parties: a parent company and its subsidiaries; subsidiaries of a common parent; an entity and trust for the benefit of employees, such as pension and profit-sharing trusts that are managed by or under the trusteeship of the entities' management; an entity and its principal owners, management, or member of their immediate families; affiliates; or other parties with the ability to exert significant influence.
		27	4 SaleLeasebackRelParty	<i>SaleLeasebackTransactionRelatedPartyTransaction</i> = An indication that the transaction involving the sale of property to another party and the lease of the property back to the seller was entered into with a party connected to the seller.
		28	4 RelPartyChTerms	<i>RelatedPartyTransactionEffectsOfAnyChangeInMethodOfEstablishingTerms</i> = Description of the effects of any change in the method of establishing the terms of a related party transaction for example, pricing terms, from that used in the preceding period.
		29	5 ChAccountingMethod	<i>ChangeInAccountingMethodAccountedForAsChangeInEstimateMember</i> = A change from one acceptable accounting method to another based upon a revision in estimated future benefits or obligations.
		30	5 ChMeasurementMethodsSegmentProfitOrLoss	<i>DescriptionOfNatureOfChangesFromPriorPeriodsInMeasurementMethodsUsedToDetermineReportedSegmentProfitOrLossAndEffectOfThoseChangesOnMeasureOfSegmentProfitOrLoss</i> = A description of the nature of any changes from prior periods in the measurement methods used to determine reportable segment profit or loss and the effect, if any, of those changes on the measure of segment profit or loss.
5 Others (OTHERS)	31	5 ChDateGoodwillImp	<i>DisclosureOfChangeOfDateForAnnualGoodwillImpairmentTest</i> = Change of date of the goodwill impairment test, which is performed at least annually.	
	32	5 FourthQuarter	<i>YearEndAdjustmentsEffectOfFourthQuarterEventsDescription</i> = Description of a material transaction, such as a business combination, disposal of business (or components of an entity), extraordinary or unusual events, significant changes in accounting estimates and the aggregate effect of year-end adjustments, that occurred during the fourth quarter.	
	33	5 Reclass	<i>Reclassifications</i> = The entire disclosure for classifying current financial statements, which may be different from classifications in the prior year's financial statements. Disclose any material changes in classification including an explanation of the reason for the change and the areas impacted.	
	34	5 UnusualOrInfrequent	<i>UnusualOrInfrequentItemGross</i> = The gross gain (loss) income statement effect of each material event or transaction (that would not reasonably be expected to recur in the foreseeable future) that possesses a high degree of abnormality and are clearly unrelated to, or incidentally related to, the ordinary and typical activities of the entity.	

Table A1 (Continued)

	#	Independent Variables or Red Flags	Variable Definitions (equates to the XBRL names and respective documentations drawn from the UGT 2011)
Category 2: Seldom Events and Bankruptcy Characteristics	6 Events (EVTS)	35	6 BusInterruption <i>BusinessInterruptionLossesNatureOfEvent</i> = A description of the event that resulted in a business interruption loss.
		36	6 ContractTermination <i>Gain Loss OnContractTermination</i> = This element represents the income received from or payment made to a third party in connection with the termination of a contract between the parties. The termination may be due to many causes including early termination of a lease by a lessee, a breach of contract by one or the other party, a failure to perform.
	7 Bankruptcy Characteristics (BANKRPTY)	37	7 RestructuringCharges <i>RestructuringCharges</i> = Amount charged against earnings in the period for incurred and estimated costs associated with exit from or disposal of business activities or restructurings pursuant to a duly authorized plan, excluding asset retirement obligations.
		38	7 SeveranceCosts <i>SeveranceCosts</i> = The charge against earnings in the period for known and estimated costs of termination benefits provided to current employees that are involuntarily terminated under a benefit arrangement associated with exit from or disposal of business activities or restructurings pursuant to a duly authorized plan, excluding costs or losses pertaining to an entity newly acquired in a business combination or a discontinued operation as defined by generally accepted accounting principles and costs associated with one-time termination benefits.
		39	7 GoodwillImpLoss <i>GoodwillImpairmentLoss</i> = Loss recognized during the period that results from the write-down of goodwill after comparing the implied fair value of reporting unit goodwill with the carrying amount of that goodwill. Goodwill is assessed at least annually for impairment.
		40	7 GoingConcern <i>LiquidityDisclosureGoingConcernNote</i> = If there is a substantial doubt about an entity's ability to continue as a going concern for a reasonable period of time (generally a year from the balance sheet date), disclose: (a) pertinent conditions and events giving rise to the assessment of substantial doubt about the entity's ability to continue as a going concern for a reasonable period of time, (b) the possible effects of such conditions and events, (c) management's evaluation of the significance of those conditions and events and any mitigating factors, (d) possible discontinuance of operations, (e) management's plans (including relevant prospective financial information), and (f) information about the recoverability or classification of recorded asset amounts or the amounts or classification of liabilities.
		41	7 DivInArrears <i>PreferredStockAmountOfPreferredDividendsInArrears</i> = Aggregate amount of cumulative preferred dividends in arrears.
		42	7 ShorttermDebtDefault <i>DebtDefaultShorttermDebtDescriptionOfViolationOrEventOfDefault</i> = Discussion of the facts and amounts pertaining to each failure to comply with an affirmative or negative covenant of a short-term debt instrument, including violating payment terms or an inability to meet certain minimum financial requirements or achieve or maintain certain financial ratios. The discussion would generally be expected to also include whether or not the failure can and will be overcome and a description of the terms of any waivers, including the amount of the waiver and the period of time covered by the waiver.
		43	7 LongtermDebtDefault <i>DefaultLongtermDebtDescriptionOfViolationOrEventOfDefault</i> = Discussion of the facts and amounts pertaining to each failure to comply with an affirmative or negative covenant of a long-term debt instrument, including violating payment terms or an inability to meet certain minimum financial requirements or achieve or maintain certain financial ratios. The discussion would generally be expected to also include whether or not the failure can and will be overcome and a description of the terms of any waivers, including the amount of the waiver and the period of time covered by the waiver, and if reclassification of long-term debt to current has been made in the current balance sheet.

Appendix B: Data Sample

Table A2
Data Sample

#	Chapter 11 Filers	Year of Bankruptcy Filing	Industry	Competitors
1	BearingPoint Inc.	2009	Consulting/Legal/Accounting	CACI International Inc.
2	Chemtura Corp.	2009	Chemicals, Manufacturing	Albermarle Corp.
3	Citadel Broadcasting Corp.	2009	Media	Radio One Inc.
4	Cooper-Standards Holdings Inc.	2009	Automobile/Auto Parts/Services, Manufacturing	Clarcor Inc.
5	FairPoint Communications Inc.	2009	Telecommunications/Cable	Comcast Corp.
6	Hayes Lemmerz International Inc.	2009**	Automobile/Auto Parts/Services, Manufacturing	Accuride Corp.
7	Idearc Inc.	2009	Business Services, Media	AT&T Inc.
8	Lear Corp.	2009	Automobile/Auto Parts/Services, Manufacturing	Johnson Controls Inc.
9	Nortek Inc.	2009	Manufacturing , Construction/Engineering	Lennox International Inc.
10	Six Flags Inc.	2009	Entertainment/Recreation	Walt Disney Corp.
11	Spansion Inc.	2009	Manufacturing, Computers & Electronics	Micron Technology Inc.
12*	The Reader's Digest Association Inc.	2009**	Advertising & Marketing, Media	Meredith Corp.
13	Visteon Corp.	2009	Automobile/Auto Parts/Services, Manufacturing	TRW Automotive Holdings Corp.
14	Circuit City Stores Inc.	2008	Retail, Computer & Electronics	Radioshack Corp.
15	Hawaiian Telcom Communications Inc.	2008	Telecommunications/Cable	Alaska Communications Systems Group Inc.
16	Linens Holding Corp.	2008	Retail, Household Products	Bed Bath & Beyond Inc.
17	Pilgrim's Pride Corp.	2008	Food & Beverage	Sanderson Farms Inc.
18	VeraSun Energy Corp.	2008	Energy, Manufacturing	Lubrizol Corp.
19	WCI Communities Inc.	2008	Construction/Engineering	Centex Corp.
20	Buffets Holdings Inc.	2008	Restaurants, Foods & Beverage	Cracker Barrel Inc.
21	Chesapeake Corp.	2008	Mail/Packaging, Manufacturing	Greif Inc.
22	Kimball Hill Inc.	2008**	Construction/Engineering, Homebuilder	The Ryland Group Inc.
23	Pierre Foods Inc.	2008	Food & Beverage	Tyson Foods Inc.
24	SIRVA Inc.	2008	Transportation	Ryder Systems Inc.
25	Movie Gallery Inc.	2007	Entertainment/Recreation, Retail	Netflix Inc.
26	Dura Automotive Systems Inc.	2006	Automobile/Auto, Parts/Services, Manufacturing	Arvinmeritor Inc.

Notes:

Our study is based on U.S. GAAP annual reports (Form 10-K or 10-K/A) of 26 US-companies that filed for Chapter 11 bankruptcy between 2006 and 2009 and 26 matched competitor companies that did not file for Chapter 11 in the respective year. For a time series analysis, we analyze the annual report with a fiscal year end directly before the bankruptcy filing year (one year before bankruptcy) and the year before (two years before bankruptcy). The (*) mark refers to the pair of companies that we eliminate for the examination of two years before bankruptcy, because there is no Form 10-K available for The Reader's Digest Association Inc. for the Fiscal Year 2007. The (***) marks refer to annual reports with a fiscal year end other than 12/31/XX.

Appendix C: Mean Usage Rates

Table A3

#	Red Flags	One year before the bankruptcy filing date			Two years before the bankruptcy filing date			
		Bankrupt (N = 26)	Healthy (N = 26)		Bankrupt (N = 25)	Healthy (N = 25)		
		Mean Usage Rate	Mean Usage Rate	Δ	Mean Usage Rate	Mean Usage Rate	Δ	
1	7 GoingConcern	50,00%	0,00%	50,00%	0,00%	0,00%	0,00%	↑
2	7 LongtermDebtDefault	34,62%	0,00%	34,62%	4,00%	0,00%	4,00%	↑
3	4 RevRelParty	30,77%	0,00%	30,77%	24,00%	0,00%	24,00%	↑
4	4 DueToRelParties	38,46%	11,54%	26,92%	40,00%	20,00%	20,00%	↑
5	7 GoodwillImpLoss	50,00%	23,08%	26,92%	20,00%	4,00%	16,00%	↑
6	3 InventoryVal	26,92%	7,69%	19,23%	0,00%	0,00%	0,00%	↑
7	5 ChMeasurementMethodsSegmentProfitOrLoss	19,23%	0,00%	19,23%	8,00%	8,00%	0,00%	↑
8	3 WarrantyCh	30,77%	15,38%	15,38%	16,00%	24,00%	-8,00%	↑
9	6 ContractTermination	30,77%	15,38%	15,38%	12,00%	4,00%	8,00%	↑
10	7 SeveranceCosts ¹	61,54%	50,00%	11,54%	52,00%	44,00%	8,00%	↑
11	7 DivInArrears	19,23%	7,69%	11,54%	0,00%	0,00%	0,00%	↑
12	1 UnbilledContractsRev	7,69%	0,00%	7,69%	0,00%	0,00%	0,00%	↑
13	2 ReserveOffBal	26,92%	19,23%	7,69%	24,00%	12,00%	12,00%	↓
14	2 ABS	26,92%	19,23%	7,69%	20,00%	16,00%	4,00%	↑
15	3 ServLife	7,69%	0,00%	7,69%	8,00%	4,00%	4,00%	↑
16	4 IncreaseDueFromRelParties	11,54%	3,85%	7,69%	8,00%	0,00%	8,00%	↓
17	5 ChAccountingMethod	7,69%	0,00%	7,69%	8,00%	4,00%	4,00%	↑
18	5 FourthQuarter	15,38%	7,69%	7,69%	48,00%	36,00%	12,00%	↓
19	5 UnusualOrInfrequent	7,69%	0,00%	7,69%	8,00%	0,00%	8,00%	↓
20	7 RestructuringCharges ¹	53,85%	46,15%	7,69%	48,00%	40,00%	8,00%	↓
21	1 GovContractRevUnbilled	3,85%	0,00%	3,85%	4,00%	0,00%	4,00%	↓
22	2 SaleLeaseback	15,38%	11,54%	3,85%	12,00%	8,00%	4,00%	↓
23	2 ProceedsABS	3,85%	0,00%	3,85%	8,00%	4,00%	4,00%	↓
24	3 ReturnsCh	3,85%	0,00%	3,85%	4,00%	4,00%	0,00%	↑
25	3 ChPensionPlans ¹	65,38%	61,54%	3,85%	56,00%	64,00%	-8,00%	↑
26	4 IncreaseDueToRelParties	11,54%	7,69%	3,85%	8,00%	0,00%	8,00%	↓
27	3 SalvValue	3,85%	3,85%	0,00%	4,00%	4,00%	0,00%	↔
28	1 UnbilledRev	0,00%	3,85%	-3,85%	4,00%	4,00%	0,00%	↓
29	1 UnbilledRevNotBillable	0,00%	3,85%	-3,85%	0,00%	0,00%	0,00%	↓
30	5 ChDateGoodwillImp	0,00%	3,85%	-3,85%	0,00%	0,00%	0,00%	↓
31	5 Reclass ¹	57,69%	61,54%	-3,85%	80,00%	72,00%	8,00%	↓
32	1 PoC	3,85%	11,54%	-7,69%	4,00%	8,00%	-4,00%	↓
33	3 ChInEstimate ¹	61,54%	80,77%	-19,23%	72,00%	88,00%	-16,00%	↓

Notes:

This table contains an overview of the mean usage rates of the red flag items within the examined annual reports (see Appendix B) with fiscal year ends one year and two years before the bankruptcy filing date of the bankrupt group of companies. The table also displays the mean usage rate difference of the single XBRL tags for the bankrupt and healthy group of companies (Δ) as well as the fact, whether the mean usage rate difference increases (↑), decreases (↓) or stays unchanged (↔) one year before the bankruptcy filing date as compared to two years before the bankruptcy filing date. The red flag items are sorted descending according to the magnitude of the mean usage rate difference for one year before the bankruptcy filing date. We calculate the mean usage rate by relating the observed frequency of occurrence of the red flags to the maximum observable frequency of occurrence of red flags. Of the red flag item list that contains 43 red flags (see Appendix A), the table omits the following 10 XBRL tags, because they are not disclosed in either of the examined annual reports for one year before the bankruptcy filing date: 1|BillHold, 1|IncreaseUnbilledRev and 1|ChangesPoC (subcategory REVREC), 2|VIENonConsolidated (subcategory OFFBALFIN), 3|AmortPeriod and 3|GoodwillImpCh (subcategory CHINEST), 4|SaleLeasebackRelParty and 4|RelPartyChTerms (subcategory RELPARTY), 6|BusInterruption (subcategory EVTS) and 7|ShorttermDebtDefault (subcategory BANKRPTY). Model 1 contains the remaining 33 red flag items. The mark ⁽¹⁾ indicates the red flag items that were eliminated for an optimized red flag item list (model 2), because of an absolute occurrence in ten or more examined annual reports for the bankrupt group of companies and the healthy group of companies respectively.

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Klaus Henselmann / Elisabeth Scherr

Content analysis as an efficient supplement of bankruptcy prediction?

Empirical evidence based on U.S. GAAP annual reports

Most of the bankruptcy prediction models developed so far have in common that they are based on quantitative data or more precisely financial ratios. However, useful information can be lost when disregarding soft information. In this work, we develop an automated content analysis technique to assess the bankruptcy risk of companies using XBRL tags. We develop a list of potential red flags based on the U.S. GAAP taxonomy and assign the elements to 2 categories and 7 subcategories. Then we test our red flag item list based on U.S. GAAP annual reports of 26 companies with Chapter 11 bankruptcy filings and a control group. The empirical results show that in total, the red flag item list has predictive power of bankruptcy risk. Logistic regression results also show that the predictive power increases the nearer the bankruptcy filing date approaches. We furthermore observe that the category 2 red flags (bankruptcy characteristics and influencing factors) have higher discriminatory power than category 1 red flags (earnings management indicators) for one year before the bankruptcy filing date. This difference narrows for two years before the bankruptcy filing date and may turn in favor of category 1 red flags for three years before the bankruptcy filing date.

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