What Drives Credit Rating Changes? A Return Decomposition Approach

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Abstract

This paper examines the relative importance of a shock to expected cash flows (i.e., cash-flow news) and a shock to expected discount rates (i.e., discount-rate news) in credit rating changes. Specifically, I use a Vector Autoregressive (VAR) model to implement the return decomposition of Campbell and Shiller (1988) and Vuolteenaho (2002) to extract cash-flow news and discount-rate news from stock returns at the firm level. I find that credit rating changes are, on average, more strongly associated with cash-flow news than with discount-rate news, consistent with cash-flow news being more permanent than discount-rate news. I further find that both cash-flow news and discount-rate news are more strongly related to credit rating changes when they convey negative information about firm value. This asymmetric association is consistent with the non-linear nature of default risk and with the fact that rating agencies incorporate bad news sooner than good news into their rating revisions.

Keywords: credit ratings, cash-flow news, discount-rate news, return decomposition, Vector Autoregression (VAR)

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I. Introduction

Since the price of an asset is equal to the sum of expected cash flows discounted by appropriate discount rates, there are, by definition, only two sources that can change asset prices: a shock to expected cash flows (i.e., cash-flow news) and a shock to expected discount rates (i.e., discount-rate news). In terms of asset returns, the unexpected return can be decomposed into cash-flow news and discount-rate news (Campbell and Shiller 1988). Using this return decomposition framework, a substantial body of research has examined the relative importance of cash-flow and discount-rate news in stock returns at the aggregate level (Campbell 1991; Campbell and Ammer 1993; Sadka 2007) and at the firm level. (Vuolteenaho 2002; Callen and Segal 2004; Callen et al. 2005). An equally important but largely unexplored issue is the effect of cash-flow news and discount-rate news on the revision of default risk. Because default risk is based on the distribution of the expected cash flows relative to its outstanding debt (Merton 1974; Cheng and Subramanyam 2008), the probability of default should increase with a negative shock to the expected cash flows and a positive shock to the expected discount rate (i.e., an increase in the riskiness of expected cash flows). If so, to what extent does the probability of default move in response to cash-flow news and/or discount-rate news? What is the relative importance of these two components? Under what circumstances does the relative importance of these two types of news vary? To date, no empirical research has addressed these questions. I seek to answer these questions by examining the relation between the two components of news and credit rating changes.

An issuer-level corporate credit rating offers an excellent research opportunity to address the question of the relative importance of cash-flow news and discount-rate news in the probability of default.[1] A corporate rating, also called "default risk rating" or "natural rating," is a current opinion by rating agencies about an issuer's overall capacity to pay its financial obligation based on the assessment of the likelihood of default of the corporation (Standard & Poor's (S&P) 2006). This issuer-level rating is different from an issue-specific credit rating assigned to an individual debt issue because the former does not reflect any priority among obligations or issue-specific characteristics such as collateral and debt covenants. Additionally, the issuer-level rating evaluates the firm's fundamental creditworthiness with respect to a very long time horizon, instead of fixed debt maturities (S&P 2006). Using this issuer-level credit rating changes as a proxy for the revision to the probability of default, I examine the relative importance of cash-flow news and discount-rate news.

A better understanding of the rating process is also important in itself. Despite the prominent role of credit ratings in the capital market, the rating process has been viewed more as a "black box" (Cifuentes 2008).[2] For example, we do not know much about what types of information are used and how different types of information are weighted in the rating process.[3] By investigating the relative weight given to the two fundamental components of new

[1] At first glance, it seems natural to study corporate bond returns to examine the effect of cash-flow news and discount-rate news on the probability of default. However, this issue cannot be addressed using the bond market, because the bond return, by definition, has a minimal cash-flow-news component due to its fixed coupon and principal payments. As the growth rate of cash flows (coupons) is zero when the present value model of Campbell and Shiller (1988) is applied to bonds, studies on the decomposition of bond returns decompose bond returns into a shock to future inflation, future real interest rate, and future excess bond return (Shiller and Beltratti 1992; Campbell and Ammer 1993; Abhyankar and Gonzalez 2009). Moreover, a bond has its own fixed maturity and issue-specific characteristics such as covenants, collaterals and priority to other securities, making it difficult to draw inferences with respect to firm-level cash-flow news and discount-rate news.

[2] Credit ratings are extensively used in loan agreements, debt covenants, investment rules of institutional investors, and other financial agreements. Ratings are also increasingly used in governmental regulation such as meeting rating requirements for money market funds and international banking supervision (see Frost (2007) for a review).

[3] For example, at the hearings by the Securities and Exchange Commission (SEC), users of credit ratings stressed the importance of transparency in the rating process. Particularly, they argue that the market needs to understand the reasoning behind a rating decision and the types of information relied upon by the rating agencies (SEC 2003, p. 33).

information in the rating process, this study enhances our understanding of how rating agencies use various types of information.

To implement the return decomposition, I adopt the Vector Autoregressive (VAR) model of Vuolteenaho (2002), which uses return on equity (ROE) as the basic cash-flow fundamentals. I extract cash-flow news and discount-rate news at the firm level from stock returns and then examine whether credit rating changes are more strongly associated with cash-flow news or with discount-rate news. I further examine whether cash-flow news and discount-rate news become more relevant in updating the probability of default when the news conveys negative information about the firm, consistent with an option-like nature of default risk.

This return decomposition approach offers great advantages in addressing my research questions for the following reasons. First, the model, derived from a dynamic accounting identity, provides a convenient and theoretically solid framework to disentangle cash-flow-news and discount-rate-news components. Second, the approach enables me to capture long-term and forward-looking information about the firm, as the news variables are measured by the stock market, which reflects the most comprehensive information set.[4] Furthermore, a shock to firm value is conceptually correctly measured as a summary of the information in all of the VAR state variables, which include stock return, profitability, and book-to-market ratio. Specifically, cash-flow news is defined as the shock to the discounted sum of expected current and future earnings over the lifetime of the firm. Such extension of the horizon to the future periods is particularly relevant in rating decisions, because credit rating agencies emphasize their long-term perspectives in rating decisions. For example, S&P indicates that "S&P's credit ratings are meant

[4] However, the stock returns includes information that is soft and unverifiable (i.e., non-contractible). Thus, it is an empirical question whether the information contained in the stock return is more strongly associated with credit ratings compared with traditional accounting performance measures.

to be forward-looking, and their time horizon extends as far as is analytically foreseeable" (S&P 2006, p. 33).[5] Finally, cash-flow news and discount-rate news can be measured in an internally consistent way (i.e., the sum of cash-flow news and discount-rate news equals the unexpected stock return), and thus a researcher can directly compare the effects of cash-flow news and discount-rate news on the variable of interest.[6]

The empirical findings are summarized as follows. I first establish that cash-flow news derived from the VAR model (Ncf_t) can better explain the credit rating change than traditional measures of cash-flow news can (e.g., changes in returns on assets (ROA) or ROE). The superiority of Ncf_t seems to arise from the fact that Ncf_t encompasses the shock to the future cash flows as well as the shock to the current cash flows. I also find that credit rating changes are, on average, more strongly associated with cash-flow news than with discount-rate news, as evidenced by the higher R^2 of cash-flow news model and greater coefficient on cash-flow news. In addition, the economic impact of cash-flow news is greater than discount-rate news. For example, the interquartile change in cash-flow news from the lower quartile (Q1) to the upper quartile (Q3) increases the likelihood of being upgraded by 1.39%, whereas the effect of discount-rate news is only 0.48%. The findings are consistent with the notion that cash-flow news is more permanent than discount-rate news (Campbell and Vuolteenaho 2004; Campbell et al. 2010). This greater role of cash-flow news compared with discount-rate news is also consistent with the standard credit rating agencies' methodology in which fundamental analysis

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5 Similarly, Moody's corporate ratings are intended to be determined by each issuer's relative fundamental creditworthiness without reference to explicit time horizons (Cantor and Mann 2003).

6 This approach is different from alternative methods in which cash-flow news is measured in one way and discount-rate news is measured the other way. For example, Botosan et al. (2009) measure cash-flow news from the analysts' revisions of earnings and target prices and measure discount-rate news from two other sources: five-year Treasury bonds and changes in estimated market beta. Likewise, Chandra and Nayar (1998) use the analysts' forecast revisions to measure cash-flow news and changes in market beta to measure discount-rate news for the sample of commercial paper downgrades.

and cash flow adequacy are emphasized(S&P 2006). For example, S&P (2006) indicates that "cash-flow analysis is the single most critical aspect of all credit rating decisions".

Further analyses that partition the sample by the nature of the news (i.e., good versus bad news) show that the relation between credit rating changes and news variables becomes much stronger when the news conveys negative information about the firm. This asymmetric association is consistent with the non-linear nature of default risk in which downside risk is more relevant than the upside potential. This finding is also consistent with the fact that rating agencies incorporate bad news sooner than good news into their rating revisions (Beaver et al. 2006).

The main findings are robust to several additional tests, including alternative VAR estimations, a direct estimation of cash-flow news and discount-rate news using analysts' earnings forecasts from IBES, controlling for a potential shareholder-bondholder conflict, and controlling for rating agencies' inefficient information process and their conflicts of interest.

This study contributes to the literature in several ways. First, it makes an important distinction between cash-flow news and discount-rate news and provides compelling evidence that cash-flow news is more relevant than discount-rate news in rating decisions. Thus, the paper extends a vast literature on the return decomposition to credit rating decisions. To my knowledge, this is the first study to formally examine the relative importance of cash-flow news and discount-rate news in credit ratings. Additionally, I examine the non-linear relation between credit rating changes and news variables, whereas most studies in this literature do not distinguish between good and bad news.

Second, my paper is closely related to several recent studies on the role of earnings in the debt market (Callen et al. 2009; Easton et al. 2009; DeFond and Zhang 2010). For example, Easton et al. (2009) examine the relation between earnings and bond returns and document that the relation is stronger when earnings convey bad news. I complement this line of research by using both cash-flow news and discount-rate news and directly comparing the effects of these two components. Furthermore, cash-flow news is appropriately measured in my study as the revision in the discounted sum of cash flows over the firm's lifetime. Hence, the way I define cash-flow news differs in an important respect from those in the previous studies on traditional proxies for cash-flow news, such as changes in historical earnings or cash flows.

Lastly, my study also contributes to the literature that investigates the determinants of credit ratings (Horrigan 1966; Kaplan and Urwitz 1979; Blume et al. 1998; Sengupta 1998; Ahmed et al. 2002; Ashbaugh-Skaife et al. 2006; Jiang 2008; Jorion et al. 2009; Lee 2008; Ayers et al. 2010). My paper complements this literature by focusing the relative importance of various types of information used in the credit rating process.

This study, however, is subject to several caveats. First, the news variables measured from stock returns may contain measurement errors in the context of credit ratings due to a potential shareholder-bondholder conflict. Second, recent papers are raising concerns about the implementation of VAR model (Chen and Zhao 2009). The third caveat is related to growing concerns that credit ratings may not reflect the probability of default in an unbiased and timely manner due to rating agencies' own incentives or inefficient information process. I try to address all of these issues in Section 6.

The rest of the paper is organized as follows. In Section 2, I review the literature and develop hypotheses. I provide the research design in Section 3 and describe the sample and descriptive statistics in Section 4. Then I report the results of empirical tests and additional tests in Sections 5 and 6. Section 7 concludes the study.

II. Literature Reviews and Hypothesis Development

2.1. Literature reviews

A credit rating provides the assessment of an obligor's overall capacity and willingness to meet its financial obligations (S&P 2006). The primary role of the credit rating in the capital market is to reduce information asymmetry by providing information on rated firms or securities based on their credit risk assessment (Boot et al. 2006). Consistent with this role, there is a large body of literature on the information content of credit rating changes. One stream examines the stock or bond market reactions to the announcement of a rating change (Holthausen and Leftwich 1986; Hand et al. 1992; Goh and Ederington 1993; Kliger and Sarig 2000; Dichev and Piotroski 2001; Jorion et al. 2005; Beaver et al. 2006). They find that both bond and stock prices respond to credit rating changes, particularly when ratings are downgraded. Another stream examines the revisions in analysts' earnings forecasts upon rating changes (Chandra and Nayar 1998; Ederington and Goh 1998). Their results suggest that analysts tend to revise their earnings forecasts downward (upward) following rating downgrades (upgrades).

There is also empirical evidence that rating changes reflect public information that is already available in the market. For example, Holthausen and Leftwich (1986) report that rating downgrades (upgrades) are followed by several months of negative (positive) stock returns. Most rating downgrades (upgrades) are also preceded by negative (positive) forecast revisions made by analysts (Ederington and Goh 1998).

While these studies provide valuable insight into the information content of rating changes, the types of information used by rating agencies and the relative importance of information are still largely unknown. A return decomposition approach of distinguishing between cash-flow news and discount-rate news by Campbell and Shiller (1988) provides a novel framework for investigating the types of new information used in rating decisions. Campbell and Shiller (1988) developed a dividend-ratio model that relates the dividend-price ratio to the expected discount rates and growth rates of dividends. Since then, the return decomposition method has led to a voluminous literature across many disciplines, including finance, macroeconomics, and accounting. While this approach has been used largely in the stock market, the framework can also be applied to the general settings because the key concept is based on the fundamental notion of asset valuation. For example, because default risk is based on the distribution of the firm's expected cash flows (Merton 1974; Cheng and Subramanyam 2008), the probability of default increases with a negative shock to the expected cash flows and an increase in the riskiness of expected cash flows. As corporate credit ratings assess the probability of default, the rating downgrades (upgrades) should occur when rating agencies revise downward (upward) their expectations of future cash flows (e.g., deterioration in the firm's future performance) and/or when they revise upward (downward) their evaluation of the riskiness of that cash flow stream (e.g., an increased volatility).

Only a few papers on credit ratings adopt this framework of distinguishing between cash-flow news and discount-rate news. For example, Cheng and Subramanyam (2008) suggest that analyst following can affect credit ratings by influencing both the mean and conditional variance of expected cash flows due to analysts' monitoring and informational roles. Their argument is conceptually consistent with the return decomposition framework that credit rating changes are affected by both cash-flow news and discount-rate news. Goh and Ederington (1993) examine short explanations of the reasons for the rating changes provided by Moody's. They find that downgrades due to expected deterioration in financial prospects, which are presumably related to cash-flow news, are most common and are associated with significant stock market reactions. Likewise, Chandra and Nayar (1998) examine analysts' earnings forecast revisions to determine whether commercial paper rating downgrades convey information about changes in expected cash flows. They also examine the change in systematic risk following downgrades to see whether rating downgrades affect the perceived riskiness of the firm. They find that commercial paper downgrades are associated with a downward revision in analysts' earnings forecasts and are also followed by an increase in the market beta. Their findings suggest that credit rating changes have implications for both firm's expected cash flows and expected returns. However, they do not provide evidence on the relative importance of these two components in rating decisions.

There is a substantial body of literature on the relative importance of cash-flow news and discount-rate news in the stock market. Campbell (1991) and Campbell and Ammer (1993) use a VAR model based on the dividend-ratio model of Campbell and Shiller (1988) to decompose the aggregate stock returns into cash-flow news and discount-rate news. They find that the variance of discount-rate news dominates the variance of cash-flow news, suggesting that the aggregate stock returns are mainly driven by news about the expected discount rate. Vuolteenaho (2002) extends this variance decomposition framework to the firm level using ROE instead of dividend growth as the basic cash-flow fundamentals. He shows that the firm-level stock returns are mainly driven by cash-flow (earnings) news. He reconciles his results with those at the aggregate level by showing that cash-flow information is largely firm-specific, while discount-rate information is driven by systematic and macroeconomic components. Hence, firm-level cash-flow-news component can be largely diversified away in aggregate portfolios. Decomposing total earnings news into accrual earnings news and cash flow earnings news, Callen and Segal (2004) find that both accrual and cash components of earnings are equally significant in driving stock returns.[7]

One novel feature of the VAR model is that it can directly decompose the realized stock return into three components: expected returns, cash-flow news, and discount-rate news (Cohen et al. 2002; Hecht and Vuolteenaho 2006; Callen et al. 2010). For example, Hecht and Vuolteenaho (2006) decompose the realized stock return into these three components and then reexamine the contemporaneous relation between earnings and each component of stock returns. Callen et al. (2010) measure cash-flow news and construct a measure for firm-level conservatism as the ratio of the current earnings shock to total earnings news. Similar to these studies, I extract cash-flow news and discount-rate news using the VAR approach of Vuolteenaho (2002).

2.2. Hypotheses development

It is not clear *ex ante* whether cash-flow news or discount-rate news drives the credit rating change. Campbell and Vuolteenaho (2004) and Campbell et al. (2010) suggest that cash-flow news has a permanent impact on stock prices, while discount-rate news has only a temporary impact. This is because poor returns driven by increases in discount rates are partially offset by improved prospects for future investment opportunities. In other words, wealth decreases, but future investment opportunities improve. On the other hand, changes in firm value due to the revision in expected cash flows are never subsequently reversed. Based on this argument, Campbell and Vuolteenaho (2004) break down firm betas into cash-flow betas and discount-rate betas and find that value stocks and small stocks have higher cash-flow betas than do growth stocks and large stocks. In addition, cash-flow news and discount-rate news have different implications for credit ratings because cash-flow news is primarily firm-specific, while

[7] Callen et al. (2005) examine the importance of foreign earnings versus domestic earnings for U.S. multinationals and find that domestic earnings are more important in explaining the variance of unexpected returns than are foreign earnings.

discount-rate news is mainly related to systematic and macroeconomic components (Vuolteenaho 2002). Due to this difference, discount-rate news may be less relevant in the revisions in the credit rating because a *relative* (i.e., ordinal) ranking of credit risk may not be affected by macroeconomic factors. From this line of reasoning, cash-flow news is expected to have a greater impact on credit rating changes than is discount-rate news.

However, cash-flow news may have limited implications for rating changes because credit ratings represent the perspectives of bondholders whose cash flows (i.e., interest and principal payments) are fixed. In summary, it is an empirical question whether rating changes are more strongly associated with cash-flow news or with discount-rate news.

I further examine whether the association between credit rating changes and news variables becomes stronger when the news conveys negative information about firm value. For example, improved expected cash flows may have a limited impact on the revision of default risk, whereas news indicating deteriorating cash flows has a direct impact on the revision in default risk. Hence, I expect that both cash-flow news and discount-rate news are more strongly related to credit rating changes when the new information conveys bad news than when it contains good news (Beaver et al. 2006; Callen et al. 2009; Easton et al. 2009).

III. Research Design

3.1. The return decomposition[8]

Unexpected stock return ($r_t - E_{t-1}(r_t)$) can be expressed by the sum of cash-flow news (Ncf) and (the negative of) discount-rate news (Nr) as follows:

$$r_t - E_{t-1}(r_t) = Ncf_t - Nr_t \qquad (1)$$

[8] Callen and Segal (2010) provide an excellent summary of the variance decomposition method.

where r_t denotes the log cum dividend stock return at time t and $E_{t-1}(r_t)$ denotes the market's expectation at time t-1 of the stock return at time t. Ncf_t is cash-flow news at time t defined as the market's revision from period t-1 to t of expected earnings over the lifetime of the firm. Intuitively, cash-flow news is the stock return that would have been realized if expected returns had not changed (Cohen et al. 2002). Nr_t is discount-rate news at time t defined as the market's revision from period t-1 to t of expected discount rates. A positive shock to expected cash flows (expected discount rate) results in a positive (negative) stock return.

Formally, cash-flow news and discount-rate news in Vuolteenaho (2002) are defined as follows:

$$Ncf_t = \Delta E_t \sum_{j=0}^{\infty} \rho^j \, roe_{t+j} \qquad (2)$$

$$Nr_t = \Delta E_t \sum_{j=1}^{\infty} \rho^j \, r_{t+j} \qquad (3)$$

where $\Delta E_t = E_t - E_{t-1}$ denotes the change in expectation from period t-1 to period t, ρ is a constant discount coefficient, and roe_t is the log return on book value equity at time t.[9]

I implement the return decomposition using a VAR model with three state variables: stock return, earnings deflated by beginning book value of equity, and book-to-market ratio (Vuolteenaho 2002).[10] All variables are cross-sectionally demeaned.

$$r_t = \alpha_1 r_{t-1} + \alpha_2 roe_{t-1} + \alpha_3 bm_{t-1} + \eta_{1t} \qquad (4a)$$

$$roe_t = \beta_1 r_{t-1} + \beta_2 roe_{t-1} + \beta_3 bm_{t-1} + \eta_{2t} \qquad (4b)$$

$$bm_t = \gamma_1 r_{t-1} + \gamma_2 roe_{t-1} + \gamma_3 bm_{t-1} + \eta_{3t} \qquad (4c)$$

where (Compustat XPF names are presented in parentheses. The firm subscript i is omitted.)

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[9] I follow the convention of denoting variables by uppercase letters and their logs by lowercase letters.

[10] State variables include book-to-market ratio, because Vuolteenaho (2002) derived the decomposition model based on the definition of the market-to-book ratio.

r_t = The log of one plus the annual cum dividend return minus the log of one plus the annualized three-month Treasury bill rate. The 12-month return cumulation period starts three months after the beginning of the current fiscal year.[11]

roe_t = The log of one plus ROE minus the log of one plus the annualized three-month Treasury bill rate. ROE is computed as income before extraordinary items (IB), divided by beginning of period book value of equity (CEQ).

bm_t = The log of the book-to-market ratio at year-end. Book-to-market ratio is book value of equity (CEQ) divided by the market value of equity (CSHO*PRCC_F).

The above equations (4a) – (4c) can be expressed in matrix notation as follows:

$$z_t = \Gamma z_{t-1} + \eta_t \quad (5)$$

where

$$z_t = \begin{pmatrix} r_t \\ roe_t \\ bm_t \end{pmatrix}, \Gamma = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \beta_1 & \beta_2 & \beta_3 \\ \gamma_1 & \gamma_2 & \gamma_3 \end{pmatrix}, \ \eta_t = \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \end{pmatrix}$$

As shown by Campbell and Shiller (1988), cash-flow news (Ncf_t) and discount-rate news (Nr_t) can be conveniently computed as follows:[12]

$$Ncf_t = (e_1+\lambda_1)'\eta_t \quad (6)$$

$$Nr_t = \lambda_1' \eta_t \quad (7)$$

where ´ denotes the transpose operator, $e_k' = (0, \ldots, 1, \ldots, 0)$ is a row vector with one as the *k*th element, and zero elsewhere, and $\lambda_k' = e_k' \rho \Gamma(I - \rho \Gamma)^{-1}$ with $(I - \rho \Gamma)^{-1}$ being the matrix equivalent of the present value of the sum.

The VAR coefficient matrix (Γ) is assumed to be constant over time and across firms.[13] I

[11] When the firm is delisted, I follow Beaver et al. (2007).

[12] As in Vuolteenaho (2002), discount-rate news is computed directly, and cash-flow news is computed residually by subtracting discount-rate news from unexpected returns. In Section 6, I explore the other options of computing cash-flow news directly (Chen and Zhao 2009).

[13] In Section 6, I relax this restriction by estimating Γ for each industry or for each subperiod sample.

use the ordinary least squares (OLS) to estimate the VAR coefficients. ρ is assumed to take on a value of 0.967 as in Vuolteenaho (2002).[14]

As cash-flow news (Ncf_t) is the sum of the shock to the current earnings and the shock to the future earnings, cash-flow news can be further decomposed into current-period cash-flow news ($CNcf_t$) and future-period cash-flow news ($FNcf_t$). The current-period cash-flow news can be measured as the residual from the Equation (4b), η_{2t}, and the future-period cash flow news is defined as the difference between total cash-flow news and current-period cash-flow news as follow (Callen et al. 2010):

$$Ncf_t = CNcf_t + FNcf_t \qquad (8)$$

3.2. The rating change model

To examine the relative importance of cash-flow news and discount-rate news in rating decisions, I use three approaches. First, I evaluate the goodness of fit (R^2) of the model, which includes either cash-flow news or discount-rate news. As the second and third approach, I compare the magnitude of the coefficients and marginal effects of the variables in the following model:

$$\Delta \mathrm{RATING}_t = \beta_0 + \beta_1 \mathrm{Ncf}_t + \beta_2 \mathrm{Nr}_t + \beta_3 \Delta \mathrm{SIZE}_t + \beta_4 \Delta \mathrm{INTCOV}_t + \beta_5 \Delta \mathrm{ROA}_t + \beta 6 \Delta \mathrm{LEVt} + \beta 7 \Delta \mathrm{CAP\_INTENt} + \beta 8 \Delta \mathrm{AGRWt} + \beta 9 \Delta \mathrm{STDRETt} + \mathrm{industry{-}and\ year} - \mathrm{fixed\ effects} + \varepsilon_t \qquad (9)$$

where (Compustat XPF names are presented in parentheses. The firm subscript i is omitted.)

$\Delta RATING_t$	=	$RATING_t - RATING_{t-1}$, $RATING_t$ is S&P's long-term issuer-level credit ratings (SPLTICRM) as of three months after the fiscal year end, converted to numerical values between 1 (CCC+ or below) and 17 (AAA) according to Panel B of Table 1.

[14] The results are not affected by the value of ρ within the range between 0.95 and 1.

Ncf_t	=	Cash-flow news as computed in Equation (6)
Nr_t	=	Discount-rate news as computed in Equation (7)
$\Delta SIZE_t$	=	$SIZE_t$ – $SIZE_{t-1}$, where $SIZE_t$ is the log of market value of equity (CSHO*PRCC_F)
$\Delta INTCOV_t$	=	$INTCOV_t$ – $INTCOV_{t-1,}$ where $INTCOV_t$ is the log of one plus interest coverage ratio. Interest coverage ratio is defined as operating income before depreciation (OIBDP) divided by interest expense (XINT).
ΔROA_t	=	ROA_t – ROA_{t-1}, where ROA_t is income before extraordinary items (IB) divided by average total assets (AT).
ΔLEV_t	=	LEV_t – LEV_{t-1}, where LEV_t is the ratio of total debt (DLTT+DLC) to total assets (AT).
ΔCAP_INTEN_t	=	CAP_INTEN_t – $CAP\_INTEN_{t-1,}$ where CAP_INTEN_t is gross property, plant and equipment (PPEGT) divided by total assets.
$\Delta AGRW_t$	=	$AGRW_t$ – $AGRW_{t-1}$, where $AGRW_t$ is the total asset growth defined as (Total $assets_t$ – Total $assets_{t-1}$)/Total $assets_{t-1}$.
$\Delta STDRET_t$	=	$STDRET_t$ – $STDRET_{t-1}$, where $STDRET_t$ is the standard deviation of daily stock returns during the fiscal year.

The dependent variable ($\Delta RATING_t$) is the change in firm's credit ratings between year t and t-1.[15] Credit ratings measured as of three months after the fiscal year-end ($RATING_t$) are converted to numerical values between 1 (CCC+ or below) and 17 (AAA) according to Panel B of Table 1. Then $\Delta RATING_t$ is defined as the first difference of $RATING_t$. A positive value of $\Delta RATING_t$ indicates a rating upgrade, a negative value indicates a rating downgrade, and a zero value indicates no rating change. Because a credit rating is an ordered categorical variable and thus a rating change does not represent an equally-spaced discrete interval, I use the ordered logit specification rather than the standard OLS.

A set of control variables that have been documented to be associated with credit rating changes are also included in the model (Jiang 2008; Lee 2008; Ayers et al. 2010). I include the

[15] The model on the determinants of the level of credit ratings may suffer from potential correlated omitted variable problems. In addition, credit ratings are "sticky," which implies that any correlated omitted variables or the error terms from a ratings-level regression are likely correlated over time. I use the "change specification" in which both dependent and independent variables are all measured as the change to mitigate the effects of correlated omitted variables and autocorrelation in the error terms (Jiang 2008; Ayers et al. 2010). Furthermore, the use of changes in ratings is consistent with my research question that examines how new information captured in cash-flow news and discount-rate news affects the rating changes.

change in firm size (ΔSIZE$_t$), interest coverage ratios (ΔINTCOV$_t$), return on assets (ΔROA$_t$), financial leverage (ΔLEV$_t$), capital intensity (ΔCAP_INTEN$_t$), asset growth (ΔAGRW$_t$), and the standard deviation of stock return (ΔSTDRET$_t$). Lastly, I include industry and year indicators to control for any effect by industry membership and macroeconomic events. Furthermore, for easier economic interpretation, I standardize all independent variables by subtracting the sample mean from them and then dividing the difference by the standard deviation. With this, I can directly compare the coefficients on cash-flow news (Ncf) and discount-rate (Nr), because they both represent one standard deviation change in each variable. (Ashbaugh-Skaife et al. 2006; Hirshleifer et al. 2009; Chava and Purnanandam 2010). I report p-values based on robust standard errors clustered by firm (Peterson 2009).

Significant coefficients on β_1 and β_2 in Equation (9) indicate that rating agencies respond to cash-flow news and discount-rate news. The coefficient on cash-flow news (β_1) is expected to be positive, while the negative sign is expected for discount-rate news (β_2).

IV. Sample and Descriptive Statistics

Panel A of Table 1 summarizes the sample selection procedure. The initial sample is from firm-year observations with available variables to estimate the VAR model on Compustat XPF during the period of 1986-2008. I exclude firms in the utilities (SIC 4900-4999) and financial services (SIC 6000-6999) industries.[16] I require firms to have a December fiscal year-end to align accounting variables across firms. I require non-missing values for current and lagged stock return, book-to-market ratios, and return on equity. I eliminate observations with

[16] The sample period starts in 1986, because credit rating data on Compustat are available from 1985 and the observations in 1985 are dropped to obtain the first difference in variables.

lagged market value less than $10 million. The VAR state variables are winsorized at a 1% and 99% level each year to mitigate outliers. The sample used to estimate the VAR model is 45,486 firm-year observations. Then, I require S&P's issuer-level credit ratings to calculate the rating changes. After excluding missing data to obtain other control variables, the final sample is 11,354 firm-year observations representing 1,541 distinct firms.

Panel B of Table 1 shows the distribution of credit ratings ($RATING_t$). $RATING_t$ takes the value between 1 and 17, with a higher value indicating better credit quality. I combine all ratings below CCC+ with CCC+ into one category because of the limited number of observations under CCC+ (Jiang 2008). Firms with investment-grade ratings (BBB- or above) are 60.2 percent of the sample, and firms with non-investment-grade ratings (BB+ or below) make up the remaining 39.8 percent. Panel C presents the distribution of credit rating changes, which are the dependent variable for all analyses.[17] The distribution shows that the majority of firm-years do not experience rating changes (76.55%), while downgrades (13.34%) are more common than upgrades (10.11%). This distribution of credit rating changes is similar to that found in prior studies (Jiang 2008; Ayers et al. 2010).

Table 2 provides the descriptive statistics for variables in the regressions. I report the descriptive statistics for the raw numbers before the standardization. The median firm-year has a $RATING_t$ of 9, corresponding to the S&P letter grade of BBB. $\Delta RATING_t$ has a mean value of -0.07 with a standard deviation of 0.75. The average values of cash-flow news (Ncf_t) and discount-rate news (Nr_t) are 6.0 percent and 0.4 percent, respectively. Ncf_t has a larger standard deviation (0.35) than Nr_t (0.11).

[17] I exclude firm-year observations with $|\Delta RATING_t|>4$. This dramatic change in ratings in adjacent years may be due to coding errors or significant events such as mergers or acquisitions (Jiang 2008).

Table 3 reports the Pearson correlation coefficients among variables. $\Delta RATING_t$ is positively associated with Ncf_t, $CNcf_t$, $FNcf_t$, $\Delta SIZE_t$, $\Delta INTCOV_t$, ΔROA_t and $\Delta AGRW_t$, while Nr_t, ΔLEV_t, ΔCAP_INTEN, and $\Delta STDRET_t$ are negatively associated with $\Delta RATING_t$ in the univariate analysis. $\Delta RATING_t$ is more strongly associated with Ncf_t ($\rho = 0.23$) than with Nr_t ($\rho = -0.04$). There is a negative correlation ($\rho = -0.18$) between Ncf_t and Nr_t (Callen et al. 2010).

V. Empirical Results

5.1. The VAR estimation

Table 4 reports the estimated VAR coefficient matrix (Γ) and variance-covariance matrix (Σ) from the pooled OLS. Note that the sample used for the VAR estimation is 45,486 observations, before requiring the S&P credit ratings or other control variables (See Panel A in Table 1). I report the OLS estimate of the parameter with robust standard errors obtained using the Rogers' (1993) method in parentheses and the jackknife method outlined by Shao and Rao (1993) in brackets.[18] The current returns (r_t) are high when past returns, return on equity, and book-to-market ratio are high. Current profitability (roe_t) is positively related to past returns, profitability, and book-to-market ratio. Finally, current book-to-market ratio (bm_t) is negatively related to past stock returns, but is positively related to past profitability and book-to-market ratio. Table 4 also presents the coefficients of the linear function λ_1' and $(e_1+\lambda_1)'$ that map the VAR innovations (η_t) to discount-rate news and cash-flow news, respectively. λ_1', defined as $e_1'\rho\,\Gamma(I-\rho\,\Gamma)^{-1}$, captures the significance of each individual VAR shock to discount-rate expectations. λ_1' shows that stock return, profitability, and book-to-market ratio are all positively related to

[18] The Shao-Rao's (1993) jackknife method estimates the parameter after dropping one cross-section at a time and results in a time series of estimates. This jackknife method yields consistent standard errors even in the presence of cross-sectional correlation (See Appendix B in Vuolteenaho (2002)).

discount-rate news, consistent with the finding in Campbell et al. (2010).

5.2. The relative importance of cash-flow news and discount-rate news

5.2.1. Comparing the R^2

As the first approach to evaluate the relative importance of cash-flow news and discount-rate news in the rating process, I compare the pseudo R^2 of the ordered logit models.[19] Since several approaches to compute pseudo R^2 have been developed for a logit regression, I use two widely used pseudo R^2: McFadden's (1973) pseudo R^2 (R^2_{MF}) and McKelvey and Zavoina's (1975) pseudo R^2 (R^2_{MZ}).[20] Table 5 reports the ordered logit results along with two measures of pseudo R^2. I first compare the pseudo R^2 across models which include several proxies for cash-flow news. In Column (1), when changes in credit ratings ($\Delta RATING_t$) are regressed on cash-flow news (Ncf_t), the coefficient is significantly positive, indicating that rating agencies tend to upgrade ratings upon good news about expected cash flows. R^2_{MF} and R^2_{MZ} are 2.6 percent and 7.4 percent, respectively. In Columns (2) though (4), I include the change in return on assets (ΔROA_t), return on equity (ΔROE_t), or operating cash flows (ΔCFO_t), which are widely used as measures for shocks to firms' cash flows. The pseudo R^2 are all lower than that of the model of Ncf_t, indicating that cash-flow news derived from the VAR approach (Ncf_t) better explains the change in credit ratings than do the traditional accounting measures for cash-flow news. To provide some evidence on the source of superiority of Ncf_t over these simple accounting variables, I decompose Ncf_t into current-period ($CNcf_t$) and future-period ($FNcf_t$) cash-flow

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[19] While it is common to compare R^2 across the models in the OLS (e.g., Dechow 1994), an equivalent statistic to the OLS R^2 does not exist for a logistic regression, because the maximum likelihood estimation is not to minimize the variance. Instead, several approaches to compute pseudo R^2 for the logit model have been developed. It is known that pseudo R^2 cannot be interpreted independently or compared across datasets. However, they are valid and useful in evaluating multiple models predicting the same outcome from the same datasets. In this case, the higher pseudo R^2 indicates which model better predicts the outcome (Freese and Long 2006).

[20] McKelvey and Zavoina's pseudo R^2 is found to be the most closely approximate of the R^2 obtained from regressions on the underlying latent variable (Hagel and Mitchell 1992).

news. Column (5) shows that the pseudo R^2 of $CNcf_t$ model is similar to that of ΔROE_t model. However, the pseudo R^2 increases substantially when future-period cash-flow news ($FNcf_t$) is added to the model as shown in Column (6). For example, R^2_{MF} (R^2_{MZ}) increases from 1.5 (4.1) percent to 2.8 (7.6) percent. This finding supports that the superiority of Ncf_t over other accounting variables arises from the fact that Ncf_t encompasses the shock to the future cash flows as well as the shock to the current cash flows.

Turning to the comparison between cash-flow news and discount-rate news, Column (7) shows that the coefficient on Nr_t is significantly negative, suggesting that rating agencies tend to downgrade when there is news indicating an increase in risk. However, discount-rate news (Nr_t) does not explain the change in credit ratings as much as cash-flow news (Ncf_t) does. The pseudo R^2 of discount-rate news model is very low at 0.2 percent for R^2_{MF} and 0.5 percent for R^2_{MZ}.[21]

In summary, the results in Table 5 suggest that cash-flow news derived from the VAR model outperforms traditional accounting measures for cash-flow shocks, because it also reflects the shock to the future cash flows. The results also reveal that cash-flow news better explains the credit rating changes than does discount-rate news.

5.2.2. Comparing the magnitude of the coefficients

Column (1) of Table 6 reports the ordered logit results when both Ncf_t and Nr_t are included along with several control variables. Ncf_t is significantly positive, and Nr_t is significantly negative, consistent with the prediction. More importantly, the coefficient on Ncf_t (0.244) is about two times greater in absolute value than the coefficient on Nr_t (-0.123). Note that I can directly compare these two coefficients on Ncf_t and Nr_t because all independent variables

[21] In the untabulated analysis, I estimate the OLS and find that the results are similar. For example, the OLS R^2 for the model with Ncf_t is 5.35 percent, while the OLS R^2 for the model with ΔROA_t (ΔROE_t) is 3.78 (3.33) percent. The OLS R^2 for the model with Nr_t is 0.13 percent.

are standardized and thus the coefficients represent one standard deviation change. The statistical test confirms that these two coefficients are statistically different (p-value=0.01). This finding supports that cash-flow news is more important in driving credit rating changes than is discount-rate news.

The coefficients on the other control variables are generally consistent with prior research (Jiang 2008; Ayers et al. 2010). The increases in firm size ($\Delta SIZE_t$), interest coverage ($\Delta INTCOV_t$), return on assets (ΔROA_t), and capital intensity (ΔCAP_INTEN_t) are positively associated with the likelihood of rating upgrades. On the other hand, the increases in financial leverage (ΔLEV_t), asset growth ($\Delta AGRW_t$), and stock return volatility ($\Delta STDRET_t$) are associated with the higher likelihood of rating downgrades. Note that ΔROA_t is only marginally significant with Ncf_t in the model.[22]

In Column (2), I decompose Ncf_t into $CNcf_t$ and $FNcf_t$. The two components of total cash-flow news are both significantly positive, and the magnitudes of the two coefficients are not statistically different (p-value=0.24).[23] This suggests that shocks to current and future cash flows are equally important in rating revisions. I also estimate the ordered logit after excluding firm-year observations with zero rating changes, because there may be concerns about many observations with zero values in the dependent variable. The sample size is reduced to 2,662. The result with the reduced sample presented in Column (3) is generally similar to those reported in Column (1).[24] I also estimate the OLS instead of the ordered logit and report the result in

[22] The multicollinearity is unlikely here, because the correlation between Ncf_t and ΔROA_t is 0.33, as reported in Table 3.
[23] In Column (3) of Table 6, ΔROA_t is not significant. This may be due to multicollinearity, because the Pearson correlation coefficient between ΔROA_t and $CNcf_t$ is high (ρ=0.59). I re-estimate the model after dropping ΔROA_t. The results do not change at all.
[24] To empirically examine the effect of many zero rating changes, I use this method of simply excluding the zero rating changes from the sample and report the results. However, the value of zero is clearly an important category in

Column (4). The result is similar, which confirms that the findings are not sensitive to the specific estimation method.

5.2.3. Comparing the economic impacts

Although the findings in Table 6 clearly support the notion that rating agencies revise their assessment of the credit quality of the firm upon cash-flow news to a greater extent than upon discount-rate news, it is not straightforward to quantify the economic impacts of changes of explanatory variables on rating changes due to the nonlinear nature of the estimation method of the logit regression with multiple categories. To more readily assess the economic significance of the results, I use an alternative classification scheme in which the dependent variable is either a rating upgrade or downgrade. I estimate the binary (instead of ordered) logit and present the marginal effects and the changes in the probability of being upgraded or downgraded in Table 7 (Ashbaugh-Skaife et al. 2006). Specifically, I define $UPGRADE_t$ ($DOWNGRADE_t$) as one if credit ratings are upgraded (downgraded), and zero otherwise. To assess the economic significance, I present the marginal effect of each variable in Columns (2) and (5), which is evaluated at the mean value of each variable, holding all other variables at their means. The marginal effect represents the change in the probability of being upgraded (or downgraded) upon infinitesimal change of the independent variable. An alternative and easy-to-interpret way to evaluate the economic impact is to calculate the change in the probability of being upgraded (or downgraded) as the value of the explanatory variable is moved from its lower quartile (1Q) to its upper quartile (3Q), while holding other variables constant at their means. I report these results in Columns (3) and (6).

The binary logit results presented in Columns (1) and (4) of Table 7 are similar to those

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the ordered logit, and thus one should be cautious when interpreting this result.

reported in Table 6. A shock to future cash flows is positively (negatively) associated with the likelihood of being upgraded (downgraded), while a shock to expected return is positively associated with the likelihood of being downgraded. The notable difference between the ordered and binary logit results is that Nr_t is not significant in Column (1) of Table 7 in which the probability of being upgraded is estimated. With respect to the economic impact, the marginal effect of Ncf_t is greater in absolute value than that of Nr_t for both upgrades (0.013 versus -0.005) and downgrades (-0.024 versus 0.014). Furthermore, the change in the probability of rating changes as a result of moving the variable from Q1 to Q3 is also greater for Ncf_t than for Nr_t. For example, an interquartile change of Ncf_t is associated with a 1.39 percent increase (Nr_t) in the probability of being upgraded while the effect of Nr_t is only 0.48 percent. Similarly, an interquartile change of Ncf_t (Nr_t) is associated with a 2.51 percent decrease (1.46 percent increase) in the probability of being downgraded. Given that the probability of being upgraded (downgraded) evaluated at the means of all variables is 7.96 percent (10.23 percent), this change in the likelihood of rating changes appears to be economically significant.

5.3. Asymmetric response of rating changes with respect to bad news

To test whether the association between credit rating changes and news variables becomes stronger when the news conveys negative information about firm value, I divide the sample into two groups by the sign of the news variables. As a starting point, the entire sample is partitioned by the sign of unexpected return ($=r_t-E_{t-1}(r_t)$), and the ordered logit is estimated separately for each group. The coefficients on cash-flow news (Ncf_t) and discount-rate news (Nr_t) are significant for both groups of positive and negative unexpected returns. The magnitude of the coefficient on Ncf_t is not statistically different from the coefficient on Nr_t for good news (p-value=0.27), while the coefficient on Ncf_t is greater than that on Nr_t for bad news (p-value=0.00). A caveat for this approach is that this measure of unexpected stock returns as a proxy for good or bad news cannot distinguish whether the news is about expected cash flows or about future discount rates, making the interpretation of this division unclear. Hence, I use the sign of either cash-flow news or discount-rate news for further partitioning.

In Columns (3) and (4) of Table 8, the sample is partitioned by the sign of cash-flow news. The results show that Ncf_t is significant only for the subsample with negative information about cash-flow news (Column 4). However, Nr_t is negative and significant for both subsamples. Regarding relative importance, cash-flow news seems to be less relevant in updating ratings when it carries positive information, whereas cash-flow news dominates discount-rate news when there is bad news about expected cash flows.

In Columns (5) and (6), when the sample is divided by the sign of discount-rate news, an asymmetric pattern emerges for discount-rate news, which mirrors the previous finding for cash-flow news. Nr_t is not significant for the subsample that has experienced a decrease in risk (Column 5), whereas it is significantly negative for the subsample that has experienced an increase in risk (Column 6). However, the coefficients on Ncf_t are significant for both groups regardless of the sign of discount-rate news. In addition, the coefficient on Ncf_t is greater in absolute value than that on Nr_t for both groups.

Overall, the relation between rating changes and news variables becomes much stronger for bad news, and the relative importance of these two components depends on the nature of the news it conveys.

VI. Additional analyses

6.1. The alternative estimations of cash-flow news and discount-rate news

Although the VAR approach is currently the state-of-the-art practice in implementing the return decomposition and is widely used in many disciplines (see Chen and Zhao 2009), it is not free from controversy. For example, the conclusions drawn from the VAR approach may be sensitive to the sample period (Chen 2009), to the choice of state variables, and to the way in which cash-flow news is measured (i.e., whether cash-flow news is directly modeled or backed out as the residual) (Chen and Zhao 2009). To address such concerns, I perform a comprehensive set of additional tests.

First, I use the weighted least squares (WLS) instead of the OLS to check the robustness to the estimation method. I deflate the data for each firm-year by the number of firms in the corresponding cross-section to weigh each cross-section equally (Vuolteenaho 2002).

Second, to address the concern whether the VAR parameters are constant across firms, I estimate the VAR system separately for each Fama-French (1997) industry as suggested by Callen and Segal (2010). This approach yields the VAR parameters at the industry level, but the news variables can be computed at the firm-year level.

Third, to address the concern that cash-flow news, when measured as the residual, inherits the large misspecification error, I use two approaches: (1) I estimate cash-flow news directly ($Ncf_t = e_2'(I - \rho\,\Gamma)^{-1}\,\eta_t$) and discount-rate news residually as the difference between the unexpected return and cash-flow news, and (2) I estimate both cash-flow news and discount rate news directly and define the residual news ($N\_residual_t$) as the third component of unexpected returns, because the equality of Equation (1) is not guaranteed when both components are directly modeled.

Fourth, I partition the full sample period into two periods (1986-1998 and 1999-2008) and estimate the VAR system separately for them to check whether the results are sensitive to the estimation period. The untabulated results are similar to those reported previously.

As a last check, I employ an alternative method proposed by Chen and Zhao (2010) that does not rely on the predictive regression of the VAR model. Following Chen and Zhao (2010), I estimate the implied cost of equity capital (ICC) using earnings forecasts from IBES as a measure of cash-flow expectation for each firm and at each point in time (Pastor et al. 2008). A price change between year t and year t+j can then be decomposed into two parts: cash-flow news defined as the price change holding ICC constant, and discount-rate news defined as the price change holding cash flows constant (see Chen and Zhao (2010) for a detail).[25] The use of this alternative method, which does not rely on the VAR model, enhances confidence in my results, although this alternative method is silent about how an expected-return component can be extracted from the price change between the two periods.[26]

I report the results for these tests described above in Table 9. In Columns (1) through (5), the coefficients on Ncf_t and Nr_t are all significant, and the coefficient on Ncf_t is greater in absolute value than that on Nr_t. In sum, I conclude that the results are not sensitive to the specific method to measure cash-flow news and discount-rate news.[27]

6.2. Shareholder-bondholder conflicts

As cash-flow news and discount-rate news are measured using stock returns and credit ratings assess the probability of default, which may be better represented by the bondholders'

[25] I follow Chen and Zhao (2010) in estimating ICC, cash-flow news, and discount-rate news, except for the assumption about the long-term growth rate (g). While Chen and Zhao (2010) set g as the consensus long-term earnings growth rates (LTG) from IBES, I find that this LTG seems to be too high as a proxy for steady-state growth rates. For example, in many cases, the LTG is higher than the estimated ICC. Thus, I follow Gebhardt et al. (2001) and use 10-year Treasury bond rate minus 3% as the proxy for g. In addition, note that discount-rate news is defined in Chen and Zhao (2010) to have a positive (instead of a negative) sign in Table 9.

[26] That is, Chen and Zhao (2010) decompose the realized return (excluding dividends) into cash-flow news and discount-rate news. However, conceptually, the realized return should also include the expected return component.

[27] The tests that compare the pseudo R^2 are not tabulated. However, the tenor of the results is similar. The pseudo R^2 is higher for Ncf_t than for Nr_t in every case.

perspective, the results can be subject to measurement errors or biases arising from potential shareholder-bondholder conflicts. However, I believe that this is not a serious concern for several reasons.[28] First, many papers argue that stockholder-bondholder conflicts are typically small (Fama and Miller 1972; Andrade and Kaplan 1998; Parrino and Weisbach 1999). Second, there is abundant empirical evidence that rating changes are associated with changes in stock prices (Holthausen and Leftwich 1986; Hand et al. 1992; Dichev and Piotroski 2001; Beaver et al. 2006). Finally, several studies find that stock returns can predict firm bankruptcy, which credit ratings aim to assess (Watts and Zimmerman 1986, p.116; Shumway 2001).

Nevertheless, to check the robustness, I examine whether the results are conditional on the magnitude of shareholder-bondholder conflicts. I use three proxies for shareholder-bondholder conflicts: leverage, stock return volatility, and whether the credit rating is investment grade or not (Ahmed et al. 2002). I expect that firms with high leverage, high return volatility, and non-investment-grade ratings likely experience greater shareholder-bondholder conflicts. If my finding of a greater role of cash-flow news is observed only for the subsample with a high level of shareholder-bondholder conflicts, it is likely that my results may be driven by measurement errors or biases. Panel A of Table 10 reports the results for partitioned samples by these three proxies. The results, however, show that the difference between the two coefficients (Ncf_t and Nr_t) is more pronounced for the subsample with a low level of shareholder-bondholder conflicts (low leverage and low stock return volatility), or the difference is statistically insignificant (investment-grade and non-investment-grade ratings). Therefore, the measurement errors due to potential conflicts between shareholders and bondholders, if any, seem to create a bias against the findings.

[28] See Beaver et al. (2006) for a similar argument.

6.3. Rating agencies' inefficient information processes and conflicts of interest

There are growing concerns that credit rating agencies lack independence due to the issuers-pay-fees structure. Recently, some have additionally questioned credit rating agencies' competence in assessing credit risk, particularly with respect to rating mortgage-backed and structured finance deals (Beales and Davies 2007). Thus, credit ratings may not reflect the probability of default in an unbiased and timely manner due to rating agencies' own incentives or inefficient information processes. To check whether these concerns affect the main conclusion, I partition the sample by the proxies for information uncertainty (firm age, analyst coverage, and firm size) and rating agencies' conflicts of interest (the amount of debt issuance) and then examine whether the results hold for partitioned groups.[29] The results presented in Panels B and C of Table 10 show that cash-flow news is more strongly associated with credit rating changes than discount-rate news for all subsamples.

6.4. The upgrades versus downgrades

The effect of cash-flow news and discount-rate news might be different for rating upgrades and for downgrades. To examine this possibility, I divide the sample into subsamples of rating upgrades (Δ $RATING_t$>0) and rating downgrades (Δ $RATING_t$<0), and estimate the ordered logit for each group. A caveat with this analysis is that the partitioning of the sample based on the dependent variable ($\Delta RATING_t$) would reduce the power of the test and bias the coefficient toward zero. That is, this subsample analysis would be limited to the effect within upgrade groups or within downgrade groups (i.e., whether cash-flow news affects the number of

[29] The underlying reasoning behind the use of the amount of debt issuance for a proxy for conflicts of interest is conceptually similar to the argument that audit fee dependence impairs auditor independence (Craswell et al. 2003). I follow Bradshaw et al. (2006) in defining the amount of debt issuance as the net cash received from the issuance (and/or reduction) of debt. The use of cash received from the issuance (not the reduction) of debt does not change the results.

notches for rating upgrades). Untabulated results show that neither Ncf_t nor Nr_t is significant for the subsample with rating upgrades. This loss of significance seems to be due to the reduced power as discussed previously. However, both Ncf_t and Nr_t are significant for the subsample with rating downgrades even in the presence of reduced power. For this subsample, the magnitude of the coefficient on Ncf_t is greater than that on Nr_t, consistent with the main findings.

6.5. Other additional analyses

I perform several untabulated sensitivity tests. First, I use standard errors clustered by both firm and year (Gow et al. 2010). Second, I use different horizons to measure credit rating changes or stock returns. I define the credit rating change using credit ratings as of four or six months after the fiscal year-end and repeat all the analyses. I also use different stock return cumulation periods, such as starting four or six months after the beginning of the current fiscal year. Third, I conduct a sub-period analysis by dividing the sample period into two or three periods. Results from all of these untabulated tests do not change the tenor of the reported results.

VII. Conclusions

Despite the prominent role of credit ratings in the capital market, relatively little is known about the rating decision process. This paper studies the relative importance of cash-flow news and discount-rate news in credit rating decision. The findings suggest that rating changes are, on average, more strongly associated with cash-flow news than with discount-rate news. When the news contains negative information about the firm, the relation becomes much stronger. Therefore, the relative importance of the two components of news should be evaluated in relation to the nature of the news.

Notwithstanding these important findings, this study is subject to several caveats. There is no consensus about which is the best method to implement the return decomposition. Cash-flow news and discount-rate news are extracted from stock returns; therefore, these variables may contain measurement errors. My study focuses on the contemporaneous association, rather than the causal relation. In addition, this paper does not examine whether rating agencies *fully* reflect the information into their ratings (Sloan 1996). Future research can explore whether rating agencies misprice (i.e., underestimate or overestimate) specific components of new information.

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Table 1
Sample Selection and the Distribution of Credit Ratings
Panel A. Sample selection

All firm-year observations with December fiscal year ends on COMPUSTAT XPF for 1986-2008 (excluding financial and utilities sector)	89,772
Less observations with missing market value of equity for year t and t-1	(22,549)
Less observations with missing or negative book value of equity for year t and t-1	(8,135)
Less observations with missing stock return and return on equity for year t and t-1	(9,753)
Less observations with lagged market value less than \$10 million	(3,849)
Firm-year observations to estimate the VAR model	45,486
Less observations without S&P long-term issuer-level credit ratings (current and lagged)	(33,648)
	11,838
Less observations with missing data for other control variables	(484)
Final sample (1,541 distinct firms)	11,354

Panel B. The distribution of credit ratings

S&P ratings	$RATING_t$	Frequency	Percentage (%)	Cumulative percentage (%)	Investment/ Non-investment
AAA	17	203	1.79	1.79	
AA+	16	75	0.66	2.45	
AA	15	364	3.21	5.66	
AA-	14	330	2.91	8.57	
A+	13	559	4.92	13.49	Investment grade (60.2%)
A	12	1060	9.34	22.83	
A-	11	890	7.84	30.67	
BBB+	10	1047	9.22	39.89	
BBB	9	1305	11.49	51.38	
BBB-	8	1001	8.82	60.20	
BB+	7	709	6.24	66.44	
BB	6	925	8.15	74.59	
BB-	5	1116	9.83	84.42	Non-investment grade (39.8%)
B+	4	1005	8.85	93.27	
B	3	419	3.69	96.96	
B-	2	211	1.86	98.82	
CCC+ or below	1	135	1.18	100	
Total		11,354	100		

Panel C. The distribution of credit rating changes

Credit Rating Changes	$\Delta RATING_t$	Frequency	Percentage (%)		Cumulative Percentage (%)
Upgrade	4	12	0.11	10.11%	0.11
	3	30	0.26		0.37
	2	194	1.71		2.08
	1	912	8.03		10.11
No change	0	8692	76.55	76.55%	86.66
Downgrade	-1	978	8.61	13.34%	95.27
	-2	369	3.25		98.52
	-3	128	1.13		99.65
	-4	39	0.35		100
Total		11,354	100		

Panel A shows the sample selection procedure in detail. In Panel B, $RATING_t$ is S&P's long-term issuer-level credit ratings (SPLTICRM) as of three months after the fiscal year ends, converted to numerical values between 1 (CCC+ or below) and 17 (AAA). A higher value of $RATING_t$ indicates better credit quality. In Panel C, $\Delta RATING_t = RATING_t - RATING_{t-1}$. The sample is the 11,354 firm-year observations for the period 1986–2008.

Table 2
Descriptive Statistics

	Mean	Std	Q1	Median	Q3
$RATING_t$	8.513	3.606	5	9	11
$\Delta RATING_t$	-0.072	0.746	0	0	0
Ncf_t	0.060	0.354	-0.108	0.082	0.270
Nr_t	-0.004	0.112	-0.060	0.000	0.060
$CNcf_t$	0.077	0.192	0.023	0.089	0.160
$FNcf_t$	-0.015	0.309	-0.180	-0.005	0.161
$\Delta SIZE_t$	0.088	0.197	-0.012	0.057	0.147
$\Delta INTCOV_t$	0.007	0.416	-0.165	0.030	0.203
ΔROA_t	-0.003	0.054	-0.021	0.000	0.018
ΔLEV_t	0.000	0.069	-0.035	-0.005	0.030
ΔCAP_INT_t	0.003	0.087	-0.026	0.008	0.039
$\Delta AGRW_t$	-0.052	0.423	-0.128	-0.008	0.092
$\Delta STDRET_t$	0.001	0.009	-0.004	0.000	0.004

This table reports descriptive statistics for the sample of 11,354 firm-year observations for the period 1986–2008. $RATING_t$ is S&P's long-term issuer-level credit ratings (SPLTICRM) as of three months after the fiscal year ends, converted to numerical values between 1 (CCC+ or below) and 17 (AAA) according to Panel B of Table 1. $\Delta RATING_t = RATING_t - RATING_{t-1}$. Ncf_t and Nr_t is cash-flow news and discount-rate news computed from Equation (6) and (7), respectively. $CNcf_t$ is current-period cash-flow news estimated as the residual of Equation (4b), η_{2t}. $FNcf_t$ is future-period cash-flow news, defined as $Ncf_t - CNcf_t$. $SIZE_t$ is the log of market value of equity (CSHO*PRCC_F). $INTCOV_t$ is the log of one plus interest coverage ratio. Interest coverage ratio is defined as operating income before depreciation (OIBDP) divided by interest expense (XINT). ROA_t is return on assets, defined as income before extraordinary items (IB) divided by average total assets (AT). LEV_t is the ratio of total debt (DLTT+DLC) to total assets (AT). CAP_INTEN_t is gross property, plant and equipment (PPEGT) divided by total assets. $AGRW_t$ is the total asset growth defined as (Total $assets_t$ –Total $assets_{t-1}$)/Total $assets_{t-1}$. $STDRET_t$ is the standard deviation of daily stock returns during the fiscal year. Change variables (Δ) are defined as the first difference of the above variables, such as $\Delta SIZE_t = SIZE_t - SIZE_{t-1}$.

Table 3
Correlation

	Ncf_t	Nr_t	$CNcf_t$	$FNcf_t$	$\Delta SIZE_t$	$\Delta INTCOV_t$	ΔROA_t	ΔLEV_t	ΔCAP_INT_t	$\Delta AGRW_t$	$\Delta STDRET_t$
$\Delta RATING_t$	0.23	-0.04	0.18	0.15	0.13	0.22	0.19	-0.20	-0.05	0.05	-0.17
	(<.0001)	(0.00)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Ncf_t	1.00	-0.18	0.49	0.82	0.15	0.22	0.33	-0.26	-0.15	0.14	-0.16
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Nr_t		1.00	0.21	-0.35	0.14	-0.03	0.10	-0.13	-0.05	0.01	0.02
			(<.0001)	(<.0001)	(<.0001)	(0.00)	(<.0001)	(<.0001)	(<.0001)	(0.12)	(0.04)
$CNcf_t$			1.00	-0.08	0.13	0.24	0.59	-0.24	-0.15	0.13	-0.11
				(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$FNcf_t$				1.00	0.10	0.09	0.01	-0.13	-0.07	0.07	-0.11
					(<.0001)	(<.0001)	(0.50)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$\Delta SIZE_t$					1.00	-0.06	0.05	0.20	-0.45	0.46	-0.06
						(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$\Delta INTCOV_t$						1.00	0.48	-0.39	-0.02	0.08	-0.11
							(<.0001)	(<.0001)	(0.04)	(<.0001)	(<.0001)
ΔROA_t							1.00	-0.33	-0.13	0.12	-0.17
								(<.0001)	(<.0001)	(<.0001)	(<.0001)
ΔLEV_t								1.00	-0.05	0.14	0.14
									(<.0001)	(<.0001)	(<.0001)
ΔCAP_INT_t									1.00	-0.32	0.08
										(<.0001)	(<.0001)
$\Delta AGRW_t$										1.00	-0.10
											(<.0001)

This table presents the Pearson correlation coefficients. The sample is the 11,354 firm-year observations for the period 1986–2008. P-values are reported in parentheses. See Table 2 for the variable definitions.

Table 4
Estimated parameters of the VAR model

	Γ					Σ		
	r_{t-1}	roe_{t-1}	bm_{t-1}	λ_1'	$(e_1+\lambda_1)'$	r_t	roe_t	bm_t
r_t	0.044	0.045	0.074	0.025	1.025	0.262	0.060	-0.150
	(0.040)	(0.033)	(0.026)			(0.035)	(0.011)	(0.024)
	[0.044]	[0.034]	[0.028]			[0.035]	[0.011]	[0.024]
roe_t	0.179	0.331	0.003	0.119	0.119	0.060	0.113	0.009
	(0.023)	(0.035)	(0.010)			(0.011)	(0.010)	(0.007)
	[0.025]	[0.036]	[0.011]			[0.011]	[0.010]	[0.007]
bm_t	-0.137	0.127	0.777	0.295	0.295	-0.150	0.009	0.244
	(0.026)	(0.028)	(0.019)			(0.024)	(0.007)	(0.028)
	[0.028]	[0.028]	[0.020]			[0.024]	[0.007]	[0.028]

This table reports the parameter estimates for the VAR model in Equation (4). The parameters in the table correspond to the following system:

$$z_t = \Gamma\, z_{t-1} + \eta_t\,,\ \Sigma = E(\eta_t, \eta_t').$$

The state variables in z_t include the mean-adjusted cum dividend annual excess return (r_t), the mean-adjusted return on equity (roe_t), and the mean-adjusted book-to-market ratio (bm_t). r_t is the log of one plus the annual cum dividend return minus the log of one plus the annualized three-month Treasury bill rate. The 12-month return cumulation period starts three months after the beginning of the current fiscal year. roe_t is the log of one plus ROE minus the log of one plus the annualized three-month Treasury bill rate. ROE is computed as income before extraordinary items (IB), divided by beginning of period book value of equity (CEQ). bm_t is the log of the book-to-market ratio at year end. Book-to-market ratio is book value of equity (CEQ) divided by the market value of equity (CSHO*PRCC_F). All variables in the VAR system are cross-sectionally demeaned. For each parameter, I report three numbers. The first number is the OLS estimate of the parameter. The second number (in parentheses) is a robust standard error computed using the Rogers' (1993) method. The third number (in brackets) is a robust jackknife standard error computed using a jackknife method outlined by Shao and Rao (1993). The top and bottom 1% of each of the state variables in the VAR model is winsorized every year to mitigate outliers. The sample for the VAR estimation is 45,486 firm-year observations for the period 1986-2008. See Panel A of Table 1 for the sample selection.

Table 5
Regression of the Change in Credit Ratings on Various Proxies for Cash-flow News and Discount-rate news

	Dependent variable = $\Delta RATING_t$						
	Ordered logit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ncf_t	0.512***						
	(0.00)						
ΔROA_t		0.428***					
		(0.00)					
ΔROE_t			0.378***				
			(0.00)				
ΔCFO_t				0.181***			
				(0.00)			
$CNcf_t$					0.373***	0.408***	
					(0.00)	(0.00)	
$FNcf_t$						0.384***	
						(0.00)	
Nr_t							-0.074***
							(0.01)
McFadden's R^2	2.65%	1.89%	1.49%	0.33%	1.49%	2.79%	0.20%
McKelvey & Zavoina's R^2	7.40%	5.30%	4.20%	1.00%	4.10%	7.60%	0.50%
N	11,354	11,354	11,354	11,354	11,354	11,354	11,354

This table reports the ordered logit results of regressing changes in credit ratings ($\Delta RATING_t$) on the various proxies for cash-flow news and discount-rate news. The dependent variable is $\Delta RATING_t$, which is the change in S&P's long-term issuer-level credit ratings as of three months after the fiscal year ends. The level of credit rating is converted to numerical values between 1 (CCC+ or below) and 17 (AAA) according to Panel B of Table 1. A positive (negative) value of $\Delta RATING_t$ indicates upgrades (downgrades). ΔROE_t is the change in return on equity, which is defined as income before extraordinary items divided by average total assets. ΔCFO_t is the change in operating cash flows, which is defined as cash flows from operation divided by average total assets. See Table 2 for the definitions of other variables. All independent variables are standardized to have a zero mean and unit variance. I reports p-values based on standard errors clustered by firm in parentheses. The sample is the 11,354 firm-year observations for the period 1986-2008. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in two-tailed tests.

Table 6
Regression of the Change in Credit Ratings on Cash-flow and Discount-rate News

	Dependent variable = $\Delta RATING_t$			
	Ordered logit			OLS
	(1)	(2)	(3) After excluding zero rating changes	(4)
Ncf_t	0.244***		0.313***	0.085***
	(0.00)		(0.00)	(0.00)
$CNcf_t$		0.217***		
		(0.00)		
$FNcf_t$		0.171***		
		(0.00)		
Nr_t	-0.123***	-0.151***	-0.163***	-0.034***
	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta SIZE_t$	0.442***	0.443***	0.603***	0.129***
	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta INTCOV_t$	0.348***	0.355***	0.523***	0.097***
	(0.00)	(0.00)	(0.00)	(0.00)
ΔROA_t	0.055*	0.003	0.078	0.026**
	(0.07)	(0.94)	(0.16)	(0.01)
ΔLEV_t	-0.362***	-0.367***	-0.490***	-0.101***
	(0.00)	(0.00)	(0.00)	(0.00)
ΔCAP_INTEN_t	0.100***	0.101***	0.151***	0.030***
	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta AGRW_t$	-0.104***	-0.106***	-0.147***	-0.027***
	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta STDRET_t$	-0.337***	-0.331***	-0.411***	-0.122***
	(0.00)	(0.00)	(0.00)	(0.00)
Industry- and year-fixed effects	Included	Included	Included	Included
Test (p-value)				
$Ncf_t = -Nr_t$	(0.01)***		(0.05)**	(0.01)***
$CNcf_t = FNcf_t$		(0.24)		
$CNcf_t = -Nr_t$		(0.11)		
$FNcf_t = -Nr_t$		(0.67)		
McFadden's R^2	8.11%	8.14%	14.92%	
McKelvey & Zavoina's R^2	20.50%	20.50%	37.70%	
OLS adj R^2				14.54%
N	11,354	11,354	2,662	11,354

This table reports the ordered logit results of regressing changes in credit ratings ($\Delta RATING_t$) on cash-flow (Ncf_t) and discount-rate news (Nr_t). Column (3) reports ordered logit results after excluding observations with zero credit rating changes. Column (4) reports the OLS results. The dependent variable is $\Delta RATING_t$, which is the change in S&P's long-term issuer-level credit ratings as of three months after the fiscal year ends. The level of credit rating is converted to numerical values between 1 (CCC+ or below) and 17 (AAA) according to Panel B of Table 1. A positive (negative) value of $\Delta RATING_t$ indicates upgrades (downgrades). See Table 2 for the definitions of other variables. All independent variables are standardized to have a zero mean and unit variance. I reports p-values based on standard errors clustered by firm in parentheses. The sample is the 11,354 firm-year observations for the period 1986-2008. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in two-tailed tests.

Table 7
Binary Logit Regression and Marginal Effects

	Dependent variable = $UPGRADE_t$			Dependent variable = $DOWNGRADE_t$		
	(1) Logit Pr(Upgrade=1)	(2) Marginal effect	(3) Change in probability (Q1vs.Q3)	(4) Logit Pr(Downgrade=1)	(5) Marginal effect	(6) Change in probability (Q1vs.Q3)
Ncf_t	0.176***	0.013	1.39%	-0.258***	-0.024	-2.51%
	(0.00)			(0.00)		
Nr_t	-0.062	-0.005	-0.48%	0.148***	0.014	1.46%
	(0.12)			(0.00)		
$\Delta SIZE_t$	0.398***	0.029	2.27%	-0.452***	-0.042	-3.47%
	(0.00)			(0.00)		
$\Delta INTCOV_t$	0.335***	0.025	2.19%	-0.343***	-0.032	-2.77%
	(0.00)			(0.00)		
ΔROA_t	-0.009	-0.001	-0.04%	-0.112***	-0.010	-0.74%
	(0.83)			(0.00)		
ΔLEV_t	-0.382***	-0.028	-2.70%	0.308***	0.028	2.67%
	(0.00)			(0.00)		
ΔCAP_INTEN_t	0.061	0.005	0.34%	-0.108***	-0.010	-0.74%
	(0.15)			(0.00)		
$\Delta AGRW_t$	0.012	0.001	0.05%	0.278***	0.026	1.35%
	(0.74)			(0.00)		
$\Delta STDRET_t$	-0.176***	-0.013	-1.17%	0.401***	0.037	3.23%
	(0.00)			(0.00)		
Industry-and year-fixed effects	Included			Included		
The probability of Upgrade=1 (or Downgrade=1) at the means of all variables	7.96%			10.23%		
Test (p-value) $Ncf_t = -Nr_t$	(0.08)*			(0.05)**		
McFadden's R^2	8.78%			13.09%		
McKelvey & Zavoina's R^2	18.20%			22.00%		
N	11,354			11,354		

This table reports the binary logit results and marginal effects of independent variables. In Columns (1) through (3), the dependent variable is $UPGRADE_t$, which is one if ratings are upgraded, and zero otherwise. In Columns (4) through (6), the dependent variable is $DOWNGRADE_t$, which is one if ratings are downgraded, and zero otherwise. See Table 2 for the definitions of other variables. The marginal effects in Columns (2) and (5) show the effects of small change in independent variables on the probability of being upgraded or downgraded. The marginal effects are computed as $e^{\beta' x}/(1 + e^{\beta' x})$ where $\beta' X$ is evaluated at the mean values of X. Columns (3) and (6) show changes in the probability of being upgraded or downgraded as a result of moving the variable of interest from the first to the third quartile, holding all other variables at their mean values. All independent variables are standardized to have a zero mean and unit variance. I reports p-values based on standard errors clustered by firm in parentheses. The sample is the 11,354 firm-year observations for the period 1986-2008. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in two-tailed tests.

Table 8
Regression of the Change in Credit Ratings on Cash-flow and Discount-rate News: Good news versus Bad news

	Dependent variable = $\Delta RATING_t$					
	Ordered logit					
	$(r_t-E_{t-1}(r_t))>0$	$(r_t-E_{t-1}(r_t))<0$	$Ncf_t>0$	$Ncf_t<0$	$Nr_t<0$	$Nr_t>0$
	(1) Good total news	(2) Bad total news	(3) Good CF news	(4) Bad CF news	(5) Good DR news	(6) Bad DR news
Ncf_t	0.090**	0.358***	0.028	0.331***	0.236***	0.237***
	(0.01)	(0.00)	(0.44)	(0.00)	(0.00)	(0.00)
Nr_t	-0.148***	-0.154***	-0.169***	-0.120***	-0.032	-0.092**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.40)	(0.02)
$\Delta SIZE_t$	0.403***	0.493***	0.451***	0.426***	0.396***	0.460***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta INTCOV_t$	0.309***	0.389***	0.331***	0.353***	0.299***	0.388***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔROA_t	0.016	0.099**	-0.011	0.141***	0.102**	0.016
	(0.68)	(0.04)	(0.77)	(0.00)	(0.02)	(0.70)
ΔLEV_t	-0.450***	-0.247***	-0.491***	-0.186***	-0.385***	-0.330***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔCAP_INTEN_t	0.067*	0.156***	0.069*	0.156***	0.139***	0.067*
	(0.10)	(0.00)	(0.08)	(0.00)	(0.00)	(0.10)
$\Delta AGRW_t$	-0.077**	-0.127***	-0.080**	-0.135***	-0.154***	-0.067**
	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.05)
$\Delta STDRET_t$	-0.295***	-0.348***	-0.269***	-0.358***	-0.289***	-0.389***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry-and year- fixed effects	Included	Included	Included	Included	Included	Included
Test (p-value) $Ncf_t= -Nr_t$	(0.27)	(0.00)***	(0.01)**	(0.00)***	(0.00)***	(0.02)**
McFadden's R^2	6.14%	9.40%	6.45%	8.90%	8.09%	8.61%
McKelvey & Zavoina's R^2	15.90%	23.40%	16.60%	22.00%	20.10%	21.80%
N	6,924	4,430	7,093	4,261	5,664	5,690

This table reports the ordered logit results for the partitioned samples. The sample is partitioned according to the sign of the news (i.e., good versus bad) of total news (= r_t-$E_{t-1}(r_t)$), cash-flow news (Ncf_t), and discount-rate news (Nr_t). The dependent variable is $\Delta RATING_t$, which is the change in S&P's long-term issuer-level credit ratings as of three months after the fiscal year ends. The level of credit rating is converted to numerical values between 1 (CCC+ or below) and 17 (AAA) according to Panel B of Table 1. A positive (negative) value of $\Delta RATING_t$ indicates upgrades (downgrades). All independent variables are standardized to have a zero mean and unit variance for the sample analyzed. See Table 2 for the definitions of other variables. I reports p-values based on standard errors clustered by firm in parentheses. The full sample is the 11,354 firm-year observations for the period 1986-2008. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in two-tailed tests.

Table 9
Alternative Estimations of Cash-flow News and Discount-rate News

	Dependent variable = $\Delta RATING_t$				
	Ordered logit				
	(1) Weighted least squares	(2) Industry-level VAR estimation	(3) Directly estimate Ncf_t	(4) Directly estimate both Ncf_t and Nr_t	(5) Ncf_t and Nr_t estimated from the implied cost of capital
Ncf_t	0.244***	0.290***	0.297***	0.289***	0.295***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nr_t	-0.118***	-0.122***	-0.232***	-0.150***	0.148**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
$N\_residual_t$				0.136***	
				(0.00)	
$\Delta SIZE_t$	0.442***	0.431***	0.424***	0.443***	0.490***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta INTCOV_t$	0.348***	0.349***	0.359***	0.354***	0.388***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔROA_t	0.055*	0.047	0.009	0.003	0.095**
	(0.07)	(0.12)	(0.79)	(0.93)	(0.01)
ΔLEV_t	-0.362***	-0.352***	-0.348***	-0.366***	-0.439***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔCAP_INTEN_t	0.100***	0.100***	0.099***	0.101***	0.149***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta AGRW_t$	-0.104***	-0.105***	-0.105***	-0.107***	-0.107***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta STDRET_t$	-0.339***	-0.342***	-0.340***	-0.331***	-0.412***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry- and year-fixed effects	Included	Included	Included	Included	Included
Test (p-value) $Ncf_t = -Nr_t$	(0.01)***	(0.00)***	(0.07)*	(0.00)***	(0.00)***
McFadden’s R^2	8.08%	8.10%	8.11%	8.16%	7.80%
McKelvey & Zavoina's R^2	20.40%	20.40%	20.40%	20.50%	19.70%
N	11,354	11,354	11,354	11,354	8,277

This table reports the results using alternative estimations of cash-flow news and discount-rate news. The dependent variable is $\Delta RATING_t$, which is the change in S&P’s long-term issuer-level credit ratings as of three months after the fiscal year ends. The level of credit rating is converted to numerical values between 1 (CCC+ or below) and 17 (AAA) according to Panel B of Table 1. A positive (negative) value of $\Delta RATING_t$ indicates upgrades (downgrades). In Column (1), the VAR system is estimated using the weighted least squares (WLS) instead of the OLS. The data is deflated for each firm-year by the number of firms in the corresponding cross-section to weigh each cross- section equally. In Column (2), the VAR system in Equation (4) is estimated separately for each Fama-French industry. This industry-level estimation results in VAR parameters at the industry level, and the Ncf_t and Nr_t can be computed at the firm level. In Colum (3), Ncf_t is directly estimated as $Ncf_t = e_2'(I-\rho\,\Gamma)^{-1}\,\eta_t$ and Nr_t is measured residually as the difference between $(r_t\text{-}E_{t\text{-}1}(r_t))$ and Ncf_t. In Column (4), both Ncf_t and Nr_t are directly estimated as $Ncf_t = e_2'(I-\rho\,\Gamma)^{-1}\,\eta_t$ and $Nr_t = \lambda_1'\,\eta_t$. $N\_residual_t$ is defined as the residual component of unexpected news. In Column (5), Ncf_t and Nr_t are measured following Chen and Zhao (2010), which is based on the implied cost of capital using analysts’ forecasts. See Table 2 for the definitions of other variables. All independent variables are standardized to have a zero mean and unit variance. I reports p-values based on standard errors clustered by firm in parentheses. The sample is the 11,354 firm-year observations for the period 1986-2008. The sample in Column (5) is 8,277 firm-year observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in two-tailed tests.

Table 10
Additional analyses

	Dependent variable = $\Delta RATING_t$	
	Ordered logit	
Panel A. Shareholder-bondholder conflict		
Leverage	**Low**	**High**
Ncf_t	0.245***	0.233***
	(0.00)	(0.00)
Nr_t	-0.077*	-0.141***
	(0.07)	(0.00)
McFadden's R^2	7.29%	8.50%
N	5,671	5,683
Stock return volatility	**Low**	**High**
Ncf_t	0.268***	0.271***
	(0.00)	(0.00)
Nr_t	-0.076*	-0.153***
	(0.07)	(0.00)
McFadden's R^2	6.36%	9.37%
N	5,671	5,683
Investment grade	**Investment grade**	**Non-investment grade**
Ncf_t	0.276**	0.315***
	(0.00)	(0.00)
Nr_t	-0.110***	-0.138***
	(0.01)	(0.00)
McFadden's R^2	6.93%	9.96%
N	6,866	4,488
Panel B. Information uncertainty		
Firm age	**Young**	**Old**
Ncf_t	0.277***	0.241***
	(0.00)	(0.00)
Nr_t	-0.150***	-0.072*
	(0.00)	(0.09)
McFadden's R^2	8.25%	8.75%
N	5,645	5,709
Analysts coverage	**Low**	**High**
Ncf_t	0.274***	0.247***
	(0.00)	(0.00)
Nr_t	-0.187***	-0.018
	(0.00)	(0.69)
McFadden's R^2	9.16%	7.52%
N	5,690	5,664
Firm size	**Small**	**Large**
Ncf_t	0.291***	0.199***
	(0.00)	(0.00)
Nr_t	-0.124***	-0.117***
	(0.00)	(0.01)
McFadden's R^2	9.27%	7.17%
N	5,671	5,683

Table 10 (Continued)

	Dependent variable = $\Delta RATING_t$	
	Ordered logit	
Panel C. Conflict of interest		
Debt issuance	**Low**	**High**
Ncf_t	0.243***	0.234***
	(0.00)	(0.00)
Nr_t	-0.165***	-0.098***
	(0.00)	(0.01)
McFadden's R^2	9.87%	7.05%
N	5,672	5,682

This table reports the ordered logit results for the partitioned samples by several variables. For brevity, the results for the other control variables are not reported. The dependent variable is $\Delta RATING_t$. The full sample is partitioned into two groups each year by leverage, stock return volatility, investment-grade rating (Panel A), firm age, analyst coverage, firm size (Panel B), the amount of debt issuance (Panel C). Leverage is the ratio of total debt to total assets; Stock return volatility is the standard deviation of daily stock return during the fiscal year; Investment-grade rating is the S&P letter grade of BBB- or above; Firm age is the number of years since the firm was first covered by the CRSP; Analyst coverage is the number of analysts following at the end of fiscal year in IBES. If there is no analyst following, zero value is assigned; Firm size is the market value of equity; The amount of debt issuance is net cash received from the issuance (and/or reduction) of debt following Bradshaw et al. (2006). See Table 2 for the definitions of other variables. All independent variables are standardized to have a zero mean and unit variance for the sample analyzed. I reports p-values based on standard errors clustered by firm in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, in two-tailed tests.