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Accounting Information Risk and Credit Ratings

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To the Graduate Council:

I am submitting herewith a dissertation written by Douglas Ray Ayres entitled "Accounting Information Risk and Credit Ratings." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

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Accounting Information Risk and Credit Ratings

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Dedication

This work is dedicated to my sons, Aiden and Dylan Ayres. Without their love and the purpose they bring to my life, none of this would have been possible.

This work is also dedicated to my mother, Jodean Ayres. Without her support, I could not have accomplished what I have.

This work is also dedicated to my fiancée, Shiona Christensen. My present and future resonate with beauty because of her.

Abstract

Using a sample of U.S. firms, this study explores whether accounting information risk has an impact upon corporate credit ratings, a long term measure of the cost of debt. Theory suggests that accounting information risk could impact shorter term measures of the cost of debt, but is unclear as to whether it will have measurable effects upon the long term cost of debt. This study employs SFAS 157 level three fair value disclosures as a proxy for accounting information risk. The findings suggest higher levels of accounting information risk negatively impact credit ratings. This is supported by both levels and changes analyses. Increases to accounting information risk are also more effective in prohibiting a credit upgrade than in effectuating a credit downgrade. These findings are also robust to matching techniques and other model specifications. Ultimately, these findings support the usefulness and efficacy of disclosures for uncertain fair value accounting estimates.

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Chapter One: Introduction

Reliability is often seen as a desired trait by financial statement users, but this often conflicts with the competing goal of relevance. Prior literature has considered various aspects of reliability and more recently this focus has been directed towards fair value measurements. The use of fair value measurements has been a hotly debated and well researched topic for the past 20 years (Barth 1994; Eccher et al. 1996; Nelson 1996; Holthausen and Watts 2001; Barth et al. 2001). Proponents of fair value measurements argue such treatments make financial statements more relevant and useful to the investor and thus assist in the efficient pricing of assets (e.g. firms) while detractors argue that such measurements are a significant source of accounting information risk as they are less reliable, are easier for management to manipulate, and lead to increased volatility. To detractors, historical cost accounting thus provides the best basis of measurement (Barth et al. 1996; Benston 2008; Ramanna 2013).

This study examines whether accounting information risk affects perceptions of a firm's credit risk. Similar to Riedl and Serafeim (2011), accounting information risk herein is defined as the relative ability of financial statement users to ascertain the valuation parameters of a particular asset. Throughout this paper, SFAS 157 fair value disclosures are employed as a proxy for accounting information risk. SFAS 157 standardized disclosures of ***how*** fair value assets and liabilities are valued. Financial statement users can now quantify each company's exposure to "difficult to value" assets and liabilities. Thus, SFAS 157 disclosures are a proxy for accounting information risk.

Theory suggests that accounting information risk could impact the short term cost of debt, but it remains unclear as to whether it will have a measurable effect on the long term cost of debt (Duffie and Lando 2001). This paper extends the empirical work of Riedl and Serafeim (2011), Song et al. (2010) and Arora et al. (2014), whom all find that SFAS 157 fair value disclosures are value relevant to investors and have differential levels of impact depending upon the disclosed level of accounting information risk. Riedl and Serafeim (2011) find that the presence of accounting information risk has an impact upon equity risk for financial institutions.[1] In a similar vein, Song et al. (2010) find that the value relevance of level one and level two SFAS 157 fair value disclosures for financial institutions is more pronounced than level three disclosures. While Riedl and Serafeim (2011) document the impact of accounting information risk on a firm's cost of equity, it is also important to examine what constitutes risk to debt holders as this risk cannot be directly inferred from the risks to equity holders (Barth et al. 2012; Blankespoor et al. 2013).

One key measure of risk used by a firm's debt holders is the firm's credit rating. Credit ratings have material economic implications as changes to credit ratings have a direct effect on the pricing of stocks and bonds (Holthausen and Leftwich 1986; Hand et al. 1992). Credit ratings also impact the decision processes of management since managers are very concerned with maintaining or improving their firm's credit rating (Graham and Harvey 2001). Credit ratings are also employed in financial contracts for covenants and other purposes (Ayers et al. 2010). Many institutional investors require certain minimum credit rating levels before they will invest in a firm

[1] Level three assets and liabilities are defined by SFAS 157. These assets and liabilities are measured using unobservable inputs / assumptions and thus are exposed to higher levels of accounting information risk than are other fair value measurements. These types of assets and liabilities are also often valued using a theoretical valuation model (e.g., the Black-Scholes option pricing model) with assumptions being made for the inputs to the model (e.g. the volatility factor within the Black-Scholes model). As a result, the choice of both the valuation model and the inputs / assumptions for the model can have a large impact on the particular asset or liability being valued.

(Daniels and Jensen 2004). Furthermore, allegations of bias in credit ratings during the financial crisis have increased the visibility of the ratings process and have raised questions in regard to what information is actually used to determine a firm's credit rating or how this information is actually employed (Barth et al. 2012; Ayers et al. 2010; Griffin and Tang 2011). Thus, determining the influence of accounting information risk upon credit ratings is an important question.

A study similar to this one is Arora et al. (2014). The authors find that accounting information risk has an effect on the term structure of credit default swaps, increasing the price of short term credit default swaps relative to long term credit default swaps. However, credit ratings are a different construct from credit default swaps for a number of reasons. First, the credit rating process is notoriously opaque and incorporates a mixture of public and private information as well as quantitative and qualitative information (Damodaran 2012; Griffin and Tang 2012).[2] Thus, credit ratings are different from other measures of the cost of debt such as bond yields, which are generally thought to be based upon public information (Barth et al. 2012; Hull et al. 2004). Second, ratings agencies tend to favor stability in credit ratings, have a longer term outlook and are more focused upon the credit worthiness of the firm as a whole, while the prices of individual bonds and credit default swaps are much more volatile and impound the idiosyncratic risk features attributable to a particular debt issue (Hull et al. 2004).[3] Third, yields and credit default swaps for a particular credit rating level at a particular point in time can also have wide variation in their spreads (Hull et al. 2004). Fourth, credit ratings are purely concerned with default risk while bond yields and credit default swaps potentially impound other features of risk (e.g. liquidity) (Longstaff

[2] For instance, Standard & Poor's describes their data gathering process as one that incorporates data from audited and unaudited financial information, site visits, meetings with management, etc. (S&P 2008).
[3] It is rare for a firm to have multiple bond issues with different credit ratings (Daniels and Jensen 2004).

et al. 2005; Bongaerts et al. 2011). Fifth, changes in ratings have an impact on the pricing of credit default swaps and help to explain pricing differences in yield spreads; ratings are thus a potential source of information for both (Daniels and Jensen 2004; Hull et al. 2004). Finally, credit ratings and ratings agencies continue to persist as economic phenomena; the rise of the credit default swap market over the past two decades has not displaced this source of information or apparently rendered it obsolete.

The results herein indicate that higher levels of accounting information risk negatively impact credit ratings. This finding applies to both levels and changes models using credit ratings as the dependent variable. This finding is mainly attributable to financial industry firms. In addition, the effect is not symmetrical – year to year changes in accounting information risk have a much higher impact on the probability of a credit upgrade than on the probability of a credit downgrade. This paper also explores the effects of the financial crisis of the late 2000s and find that the financial crisis does not appear to be driving these results, as the overall relationship continues to hold in the years following the crisis. These results are robust to matching techniques and other model specifications.

This paper makes a contribution to the extant literature by showing that accounting information risk is a determinant of credit ratings, a result not necessarily predicted by the theory of Duffie and Lando (2001). This study also builds upon the works of Riedl and Serafeim (2011), Song et al. (2010), and Arora et al. (2014) in further developing our understanding of accounting information risk disclosures, especially within the context of credit markets. In a grander sense, the findings herein lend support and insight into the efficacy and usefulness of mandatory disclosures concerned with fair value accounting estimates.

Chapter Two: Relevant Literature and Hypothesis Development

Relevant Literature and Background

Accounting information risk has been thought to play a part in the pricing of assets. Lambert et al. (2007) derive a model which predicts that accounting information risk can affect the cost of capital of a firm beyond the effect of the underlying assets of the firm. From a debt holder's perspective, Duffie and Lando (2001) advocate that higher levels of accounting information risk can impact the credit term structure of a firm, (i.e. the difference between short and long term credit spreads) by essentially making shorter term credit maturities more expensive relative to longer term credit maturities. However, this theory does not predict any measurable impact upon the pricing of longer term maturities.

Riedl and Serafeim (2011), using level three assets and liabilities as a proxy for accounting information risk, build upon the work of Lambert et al. (2007) and empirically find that the presence of SFAS 157 level three assets and liabilities increases the cost of equity for financial institutions relative to level one and two assets and liabilities. In a similar fashion, Song et al. (2010) analyze banking firms during the financial crisis and find that the value relevance of level one and level two SFAS 157 fair value disclosures for financial institutions is greater than for level three disclosures. The prospect of accounting information risk thus appears to affect asset pricing from the standpoint of an equity investor.

Arora et al. (2014) explore whether accounting information risk has an impact on the term structure of credit default swaps. They test the theoretical work of Duffie and Lando (2001) and find that SFAS 157 level two and level three assets affect the pricing of short term credit default swaps relative to longer term credit default swaps. However, their analysis is limited to the time period of the financial crisis and they thus caution in regard to the generalizability of their results.

Aside from these studies in regards to SFAS 157 fair value disclosures, the role of fair value in accounting and its influence on accounting information risk has been heavily debated and well-researched. Proponents of fair value accounting argue that fair value accounting is more relevant than historical cost accounting while detractors argue that fair value accounting is less reliable (Barth 1994; Ramanna 2013). Historically, research on fair value disclosures has been mixed. Some studies found that historical cost yielded more explanatory power in regard to asset pricing than did replacement cost or that fair value disclosures yielded very little incremental explanatory power over historical cost disclosures (Beaver et al. 1982; Bernard and Ruland 1987; Eccher et al. 1996; Nelson 1996; Harris and Ohlson 1987). In contrast, many competing studies found convincing evidence that fair value disclosures are in fact valued by the users of financial statements (Barth 1994; Barth et al. 1996; Venkatachalam 1996; Bell 1983; Haw and Lustgarten 1988; Blankespoor et al. 2013). Thus, the debate continues in regard to the costs and benefits of fair value disclosures.

SFAS 157 brought about an increased level of clarity to fair value accounting. Not only did it provide a uniform definition of fair value, but it also required uniform disclosure as to the *quality* of fair value measurement (FASB 2007). By requiring management to trifurcate their disclosure of fair value into three levels of measurement, financial statement users were provided a better means to assess accounting information risk. However, SFAS 157 did not require any new forms of fair value measurement. SFAS 157 applies to all fiscal years beginning after November 15, 2007 and requires that all assets and liabilities measured using fair value be grouped and disclosed into the following three levels based upon how the asset / liability is valued (FASB 2007):

Level One - measured using identifiable and quoted prices in active markets of the same asset / liability.

Level Two – measured using quoted prices for *similar* assets / liabilities in active markets or the same asset / liability in inactive markets, as well as other valuation inputs that are not quoted (e.g. interest rates).

Level Three – measured using unobservable inputs for the asset / liability, typically involving some theoretical method of valuation. These types of assets are usually untraded and can typically take the form of distressed securities, exotic derivatives, etc.

The nature of valuing level three assets and liabilities thus innately presents more accounting information risk to an investor. Measurement could simply be noisier and less precise due to the unobservable nature of the inputs and valuation model employed, even in an environment devoid of managerial bias. Level three measurements are thus subject to greater levels of information asymmetry than are level one and two measurements (Song et al. 2010).

An anecdotal examination of Bank of America's fair value measurements disclosure from its December 31, 2013 financial statements reveals that a wide range of assets falls within the three levels of disclosure and a material amount of the bank's fair value assets fall specifically within the level three disclosure level. These include assets as diverse as loans, derivatives and servicing rights.[4] While the overall holdings of level three assets is small relative to level one and level two assets, a small change in the values of the level three assets could have a material impact upon the earnings of Bank of America for any given financial reporting period.[5]

Hypothesis Development

Given the findings of Song et al. (2010), Riedl and Serafeim (2011), and Arora et al. (2014), it would be reasonable to assume that increased accounting information risk would be expected to negatively impact credit ratings. As potential estimation errors increase when assets and liabilities are valued with unobservable inputs using theoretical asset pricing models, it is not inconceivable to imagine that ratings agencies would factor this into their analysis of credit risk. However, the effect of accounting information risk upon credit ratings remains an empirical question. To date, no academic papers have examined the nexus of accounting information risk (especially as promulgated by SFAS 157) and credit ratings. The methods of the credit rating agencies to determine credit ratings has always been a mysterious and subjective process that incorporates a substantial amount of qualitative and quantitative information about each firm being rated (Damodaran 2012). Thus, we do not know if accounting information risk is actually incorporated into current decision making processes for rating agencies.

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[4] Other common examples of level thee assets include mortgage backed securities, non OTC derivatives, and long dated derivatives and/or options such as those used in the energy industry. Level three assets are thus fairly heterogeneous on a firm by firm basis and exist for both investment and hedging purposes.

[5] According to its December 31, 2013 Form 10-K, Bank of America had $31.8 billion in level three fair value assets and $9.3 billion in level three fair value liabilities on its December 31, 2013 balance sheet. It also had approximately 10.8 billion shares of common stock outstanding. A 1% directional error in the valuation of these assets and liabilities could result in an additional .04 in earnings per share (assuming all adjustments would flow through net income). Similar effects could also impact important balance sheet metrics commonly used in the analysis of financial statements, especially for highly levered firms.

Furthermore, because credit ratings agencies are concerned with the risk to creditors, they likely consider factors only relevant to creditors. Since creditors typically rank ahead of equity investors in regard to the rights of the cash flows of the firm or from the liquidation of its assets, they may be less concerned with accounting information risk because creditors are often buffeted by a larger margin of error to protect against losses. In a similar fashion, any cash flow effect (in terms of percentage change) from accounting information risk is likely to be more pronounced for the cash flows of interest to equity investors (e.g. net income, free cash flow to equity) as opposed to creditors (e.g. operating income, free cash flow to invested capital) due to the effects of leverage. If so, this could allow the cost of equity to be measurably affected by accounting information risk, as documented by the works of Riedl and Serafeim (2011) and Song et al. (2010), while a measurable impact could not exist for the cost of debt, especially longer term measures of the cost of debt. Furthermore, Duffie and Lando (2001) argue that accounting information risk is most likely to manifest itself in the pricing of short term debt and this effect could be negligible in the pricing of long term debt. Ratings agencies typically have a long term outlook in their ratings process. Hence, for these reasons, accounting information risk may not be a factor in the determination of credit ratings.

However, this paper's proxy for accounting information risk, SFAS 157 level three measurements, may not have a negative impact on credit ratings and could possibly have a positive impact because of the nature of some of the assets themselves. Many, but not all, of these assets take the form of derivative securities which are often designed in theory to reduce risk and cash flow volatility. Prior research has indicated that the proper use of derivatives can accomplish this (Nance et al. 1993; Geczy et al. 1997). If a substantial portion of level three measurements accomplish this task, then the presence of these types of securities could possibly reduce credit risk and improve ratings. Furthermore, Skreta and Veldkamp (2009) argue that increasing the complexity of the underlying assets to a ratings process could in fact increase ratings due to ratings inflation and opinion shopping, even in an environment devoid of bias or opportunism on the part of the ratings agencies themselves. Thus, for these reasons, the presence of SFAS 157 level three measurements, this paper's proxy for accounting information risk, could potentially improve ratings.

Given these differing reasons for why accounting information risk may be positively related, unrelated or negatively related to credit ratings, it remains an empirical question in regard to its actual relation to credit ratings. As a result, the following hypothesis is formulated in null form:

Hypothesis – No relation exists between a firm's accounting information risk and its credit ratings.

Chapter Three: Research Design, Sample Selection, and Main Results

Research Design

To explore the relation between accounting information risk and credit ratings, this paper employs the following pooled cross sectional model using ordered logistic regression:

$$[1] \quad RATING_{it} = \lambda_0 + \lambda_1 \, LVL\_3\_ASSETS_{it} + \lambda_2 \, OTHER\_FV\_ASSETS_{it} + \lambda_3 \, RETURN_{it} + \lambda_4 \, STD\_DEV_{it} + \lambda_5 \, SUBORDINATED_{it} + \lambda_6 \, INT\_COV_{it} + \lambda_7 \, BOOK\_MKT_{it} + \lambda_8 \, LIQUIDITY_{it} + \lambda_9 \, LOSS_{it} + \lambda_{10} \, ROA_{it} + \lambda_{11} \, MARGINS_{it} + \lambda_{12} \, LEVERAGE_{it} + \lambda_{13} \, LN\_AT_{it} + \lambda_{14} \, RATING_{it-1} + \sum INDUSTRY_{it} + \sum YEAR_{it} + \mu_{it}$$

Variable Definitions:

$RATING_{it}$	Firm *i*'s Standard & Poor's domestic long-term issuer credit rating (Compustat variable *splticrm*) for year *t.*[6] Ratings are assigned a number from 1 to 22 where the highest rating AAA = 22 and the lowest rating D = 1.
$LVL\_3\_ASSETS_{it}$	Firm *i*'s total dollar value of SFAS 157 level three assets (Compustat variable *aul3*) scaled by the book value of firm *i*'s total assets (Compustat variable *at).*
$OTHER\_FV\_ASSETS_{it}$	Firm *i*'s combined total dollar value of SFAS 157 level one and level two assets (Compustat variables *aqpl1*and *aol2*) scaled by the book value of firm *i*'s total assets (Compustat variable *at).*[7]
$RETURN_{it}$	Firm *i*'s buy and hold stock return (including dividends) from *t-1* until *t.*
STD_DEV_{it}	Firm *i*'s standard deviation of monthly stock returns from period *t-1* until *t.*

[6] This variable is lead four months following the end of the fiscal year to allow for the issuance of the financial statements and the incorporation of this information into credit ratings. Robustness tests also use three and five month leads of this variable. This variable is not lead for a full year or more months than five as subsequent quarterly financial statements may begin to have a confounding effect. This measurement treatment is similar to the one employed by Barth et al. (2012).

[7] In the robustness section this is split into separate variables. Song et al. (2010) do not find a meaningful difference in terms of value relevance between level one and level two assets.

$SUBORDINATED_{it}$	A dichotomous variable equal to 1 if firm *i* had subordinated debt as of time *t*.
INT_COV_{it}	Firm *i*'s interest coverage ratio as of time *t*. Defined as earnings before interest and taxes (Compustat variable *ebit*) divided by interest expense (Compustat variable *xint*).[8]
$BOOK\_MKT_{it}$	Firm *i*'s book value of equity (Compustat variable *ceq*) divided by the market value of equity (Compustat variable *mkvalt*).
$LIQUIDITY_{it}$	Firm *i*'s operating cash flows (Compustat variable *oancf*) divided by the total liabilities (Compustat variable *lt*).
$LOSS_{it}$	A dichotomous variable equal to one if firm i incurred negative net income (Compustat variable *ni*) during the year *t*.
ROA_{it}	Firm *i*'s return on assets as measured by net income (Compustat variable *ni*) before special items (Compustat variable *spi*) divided by total assets (Compustat variable *at*) during the year *t*.
$MARGINS_{it}$	Firm *i*'s ratio of earnings before taxes (Compustat variable *ebit*) to revenue (Compustat variable *revt*) during the year *t*.
$LEVERAGE_{it}$	Firm *i*'s ratio of short term debt (Compustat variable *dlc*) and long term debt (Compustat variable *dlt*) to total assets (Compustat variable *at*) during the year *t*.
LN_AT_{it}	Firm *i*'s natural log of total assets (Compustat variable *at*).
$INDUSTRY_{it}$	Indicator variable for firm *i*'s industry according to the Fama French 48 industry taxonomy (Fama and French 1997).
$YEAR_{it}$	Firm *i*'s fiscal year.
$RATING_{it-1}$	The one year lagged annual *RATING* for firm *i*.

The dependent variable, $RATING_{it}$, is an ordered variable ranging from 1 to 22 depending upon firm *i*'s Standard & Poor's domestic long-term issuer credit rating. A high number (e.g. 22) represents an excellent credit rating while a low number represents a poor credit rating. The model

[8] To minimize the effect of having observations with zero interest expense in the denominator and to keep these firms within the sample, this paper assumes a minimal amount of interest and then winsorizes this variable at the 1% and 99% levels to limit the effect of these extreme observations. Firms with no interest expense are important because they are likely to have the higher levels of credit quality and thus should remain in the sample.

is regressed using ordered logistic regression since the dependent variables are ordinal in nature.[9] All standard errors are clustered at the firm level.

The primary variable of interest and proxy for accounting information risk is $LVL\_3\_ASSETS_{it}$ which represents the firm's total disclosed level three fair value assets scaled by the total assets of the firm. This measure is similar to Song et al. (2010) and Riedl and Serafeim (2011). No directional prediction on the relation between this variable and a firm's level of credit ratings is made; it is possible that no true relation exists between these assets and a firm's credit ratings.

Following prior literature [e.g. (Cheng and Subramanyam 2008; Ayers et al. 2010; Ashbaugh-Skaife et al. 2006; Lee 2008; Barth et al. 2012)], this paper controls for other factors previously found to affect credit ratings. $OTHER\_FV\_ASSETS_{it}$ is used to control for the firm's level of exposure to other types of fair value assets as a positive correlation likely exists between level three assets and the other types of fair value assets (i.e. levels one and two).

A strong negative relation between the standard deviation in monthly stock returns, STD_DEV_{it}, and a firm's level of credit ratings is expected, as higher volatility in stock returns is often indicative of higher levels of risk. INT_COV_{it} is expected to be a proxy for the firm's ability to service its debt; thus, it should have a positive relation with credit ratings. $BOOK\_MKT_{it}$ is used to proxy for a firm's growth prospects and a negative relation between this ratio and a firm's credit ratings is expected since a higher ratio signals lower levels of expected growth. $LIQUIDITY_{it}$ is used to measure a firm's ability to meet its short term obligations and a positive relation between

[9] In a similar fashion, ordered logistic regression is employed by Barth et al. (2012) when credit ratings are the dependent variable.

$LIQUIDITY_{it}$ and $RATING_{it}$ should exist. A negative relation between $LOSS_{it}$ and $RATING_{it}$ and a positive relation between ROA_{it} and $RATING_{it}$ should also exist. Unprofitable firms should present higher levels of credit risk while profitable firms should display the contrary. Wider (larger) profit margins, $MARGINS_{it}$, should be associated with better credit ratings. $LEVERAGE_{it}$ measures the firms' usage of debt and a negative relation between $LEVERAGE_{it}$ and $RATING_{it}$ should be present. LN_AT_{it} is used to proxy for firm size and a positive relation between firm size and its credit ratings should be apparent as larger firms, in general, tend to be less risky and have lower costs of capital. $RATING_{it-1}$ is used to control for serial correlation in ratings as ratings are notorious for their "stickiness" (Ayers et al. 2010).[10]

Sample Selection and Data

The sample consists of all firm years beginning after November 15, 2007 (the date in which SFAS 157 first became mandatory) and ending on or before December 31, 2013. Standard & Poor's domestic long-term credit ratings and all financial statement variables are obtained from Compustat. Data for stock returns is provided by CRSP (Center for Research in Security Prices). The final sample only includes those observations for which all relevant variables are present and populated. This results in an overall sample size of 7,602 firm-years. Table One provides detail of the univariate descriptive statistics of the sample.[11]

Table One is separated into two panels. Panel A provides the descriptive statistics for the entire sample of firms. Because financial firms alone have been a prominent feature of this stream

[10] In robustness tests, the levels model is also estimated without the lagged ratings control variable and similar inferences are found, but for financial industry firms alone.
[11] To limit the impact of statistical outliers, all continuous variables have been winsorized at the 1% and 99% levels throughout the analysis, similar to Ayers et al. (2010) and Blankespoor et al. (2013).

of research given their propensity to hold large quantities of fair value assets (Arora et al. 2014; Song et al. 2010; Riedl and Serafeim 2011), separate descriptive statistics for financial industry firms are included in Panel B of Table One.[12] Fair value assets, by and large, represent a moderate proportion of company assets at approximately 9.9% of total assets (*LVL_3_ASSETS* and *OTHER_FV_ASSETS* combined), but they are much more prominent for financial firms at approximately 30.0% of assets. The same story holds for difficult to value assets (*LVL_3_ASSETS*) as these only comprise 0.5% of total assets for all firms on average but comprise 1.6% of total assets for financial firms.

The median rating (*RATING*) for all firms is BBB- (BBB for financial firms), which means that approximately one half of the sample could be considered investment grade or higher. This results in a slightly lower median credit rating for financial firms than those of Barth et al. (2012), but this is understandable given that their sample precedes the financial crisis while the sample herein is confined to the financial crisis and its aftermath, a period of heavy downgrade activity. Very few firm-years fall at the extremes of the ratings spectrum; only 34 firm years receive a credit rating of AAA while fewer (26) receive a credit rating of D.

Stock returns (*RETURN*) show a wide range of variation, as expected, given that the sample begins around the time of the inception of the financial crisis and the large negative stock returns that occurred during this time period, and it concludes in 2013 after several years of large positive stock market returns. The vast majority of firms appear to be able to service their debt commitments as the interest coverage ratio (*INT_COV*) exceeds one for the bulk of the sample. The majority of firms have market values that exceed book value (*BOOK_MKT*), as expected.

[12] Financial firms are defined as those being within the 6000's series of SIC codes.

14.3 % of all firm-years experience a net loss (*LOSS*) and this rate is higher (15.7%) for financial firms. Return on assets (*ROA*) is also lower for financial firms. Table Two provides Pearson (lower right-hand portion of the matrix) and Spearman (upper right – hand portion of the matrix) correlation coefficients for all variables for both the total sample and for financial firms alone. All correlations significant at the 0.10 level or lower are in bold.

Results

Table Three contains the results of the regression analysis using equation one via ordered logistic regression. All relevant z-statistics are presented in parentheses and all measures of statistical significance are two-tailed. All standard errors are clustered at the firm level. Column one represents the full sample of firms while column two represents only financial industry firms.

The variable of interest, *LVL_3_ASSETS*, is negatively related to *RATING* and is statistically significant in both regressions. This suggests that level three assets are representative of higher levels of risk to creditors. In an untabulated analysis, this model is analyzed for non-financial industry firms alone. *LVL_3_ASSETS* has a negative coefficient loading but no statistical significance (pval = 0.22). Column one is also re-estimated (untabulated) with the addition of an indicator variable for financial industry firms and an interaction between this indicator and *LVL_3_ASSETS*. This results in a negative coefficient on the interaction term, but the interaction term displays no statistical significance. The main effect thus appears more concentrated in financial firms but this is not entirely conclusive.[13] Given the results of Table Three, the null

[13]Industry fixed effects are employed for the regressions on financial firms based on the four financial industries (banks, insurance, real estate, and other finance) contained within the Fama French 48 taxonomy.

hypothesis stating that accounting information risk is unrelated to a firm's credit rating is rejected.[14]

This result does not appear to transfer to other types of fair value assets, as the coefficients on *OTHER_FV_ASSETS* are largely insignificant. The other covariates appear to display appropriate relations with *RATING*. Volatility in stock returns (*STD_DEV*) is negatively associated with ratings. Firms with lower growth prospects (high ratio of *BOOK_MKT*) are associated with lower ratings. Increased liquidity (*LIQUIDITY*) is related to higher levels of credit ratings. The presence of a loss (*LOSS*) is associated with lower ratings and a higher return on assets (*ROA*) is associated with higher ratings. Higher levels of leverage (*LEVERAGE*) is associated with lower credit ratings while firm size (*LN_AT*) is associated with higher credit ratings.

In order to gauge economic significance and similar to Barth et al. (2012), column two of Table Three is re-estimated (untabulated) using OLS instead of ordered logistic regression. Doing so allows one to assess the average effect of the variable of interest. The coefficient on *LVL_3_ASSETS* becomes -1.26 and retains its statistical significance. This means that a one standard deviation change (0.029) in *LVL_3_ASSETS* for financial industry firms results in a lower credit rating of 0.037, on average. However, the results herein could also be driven by non-linear relationships that compound in magnitude as the variable of interest increases. Accordingly, an untabulated quintile rank analysis is performed, replacing the continuous measure

[14] This model is also estimated (untabulated) using firm-level fixed effects via an indicator variable for each firm. The inferences from Table Three remain intact for this approach; the coefficients on *LVL_3_ASSETS* are negative and retain statistical significance, but only for the analysis of financial firms. This alleviates concerns that the results in Table Three are driven by additional unobserved firm-level traits.

LVL_3_ASSETS, with a quintile rank variable (taking ordinal values from one through five) in its place.[15] First, column two of Table Three is re-estimated and similar results are found using this ranked variable. A similar procedure is conducted using OLS. The OLS coefficient on the ranked variable becomes -0.019. This suggests that belonging to the fifth quintile results in an approximately 0.076 (0.019 x 4) lower credit rating than belonging to the first quintile. Given that the yield spread between levels of credit ratings can be as much as 80 or more basis points, this result appears to be economically meaningful.[16]

To further explore potential non-linear effects of level three assets on credit ratings, separate dummy variables for each of the quintiles of *LVL_3_ASSETS* are also created and analyzed (untabulated). These dummy variables *(*quintiles two through five with quintile one serving as the base quintile of the regression) replace *LVL_3_ASSETS* and column two of Table Three is re-estimated. The coefficients on quintiles two and three are slightly negative but statistically insignificant. However, the coefficients on quintiles four and five are -0.29 and -0.37, respectively and both are statistically significant. Furthermore, a coefficient chi-squared test of quintile four = quintile five does not result in a statistically significant difference. However, statistically significant differences exist between quintile four and quintiles two and three, as well as between quintile five and quintiles two and three. This supports the notion that a potential non-linear effect exists and it manifests itself somewhere between the third and fourth quintiles of the variable of interest.

[15] Since the sample contains a great deal of firm years with zero balances, quintile one contains all zero balance firms and the remainder of firm years are split ratably between quintiles two through five.
[16] This spread of 80 basis points is based on the differences for noninvestment grade firms as of March 2014, according to www.bondsonline.com. For investment grade securities bond spreads can be lower than this.

Chapter Four: Additional Analysis and Robustness Testing

Changes Analysis

To better establish a sense of causality, a changes analysis is also employed. Because a change in difficult to value fair value assets should conceivably "push" a firm's creditworthiness closer to a threshold for a ratings change, results consistent with those in Table Three should exist. The models employed for the changes analysis are as follows:

$$[2] \quad (\Delta RATING_{it} \text{ or } CHANGE_{it}) = \lambda_0 + \lambda_1\, \Delta LVL\_3\_ASSETS_{it} + \lambda_2\, \Delta OTHER\_FV\_ASSETS_{it} + \lambda_3\, \Delta RETURN_{it} + \lambda_4\, \Delta STD\_DEV_{it} + \lambda_5\, \Delta SUBORDINATED_{it} + \lambda_6\, \Delta INT\_COV_{it} + \lambda_7\, \Delta BOOK\_MKT_{it} + \lambda_8\, \Delta LIQUIDITY_{it} + \lambda_9 \Delta LOSS_{it} + \lambda_{10} \Delta ROA_{it} + \lambda_{11} \Delta MARGINS_{it} + \lambda_{12}\, \Delta LEVERAGE_{it} + \lambda_{13}\, \Delta LN\_AT_{it} + \sum INDUSTRY_{it} + \sum YEAR_{it} + \mu_{it}$$ [17]

$\Delta RATING_{it}$ represents the change in the ordinal dependent variable, $RATING_{it},$ and follows bond ratings changes models used in prior literature (Ayers et al. 2010; Jiang 2008). This model also employs ordered logistic regression. However, changes in ratings at different beginning levels could have different magnitudes or meanings. For instance, a change from AA to AAA would be a positive change of two while a change from BBB- to BBB+ would also represent a positive change of two, but it is unclear if these positive changes in credit worthiness are in fact equals. As a result, a new variable is created, $CHANGE_{it},$ which is coded as a one if the firm had a credit upgrade, zero if there was no change in $RATING_{it},$ and negative one if the firm experienced a credit

[17] The $\Delta RATING_{it}$ variable is computed by subtracting $RATING_{it-1}$ from $RATING_{it}$ and is similar to Jiang (2008).

downgrade. In using $CHANGE_{it}$ as the dependent variable for the model, ordered logistic regression is also employed. Table Four details the results of this analysis.[18]

The results displayed in Table Four appear to support the initial results in Table Three - an increase in difficult to value fair value assets ($\Delta LVL\_3\_ASSETS_{it}$) is associated with a decline in credit rating. This result holds if either $\Delta RATING_{it}$ or $CHANGE_{it}$ is the dependent variable. The coefficients for all columns are negative and significant from a statistical standpoint.[19]

Similar to Table Three, economic significance is also explored using an OLS regression on column two of Table Four. This results in a statistically significant coefficient -1.56 (untabulated). A one standard deviation change in $\Delta LVL\_3\_ASSETS_{it}$ (0.0153 for financial firms) results in an effect of -0.024 on $CHANGE_{it}$. Within the sample, a change in rating only occurs 20.2% of the time for financial firms. Thus the OLS results support an economically significant effect. Specifically, a one standard deviation change in level three asset holdings increases to overall likelihood of ratings change by 11.9% (0.024 / 0.202) for financial firms. Thus, a changes analysis appears to provide a higher level of insight into the effect of difficult to value fair value assets on credit ratings.

The year to year addition and removal of level three assets is also explored as a treatment effect (untabulated). The regressions in columns two and four of Table Four are re-estimated using

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[18] The overall sample size drops for the changes analysis as one full year of analysis is lost. The analysis also does not capture the change for the first year of the analysis within Table Three (fiscal years beginning November 15, 2007 through November 15, 2008) as the first year in the analysis is the same year that the SFAS 157 disclosures went into effect.

[19] Since certain beginning levels of ratings could present truncation issues (e.g. a AAA rating cannot be upgraded), Table Four is also re-estimated with the one year lagged level of ratings (the starting point for the change) as an additional control variable. Table Four is also re-estimated with additional controls for lagged ratings changes to control for potential momentum in ratings. Past changes in ratings appear to predict future changes in ratings. However, the results and inferences in regard to ΔLVL_3_ASSETS remain unchanged in both cases.

a slightly different methodology. Four dummy variables are created for whether 1) the firm went from zero level three asset holdings to a positive balance ("received treatment") in the year, or 2) the firm went from having positive level three asset holdings to having zero ("lost treatment") in the year, or 3) the firm had zero level three asset holdings for both years or 4) the firm had positive level three asset holdings for both years. These dummy variables are included in the regressions in lieu of *ΔLVL_3_ASSETS* with firms having zero level three assets holdings in both years serving as the base of the regressions. The coefficient for "received treatment" is negative in both cases and also statistically significant. The coefficient for "lost treatment" is positive in both cases but is statistically insignificant. However, for both regressions, a chi-squared test of "received treatment" = "lost treatment" results in significant and near significant chi-squared values of 2.72 (p-value = 0.0991) and 2.67 (p-value = 0.1024), signaling that differences exist between initially adding and completely removing level three assets from a firm's balance sheet.[20] These findings further support the notion that a firm's potential movement in and out of level three asset holdings can differentially impact credit ratings.

Upgrades vs. Downgrades

Given the results documented in Table Four, it is interesting to determine whether the observed effect upon changes in ratings is primarily driven through credit downgrades activity, upgrades activity or both. Changes to accounting information risk and its effect upon ratings changes could differentially manifest itself between upgrades and downgrades to credit. Given this, equation two is re-estimated using two logistic regressions with two separate binary

[20] The lack of statistical strength on these stand-alone dummy variables is not unsurprising given that "received treatment" only happens in 41 observations and "lost treatment" only happens in 29 observations. This likely results in greatly reduced statistical power.

dependent variables, *UPGRADE* and *DOWNGRADE*. *UPGRADE* is equal to one if the firm experienced a credit upgrade during the period and equal to zero otherwise. *DOWNGRADE* is equal to one if the firm experienced a credit downgrade during the period and equal to zero otherwise. Table Five documents the results of this analysis.

The results of Table Five indicate that changes in accounting information risk has a differential impact on the credit upgrades versus downgrades. Specifically, the results are much stronger for upgrades, a positive change in accounting information risk is negatively related to the likelihood of a credit upgrade and this result has strong statistical strength. Downgrades experience an opposite effect, a positive change in accounting information risk is associated with an increased likelihood of a downgrade, but this effect has no statistical significance. An average marginal effects analysis of columns two and four also supports the notion that increased levels of accounting information risk may be more impactful in prohibiting an upgrade as opposed to facilitating a downgrade - the untabulated average marginal effect coefficient for *ΔLVL_3_ASSETS* in column one is -1.15 while the untabulated average marginal effect coefficient for *ΔLVL_3_ASSETS* in column two is 0.52. These marginal effects also appear to be economically significant; a one percentage increase in level three assets (as a percentage of total assets) results in a -1.15% lower likelihood of receiving a credit upgrade and a 0.52% higher likelihood of receiving a credit downgrade. Overall, upgrades only occur in 8.6% of the sample for financial industry firms and downgrades occur in 14.6% of the sample for financial industry firms.

Initial Year of SFAS 157 Disclosure Analysis

To further explore whether the addition of SFAS 157 disclosures potentially supplied new information to the ratings process, a similar analysis to Table Four is conducted using a pair matched sample of firms for the initial year (fiscal years beginning November 15, 2007 through November 15, 2008) that SFAS 157 first became effective. More specifically, all firms that reported a positive balance of level three assets during this time period are matched to similar industry and sized firms who did not possess level three assets for the same reporting period.[21] The same econometric model used in Table Four is employed with *ΔLVL_3_ASSETS* being the end of period balance of level three assets, scaled by total assets. For the matched firms, this results in a zero value for *ΔLVL_3_ASSETS*.

The results of this test appear to support the notion that the SFAS 157 disclosures supplied the ratings agencies with a potentially new source of information during the first required year for SFAS 157. This effect appears to be highly concentrated in financial firms alone as the *ΔLVL_3_ASSETS* coefficients are negative and statistically significant for only the analyses concerning financial firms. The overall effect size in terms of economic significance is also pronounced for this test – an untabulated OLS regression yields a coefficient of -3.46 on *ΔLVL_3_ASSETS*, which is considerably larger than the similar OLS coefficient (untabulated) of -1.56 for column two of Table Four. This suggests that the initial year of SFAS 157 disclosures may have provided ratings agencies with a considerable amount of information, especially for financial industry firms.

[21] Matches are based upon size and industry. For each firm that reports a positive balance in level three assets, the closest firm in terms of size within the same Fama French 48 industry specification that did not report level three assets is matched without replacement. This matching technique results in a large loss of sample size as many firms do not have adequate matches. The majority of firms within the financial industries reported positive balances of level three assets for the first effective year of SFAS 157, leaving many without an adequate match.

Propensity Score Matching Analysis

To employ an additional level of control, a propensity score matching technique is also employed, similar to the one employed by Barth et al. (2012).[22] To facilitate this approach, a treatment variable is constructed, which is an indicator variable equal to one if the firm carries level three assets on its balance sheet and equal to zero if not. This variable is first employed in lieu of *LVL_3_ASSETS*, using the specification from equation one. This variable thus becomes the variable of interest. A propensity score matching analysis is then conducted; the sample for this analysis is formulated based on the propensity to receive this treatment using all of the control variables from equation one as predictive variables for receiving this treatment effect.[23] Once this matched pair sample is formed, Table Three is re-estimated (untabulated) using the propensity score matched sample.

Overall, despite the large loss of sample size due to propensity score matching, the overall inferences from Table Three remain intact. In all regressions, the treatment variable has a negative coefficient loading and is statistically significant. This further supports previous inferences that higher levels of accounting information risk are associated with decreased credit ratings for firms who choose to hold these assets.

[22] Propensity score matching helps to control for non-linearity in the regression specification, to control for interactions amongst the various control variables and to better formulate a sample based upon the likelihood that a firm would need to utilize difficult to value fair value assets for its business purposes.
[23] A caliper of 3% is employed to match observations without replacement. A test of differences in means does not reveal any statistical differences between the covariates in the propensity score matched treatment and control groups.

Additional Robustness

The first additional robustness test decomposes *OTHER_FV_ASSETS* into its components (level one and level two fair value assets) scaled by total assets and treats each as standalone variables in equation one. Table Three is re-estimated with this decomposition. The main inferences in regard to *LVL_3_ASSETS* remain unchanged.

The second additional robustness test "leads" *RATING* for both three months and five months instead of the four months used throughout the tables herein. It is unknown as to how fast, on average, the ratings agencies might impound the financial statements into their ratings process. The results for Tables Three and Four remain unchanged when this assumption change is introduced.

The third additional robustness test deals with concerns that *LVL_3_ASSETS* may simply be a proxy for the overall level of opacity within a firm. To rule out this possibility, two well-known measures for opacity are employed, the level of analyst following and the overall level of dispersion in analyst forecasts. Both are obtained from the IBES database; analyst following is simply the total number of analysts that follow the firm for period *t* while the dispersion in analyst forecasts is measured using the coefficient of variation in analyst forecasts for period *t*. Both measures are included as additional control variables in the regressions employed in Table Three and the results are unchanged. This alleviates any concerns with *LVL_3_ASSETS* being a proxy for the overall opacity of the firm.[24]

[24] These variables are also included in the changes analysis in Table 4 (untabulated). The results are qualitatively similar but fall just outside of statistical significance. Upon further analysis, this appears to be primarily due to a loss of sample size as a minimum level of analyst following is required in order to compute forecast dispersion and many firms do not have this minimal level of analyst following. It does not appear to be due to omitted variables

The fourth additional robustness test is related to concerns that the results documented herein may simply be driven by the financial crisis of 2007 – 2009. The previous works of Song et al. (2010), Riedl and Serafeim (2011) and Arora et al. (2014) find various cost of capital effects in regard to difficult to value fair value assets, but all of their analyses are primarily limited to the time period of the financial crisis. Perhaps the results herein are driven by the heightened levels of fear and distressed selling that occurred during the crisis time period.[25] In addition, this period of time coincided with the time in which ratings agencies were under intense scrutiny for a perceived lack of foresight in what became the financial crisis. In order to test this notion, an interaction term is created between a financial crisis indicator variable and the main variable of interest. Equation (1) is then re-estimated with the inclusion of this interaction term. The interaction term does not have a statistically significant coefficient loading.[26] Thus, the financial crisis does not appear to have a discernable impact upon the findings herein.

The fifth additional robustness concerns fair value liabilities. Thus far, this paper has only empirically examined the impact of difficult to value fair value assets. However, liabilities measured at fair value, especially those that are difficult to value, may also have a similar impact. In their analysis, Riedl and Serafeim (2011) find that difficult to value fair value liabilities have a similar effect in increasing the equity beta of a firm as does difficult to value fair value assets. As a result, if the main results in Table Three are in fact true in regard to fair value assets, one should

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bias, as these measures (analyst following and forecast dispersion) only correlate with *LVL_3_ASSETS* at the -.03 and .03 levels, respectively.

[25] This could be of particular interest to the sample of financial industry firms as confounding events such as TARP (Troubled Asset Relief Program) could have an impact, especially if holdings of level three assets were associated with the propensity of a firm to seek assistance under this program. The fact that the time period of the financial crisis does not drive the main result also alleviates this concern.

[26] Equation (1) is also re-estimated after dropping all financial crisis firm years. The results of Table Three are unchanged.

expect to find a similar result for fair value liabilities. To test this notion, two new variables are formulated, the total value of level three liabilities scaled by total assets and the total combined value of level one and level two liabilities also scaled by total assets. To conduct this analysis, the analysis in Table Three is supplemented with these two new variables. *LVL_3_ASSETS* retains its negative and statistically significant relationship to the dependent variable. The measure for level 3 liabilities also has a negative coefficient loading, but is not statistically significant, however it does display statistical significance when included in a separate regression excluding *LVL_3_ASSETS*.[27] Level 3 assets and level 3 liabilities are also combined into a single variable in a separate analysis and this combined variable has similar statistically significant negative coefficient loadings.[28] The results are thus robust to the inclusion of fair value liabilities.

The sixth additional robustness test concerns endogeneity manifested in the form of firm-level corporate governance issues. More specifically, better governed firms may be more or less inclined to invest in level three assets and corporate governance has also been shown to impact credit ratings (Ashbaugh-Skaife et al. 2006). Given these concerns, Table Three is supplemented with five additional governance variables: 1) whether the company has a big four auditor, 2) whether the CEO and Chairman of the Board positions are held by the individual, 3) the percentage of independent board members, 4) whether the firm was cited for internal control weaknesses, and

[27] This test and result also serve another purpose in that they potentially rule out asset liquidity concerns as the sole explanation for the findings in Table Three. In other words, the results of Table Three could potentially be interpreted as being the result of risk aversion in regard to a firm holding quantities of illiquid assets (level three assets being a proxy for illiquid assets). If this were true and the results are not at least partially being driven by accounting information risk, then a similar result would not be expected for level three liabilities as the liquidity of fair value liabilities should be of little concern to the other creditors of a firm. Since a similar result exists for level three liabilities as does for level three assets, this supports the notion that accounting information risk remains a potential causal factor for credit ratings not ruled out by the alternative explanation of underlying asset liquidity.

[28] This approach essentially treats level 3 assets and liabilities as the same construct (as a proxy for accounting information risk). These measurements correlate at the .44 level within the overall sample (.50 for financial industry firms).

5) whether the audit committee possesses a financial expert. These additional variables are obtained from the Risk Metrics and Audit Analytics databases. Inclusion of these variables results in a greatly reduced sample size, but the overall inferences in regard to *LVL_3_ASSETS* remain unchanged. This alleviates concerns in regard to omitted governance characteristics driving the results.

Chapter Five: Conclusion

This paper examines whether accounting information risk affects a firm's credit ratings. Operationally, it explores the effects of a firm's level three fair value asset holdings on credit ratings for fiscal years-ended November 15, 2008 through December 31, 2013. The paper's primary finding shows that increased levels of accounting information risk negatively impact credit ratings and this result manifests itself in both levels and changes analyses.

This result is robust to numerous specifications and other forms of analysis. In addition, this result does not appear to be solely driven by the financial crisis of the late 2000s. Furthermore, increases to level three fair value assets are more effective in prohibiting a credit upgrade than in effectuating a credit downgrade. The main result is also robust to the inclusion of level three fair value liabilities and other matching techniques. These results are also robust to numerous other model re-specifications. The findings herein primarily manifest in financial industry firms, firms which are potentially more likely to hold level three assets for investment purposes as opposed to hedging purposes.

This paper builds upon the works of Song et al. (2010), Riedl and Serafeim (2011), and Arora et al. (2014), all of which find that accounting information risk affects the pricing of assets. This paper provides insight into whether accounting information risk is a criteria considered by ratings agencies in their assessment of a firm's level of credit risk. Understanding the determinants of credit ratings is an important area of research given the large scale economic effects that ratings impose upon the economy. In addition, the findings herein provide additional support for the usefulness and efficacy of disclosures for uncertain fair value accounting estimates. Finally, these results demonstrate that accounting information risk has measurable effects on the long term perspective of the credit worthiness of the firm - a result not necessarily predicted by the theoretical work of (Duffie and Lando (2001)).

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Appendix

Terms and Definitions

$RATING_{it}$	Firm *i*'s Standard & Poor's domestic long-term issuer credit rating (Compustat variable *splticrm*) for year *t*. These ratings are assigned a number from 1 to 22 where the highest rating AAA = 22 and the lowest rating D = 1.
$\Delta RATING_{it}$	$RATING_{it}$ - $RATING_{it-1}$.
$CHANGE_{it}$	Coded as a one if the firm had an increase to $RATING_{it}$ from *t-1* to *t*, zero if there was no change in $RATING_{it}$, and negative one if the firm experienced a decrease to $RATING_{it}$ from *t-1* to *t*.
$LVL\_3\_ASSETS_{it}$	Firm *i*'s total dollar value of SFAS 157 level three assets (Compustat variable *aul3*) scaled by the book value of Firm *i*'s total assets (Compustat variable *at).*
$OTHER\_FV\_ASSETS_{it}$	Firm *i*'s combined total dollar value of SFAS 157 level one and level two assets (Compustat variables *aqpl1*and *aol2*) scaled by the book value of Firm *i*'s total assets (Compustat variable *at).*
$RETURN_{it}$	Firm *i*'s buy and hold stock return from *t-1* until *t.*
STD_DEV_{it}	Firm *i*'s standard deviation of monthly stock returns from period *t-1* until *t.*
$SUBORDINATED_{it}$	A dichotomous variable equal to one if firm *i* had subordinated debt as of time *t*.
INT_COV_{it}	Firm *i*'s interest coverage ratio as of time *t*, defined as earnings before interest and taxes (Compustat variable *ebit*) divided by interest expense (Compustat variable *xint*).
$BOOK\_MKT_{it}$	Firm *i*'s book value of equity (Compustat variable *ceq*) divided by the market value of equity (Compustat variable *mkvalt*).
$LIQUIDITY_{it}$	Firm *i*'s operating cash flows (Compustat variable *oancf*) divided by the total liabilities (Compustat variable *lt*).
$LOSS_{it}$	A dichotomous variable equal to one if firm i incurred negative net income (Compustat variable *ni*) during the year *t*.
ROA_{it}	Firm *i*'s return on assets as measured by net income (Compustat variable *ni*) before special items (Compustat variable *spi*) divided by total assets (Compustat variable *at*) during the year *t*.
$MARGINS_{it}$	Firm *i*'s ratio of earnings before taxes (Compustat variable *ebit*) to revenue (Compustat variable *revt*) during the year *t*.

$LEVERAGE_{it}$	Firm *i*'s ratio of short term debt (Compustat variable *dlc*) and long term debt (Compustat variable *dlt*) to total assets (Compustat variable *at*) during the year *t*.
LN_AT_{it}	Firm *i*'s natural log of total assets (Compustat variable *at*).
$RATING_{it-1}$	The one year lagged annual *RATING* for firm *i*.
$UPGRADE_{it}$	A dichotomous variable equal to one if the firm experienced a credit upgrade during period *t*, zero otherwise.
$DOWNGRADE_{it}$	A dichotomous variable equal to one if the firm experienced a credit downgrade during period *t*, zero otherwise.

Table One: Descriptive Statistics

Table One, Panel A presents the descriptive statistics for the full sample of 7,602 firm-year observations. Panel B presents the descriptive statistics for the subsample of 1,588 financial industry firm-year observations. All variables are defined in the Appendix.

Panel A: All Firms

	N	Mean	10th %tile	25th %tile	Median	75th %tile	90th %tile
RATING	7,602	12.647	8.000	10.000	13.000	15.000	17.000
LVL_3_ASSETS	7,602	0.005	0.000	0.000	0.000	0.001	0.014
OTHER_FV_ASSETS	7,602	0.094	0.000	0.000	0.009	0.082	0.324
RETURN	7,602	0.145	-0.450	-0.145	0.121	0.355	0.680
STD_DEV	7,602	0.113	0.045	0.063	0.093	0.140	0.205
SUBORDINATED	7,602	0.260	0.000	0.000	0.000	1.000	1.000
INT_COV	7,602	10.501	0.436	1.669	3.772	8.821	18.959
BOOK_MKT	7,602	0.491	0.010	0.161	0.442	0.748	1.091
LIQUIDITY	7,602	0.149	0.016	0.062	0.122	0.204	0.312
LOSS	7,602	0.143	0.000	0.000	0.000	0.000	1.000
ROA	7,602	0.042	-0.011	0.011	0.038	0.071	0.111
MARGINS	7,602	0.148	0.018	0.064	0.128	0.222	0.341
LEVERAGE	7,602	0.327	0.079	0.180	0.304	0.444	0.591
LN_AT	7,602	10.773	6.978	7.755	8.741	9.899	10.993

Panel B: Financial Firms

	N	Mean	10th %tile	25th %tile	Median	75th %tile	90th %tile
RATING	1,588	13.998	10.000	13.000	14.000	16.000	17.000
LVL_3_ASSETS	1,588	0.016	0.000	0.000	0.003	0.020	0.047
OTHER_FV_ASSETS	1,588	0.284	0.000	0.002	0.164	0.576	0.740
RETURN	1,588	0.114	-0.441	-0.115	0.108	0.321	0.585
STD_DEV	1,588	0.108	0.042	0.057	0.085	0.131	0.201
SUBORDINATED	1,588	0.475	0.000	0.000	0.000	1.000	1.000
INT_COV	1,588	9.855	0.247	1.148	2.710	7.720	15.181
BOOK_MKT	1,588	0.516	0.001	0.001	0.412	0.863	1.276
LIQUIDITY	1,588	0.066	-0.004	0.015	0.040	0.093	0.155
LOSS	1,588	0.157	0.000	0.000	0.000	0.000	1.000
ROA	1,588	0.020	-0.006	0.004	0.012	0.033	0.056
MARGINS	1,588	0.234	0.021	0.102	0.236	0.368	0.497
LEVERAGE	1,588	0.253	0.036	0.064	0.170	0.437	0.577
LN_AT	1,588	11.992	7.741	8.503	9.623	10.920	12.909

Table Two: Correlation Matrix

Table Two, Panel A presents a Pearson (lower left hand side) and Spearman (upper right hand side) Correlation Coefficient matrix for all firms in the sample. Panel B presents similar data for financial industry firms alone. All variables are defined in Appendix One. Bold values indicate significance at the 0.10 level or stronger (based on two-tailed tests).

Panel A: All Firms

	RATING	*LVL_3_ASSETS*	*OTHER_FV_ASSETS*	*RETURN*	*STD_DEV*	*SUBORDINATED*	*INT_COV*	*BOOK_MKT*	*LIQUIDITY*	*LOSS*	*ROA*	*MARGINS*	*LEVERAGE*	*LN_AT*
RATING		**0.194**	**0.271**	**0.024**	**-0.504**	**0.082**	**0.542**	**-0.138**	**0.184**	**-0.370**	**0.336**	**0.377**	**-0.460**	**0.641**
LVL_3_ASSETS	**0.053**		**0.491**	-0.018	**0.059**	**0.243**	-0.008	**0.050**	**-0.251**	0.019	**0.194**	**0.080**	**-0.214**	**0.354**
OTHER_FV_ASSETS	**0.222**	**0.339**		0.013	**-0.118**	**0.131**	**0.169**	0.014	**-0.124**	**-0.056**	**-0.040**	**0.066**	**-0.344**	**0.330**
RETURN	**-0.021**	-0.008	-0.001		**-0.205**	**-0.033**	**0.115**	**-0.164**	**0.092**	**-0.141**	**0.108**	**0.090**	**-0.037**	-0.009
STD_DEV	**-0.496**	**0.069**	**-0.044**	-0.013		**-0.047**	**-0.387**	**0.074**	**-0.137**	**0.365**	**-0.287**	**-0.360**	**0.175**	**-0.291**
SUBORDINATED	**0.072**	**0.103**	**0.185**	**-0.036**	-0.004		**-0.188**	**0.131**	**-0.311**	0.018	**-0.273**	**0.105**	**-0.025**	**0.177**
INT_COV	**0.285**	**-0.019**	**0.111**	0.017	**-0.135**	**-0.103**		**-0.138**	**0.500**	**-0.555**	**0.754**	**0.357**	**-0.545**	**0.188**
BOOK_MKT	**-0.087**	**0.034**	**0.026**	**-0.172**	**0.039**	**0.111**	**-0.073**		**-0.087**	**0.038**	**-0.214**	**-0.162**	**-0.141**	**-0.052**
LIQUIDITY	**0.226**	**-0.137**	**-0.152**	**0.066**	**-0.140**	**-0.256**	**0.362**	**-0.084**		**-0.273**	**0.605**	**0.174**	**-0.149**	**-0.115**
LOSS	**-0.390**	**0.059**	-0.011	**-0.094**	**0.413**	0.018	**-0.165**	**0.050**	**-0.232**		**-0.606**	**-0.439**	**0.202**	**-0.139**
ROA	**0.385**	**-0.105**	**-0.078**	**0.097**	**-0.341**	**-0.198**	**0.327**	**-0.154**	**0.514**	**-0.622**		**0.363**	**-0.196**	-0.014
MARGINS	**0.328**	**0.080**	**0.041**	**0.068**	**-0.324**	**0.088**	**0.146**	**-0.113**	**0.147**	**-0.456**	**0.439**		0.005	**0.228**
LEVERAGE	**-0.465**	**-0.068**	**-0.352**	-0.003	**0.244**	**-0.020**	**-0.312**	**-0.224**	**-0.245**	**0.223**	**-0.205**	-0.013		**-0.315**
LN_AT	**0.629**	**0.169**	**0.313**	**-0.053**	**-0.238**	**0.220**	**0.098**	**-0.020**	**-0.095**	**-0.121**	0.011	**0.187**	**-0.316**	

Table Two: Correlation Matrix (Continued)

Panel B: Financial Firms

	RATING	*LVL_3_ASSETS*	*OTHER_FV_ASSETS*	*RETURN*	*STD_DEV*	*SUBORDINATED*	*INT_COV*	*BOOK_MKT*	*LIQUIDITY*	*LOSS*	*ROA*	*MARGINS*	*LEVERAGE*	*LN_AT*
RATING		**0.184**	**0.283**	-0.012	**-0.190**	**0.325**	**0.285**	-0.024	**-0.173**	**-0.236**	**0.048**	**0.124**	**-0.329**	**0.593**
LVL_3_ASSETS	-0.014		**0.607**	0.007	**0.090**	**0.195**	**0.151**	**0.110**	**-0.318**	**0.046**	**-0.171**	**-0.146**	**-0.320**	**0.365**
OTHER_FV_ASSETS	**0.224**	**0.249**		0.023	-0.037	**0.243**	**0.360**	**0.123**	**-0.282**	-0.035	**-0.085**	**-0.333**	**-0.590**	**0.328**
RETURN	-0.026	0.009	0.013		**-0.272**	-0.028	**0.231**	-0.015	0.033	**-0.178**	**0.169**	**0.161**	-0.024	-0.015
STD_DEV	**-0.286**	**0.154**	-0.001	**-0.178**		**0.067**	**-0.424**	**-0.107**	**-0.150**	**0.404**	**-0.409**	**-0.331**	**0.133**	**0.055**
SUBORDINATED	**0.276**	-0.001	**0.201**	**-0.047**	**0.053**		**-0.078**	**0.222**	**-0.454**	-0.001	**-0.341**	0.007	**-0.278**	**0.570**
INT_COV	**0.142**	-0.022	**0.133**	**0.057**	**-0.094**	**-0.109**		**-0.055**	**0.184**	**-0.565**	**0.653**	**0.267**	**-0.467**	-0.006
BOOK_MKT	**-0.091**	0.027	**0.083**	**-0.063**	-0.030	**0.171**	**-0.051**		**-0.230**	0.030	**-0.174**	-0.001	**-0.155**	**0.155**
LIQUIDITY	-0.021	**-0.109**	**-0.202**	**0.044**	**-0.138**	**-0.333**	**0.128**	**-0.164**		**-0.164**	**0.512**	**0.102**	**0.256**	**-0.524**
LOSS	**-0.276**	**0.086**	-0.029	**-0.168**	**0.502**	-0.001	**-0.154**	**0.078**	**-0.150**		**-0.630**	**-0.451**	**0.104**	0.023
ROA	**0.127**	**-0.062**	**-0.102**	**0.168**	**-0.366**	**-0.255**	**0.363**	**-0.119**	**0.422**	**-0.479**		**0.405**	0.006	**-0.386**
MARGINS	**0.162**	0.014	**-0.324**	**0.169**	**-0.413**	-0.019	**0.122**	**-0.063**	**0.155**	**-0.505**	**0.434**		**0.244**	**-0.046**
LEVERAGE	**-0.282**	-0.018	**-0.524**	-0.003	**0.134**	**-0.334**	**-0.224**	**-0.181**	**0.083**	**0.110**	-0.003	**0.206**		**-0.296**
LN_AT	**0.539**	**0.136**	**0.279**	**-0.047**	**0.072**	**0.564**	0.000	**0.081**	**-0.372**	**0.033**	**-0.297**	**-0.049**	**-0.271**	

Table Three: Levels Analysis

Table Three presents the results of ordered logistic regression analysis for equation (1). The dependent variable in each column is *RATING*. The variable of interest in this table is *LVL_3_ASSETS*. Column 1 presents the results of the regression for all firms while Column 2 presents the same regression for financial industry firms alone. All variables are defined in the Appendix. Robust two-tailed z-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively. All standard errors are clustered at the firm level.

	(1) All Firms	(2) Financial Firms
DEPENDENT VAR	*RATING*	*RATING*
LVL_3_ASSETS	-3.9345***	-4.1187**
	(-2.5592)	(-2.5156)
OTHER_FV_ASSETS	0.0973	0.2981
	(0.4985)	(1.2760)
RETURN	0.8366***	1.0669***
	(11.7689)	(6.8693)
STD_DEV	-5.5151***	-8.7699***
	(-8.7080)	(-5.6436)
SUBORDINATED	0.0807	-0.2226*
	(1.2778)	(-1.8790)
INT_COV	-0.0000	-0.0027**
	(-0.0356)	(-2.0727)
BOOK_MKT	-0.3128***	-0.2754**
	(-4.5212)	(-2.5237)
LIQUIDITY	1.8112***	0.5325
	(7.9578)	(1.4274)
LOSS	-0.7860***	-0.9292***
	(-7.3903)	(-4.8296)
ROA	5.0521***	3.8514*
	(6.2298)	(1.7191)
MARGINS	0.5203*	0.4978
	(1.9226)	(1.1283)
LEVERAGE	-1.5090***	-1.2067***
	(-6.8859)	(-3.5637)
LN_AT	0.2322***	0.2728***
	(10.0444)	(5.3076)
$RATING_{t-1}$	2.9751***	2.6862***
	(34.3274)	(13.4766)
INDUSTRY F.E.'s	Yes	Yes
YEAR F.E.'s	Yes	Yes
INTERCEPT	Yes	Yes
PSEUDO R-SQUARED	0.6342	0.5747
N	7,602	1,588

Table Four: Changes Analysis

Table Four presents the results of ordered logistic regression analysis for equation (2). The dependent variables employed are *ΔRATING* and *CHANGE*. The variable of interest in this table is *ΔLVL_3_ASSETS*. Columns (1) and (3) present the results of the regression for all firms using both dependent variable specifications. Columns (2) and (4) present the results of the same regression for financial industry firms alone using both dependent variable specifications. All variables are defined in the Appendix. Robust two-tailed z-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively. All standard errors are clustered at the firm level.

	(1)	(2)	(3)	(4)
	All Firms	Financial Firms	All Firms	Financial Firms
DEPENDENT VAR	*CHANGE*	*CHANGE*	*ΔRATING*	*ΔRATING*
ΔLVL_3_ASSETS	-4.4440*	-9.4841**	-4.5144*	-10.9694**
	(-1.7131)	(-2.2230)	(-1.6759)	(-2.0844)
ΔOTHER_FV_ASSETS	0.3766	-0.1933	0.4780	0.3019
	(0.5570)	(-0.1521)	(0.7236)	(0.2283)
ΔRETURN	-0.0488	0.0721	-0.0239	0.1189
	(-0.7955)	(0.4742)	(-0.3727)	(0.7665)
ΔSTD_DEV	-2.9361***	-3.1488**	-3.2783***	-3.6359**
	(-4.8573)	(-2.2538)	(-5.0899)	(-2.3663)
ΔSUBORDINATED	-0.2301	0.5571	-0.2605	0.5606
	(-1.3235)	(1.4468)	(-1.4216)	(1.4623)
ΔINT_COV	-0.0010	-0.0086	-0.0012	-0.0077
	(-0.3477)	(-1.4771)	(-0.4571)	(-1.5879)
ΔBOOK_MKT	-0.2195*	-0.1865	-0.2570**	-0.2331
	(-1.8718)	(-1.1999)	(-2.0700)	(-1.4576)
ΔLIQUIDITY	1.6006***	0.6089	1.6216***	0.3918
	(3.9686)	(0.6919)	(4.0520)	(0.4362)
ΔLOSS	-0.4281***	-0.7149***	-0.4596***	-0.6490***
	(-3.7847)	(-3.0799)	(-3.9054)	(-2.7533)
ΔROA	3.7885***	-2.2633	4.0410***	-3.5681
	(3.7050)	(-0.5279)	(3.6281)	(-0.7715)
ΔMARGINS	0.5319	1.6431**	0.4094	2.1236**
	(1.3123)	(2.2996)	(0.8812)	(2.5306)
ΔLEVERAGE	-6.2614***	-0.7576	-6.5432***	-1.2957
	(-8.7027)	(-0.3710)	(-8.8688)	(-0.5948)
ΔLN_AT	1.5277***	1.8944**	1.5792***	2.0944***
	(5.4671)	(2.4750)	(5.4658)	(2.6454)
INDUSTRY F.E.'s	Yes	Yes	Yes	Yes
YEAR F.E.'s	Yes	Yes	Yes	Yes
INTERCEPT	Yes	Yes	Yes	Yes
PSEUDO R-SQUARED	0.0807	0.0895	0.0711	0.0795
N	5,888	1,255	5,888	1,255

Table Five: Upgrade vs. Downgrade Activity

Table Five presents the results of logistic regression analysis for equation (2) using the binary dependent variables, *UPGRADE* and *DOWNGRADE*. The variable of interest in this table is *ΔLVL_3_ASSETS*. Columns (1) and (2) present the results of the regression with *UPGRADE* as the dependent variable. Columns (3) and (4) present the results of the regression with *DOWNGRADE* as the dependent variable. All variables are defined in the Appendix. Robust two-tailed z-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively. All standard errors are clustered at the firm level.

	(1)	(2)	(3)	(4)
	All Firms	Financial Firms	All Firms	Financial Firms
DEPENDENT VAR	*UPGRADE*	*UPGRADE*	*DOWNGRADE*	*DOWNGRADE*
ΔLVL_3_ASSETS	-5.8439*	-14.0029***	2.8972	6.3550
	(-1.7765)	(-2.6314)	(0.6340)	(0.7870)
ΔOTHER_FV_ASSETS	0.3447	-0.5527	-0.1125	0.4665
	(0.5183)	(-0.4257)	(-0.0946)	(0.2466)
ΔRETURN	-0.1065	-0.0857	-0.0437	-0.1367
	(-1.4189)	(-0.3068)	(-0.5336)	(-0.9957)
ΔSTD_DEV	-1.2178*	0.1213	4.4130***	4.5774***
	(-1.7070)	(0.0517)	(5.0002)	(2.7186)
ΔSUBORDINATED	-0.2159	0.3286	0.3370	-1.0024
	(-0.9708)	(0.6809)	(1.1581)	(-1.4280)
ΔINT_COV	0.0020	-0.0017	0.0055*	0.0109**
	(0.5334)	(-0.2080)	(1.6993)	(2.1241)
ΔBOOK_MKT	-0.1846	0.0217	0.2897**	0.3805*
	(-1.3021)	(0.1154)	(1.9605)	(1.8211)
ΔLIQUIDITY	2.2331***	-0.4059	-0.8476	-2.5149
	(4.4157)	(-0.3894)	(-1.3703)	(-1.5858)
ΔLOSS	-0.2546*	-0.7007**	0.6116***	0.8967***
	(-1.8836)	(-2.2143)	(3.5652)	(2.8790)
ΔROA	3.8818***	-3.9563	-4.5201***	1.1200
	(3.2124)	(-0.6492)	(-2.8773)	(0.2152)
ΔMARGINS	0.1629	0.8186	-1.2666**	-1.9188**
	(0.3033)	(0.7238)	(-2.2199)	(-2.1676)
ΔLEVERAGE	-5.9988***	-1.7807	7.3819***	0.0725
	(-6.6559)	(-0.6968)	(6.8204)	(0.0195)
ΔLN_AT	0.7935***	0.6597	-2.7109***	-3.7171*
	(3.0537)	(1.0549)	(-4.8808)	(-1.6981)
INDUSTRY F.E.'s	Yes	Yes	Yes	Yes
YEAR F.E.'s	Yes	Yes	Yes	Yes
INTERCEPT	Yes	Yes	Yes	Yes
PSEUDO R-SQUARED	0.0852	0.0534	0.1245	0.1662
N	5,874	1,255	5,780	1,255

Table Six: Initial Year of SFAS 157 Disclosure Analysis

Table Six presents the results of ordered logistic regression analysis for equation (2). All observations follow a matched pair design whereas each firm that disclosed positive level three assets during the first required year for SFAS 157 are matched to a same industry, similar sized firm that did not possess these assets. The dependent variables employed are *ΔRATING* and *CHANGE*. The variable of interest in this table is *ΔLVL_3_ASSETS*. All variables are defined in Appendix One. Robust two-tailed z-statistics are presented in parentheses below the coefficients. *, ** and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
	All Firms	Financial Firms	All Firms	Financial Firms
DEPENDENT VAR	*CHANGE*	*CHANGE*	*ΔRATING*	*ΔRATING*
ΔLVL_3_ASSETS	-5.9642	-17.2066***	-6.9263	-10.9318***
	(-0.8030)	(-3.5108)	(-0.9619)	(-2.8080)
ΔOTHER_FV_ASSETS	0.3900	0.9951	0.2135	-0.1129
	(0.6582)	(1.4944)	(0.2767)	(-0.0928)
ΔRETURN	-0.5718*	-0.0707	-0.3620	-0.0115
	(-1.7810)	(-0.2010)	(-1.2105)	(-0.0256)
ΔSTD_DEV	-10.2931***	-16.9629***	-10.2263***	-11.9498***
	(-3.2179)	(-5.5235)	(-3.4714)	(-77.9874)
ΔSUBORDINATED	-0.3236	-13.3788***	-0.1878	0.2027
	(-0.3377)	(-10.3710)	(-0.2740)	(0.1510)
ΔINT_COV	0.0028	0.0338***	0.0017*	0.0026
	(1.5240)	(6.2557)	(1.6503)	(1.1979)
ΔBOOK_MKT	-0.7007***	-0.5795*	-0.3862	-0.3400
	(-2.8703)	(-1.7037)	(-1.4584)	(-1.5823)
ΔLIQUIDITY	2.3779**	8.2867***	1.9650*	4.7336***
	(2.0337)	(2.9859)	(1.8647)	(7.0235)
ΔLOSS	-0.3183	0.2229	-0.3452	-0.5600
	(-0.8156)	(0.1735)	(-1.0164)	(-0.4347)
ΔROA	5.0947**	9.7711***	3.0170	4.4423***
	(2.0965)	(3.4474)	(1.4634)	(16.6898)
ΔMARGINS	-0.4888	-1.2697	-0.3936	-0.1193
	(-0.6072)	(-1.5318)	(-0.4531)	(-0.0821)
ΔLEVERAGE	-6.2049***	0.6917	-6.9372***	0.3632
	(-2.9991)	(0.1070)	(-3.8367)	(0.0800)
ΔLN_AT	2.0001***	-0.2410	2.0408***	-0.1743
	(2.6614)	(-0.1734)	(2.6997)	(-0.1555)
INDUSTRY F.E.'s	Yes	Yes	Yes	Yes
YEAR F.E.'s	Yes	Yes	Yes	Yes
INTERCEPT	Yes	Yes	Yes	Yes
PSEUDO R-SQUARED	0.1478	0.2213	0.1158	0.1451
N	540	132	540	132

Vita

Douglas Ayres was born in Muncie, Indiana, to the parents of Burl and Jodean Ayres. The eldest of four boys, Douglas was raised on a farm in rural Indiana. Douglas attended Sulphur Springs Elementary School, Shenandoah Middle School, and Shenandoah High School. After graduation from high school, Douglas attended Ball State University and studied accounting. Douglas completed his Bachelor of Science degree at Ball State University and graduated summa cum laude. Upon graduation, Douglas worked for approximately ten years in public accounting, becoming a certified public accountant while raising two children, Aiden and Dylan Ayres. Douglas was accepted into the University of Tennessee, Knoxville doctoral program in accounting and graduated in May 2015. Prior to graduation, Douglas accepted a tenure track assistant professor position with his alma mater, Ball State University, and will continue his passion for teaching and academic research in the community of his birth.