ACCOUNTING QUALITY AND CREDIT RATINGS' ABILITY TO PREDICT DEFAULT

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DEDICATION

To my wife, Jessie, for your selfless sacrifice and love every single day. Your belief conquered my doubts and carried me through. You have made my life greater than I ever hoped it could be.

To my children, Amelia, Colin, and Jack, for giving me perspective and keeping my life exciting. Your love means more than I can say.

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ABSTRACT

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Michael V. Chin

Catherine Schrand

This study examines whether the quality of borrowers' accounting information determines the accuracy and timeliness of credit ratings issued by rating agencies. I consider two possible effects. The news effect implies higher quality accounting provides better information to credit rating agencies, enabling them to develop better ratings. The discipline effect describes how the disclosure of financial information, particularly that which recognizes bad news in a timely manner, can limit rating agencies' ability to issue inflated ratings to appease their clients. I further explore whether these effects vary with the characteristics of private information, which can influence both the incremental news provided by accounting information and the agencies' inclination to issue inflated ratings. I utilize rating data from two major agencies: Standard & Poor's (S&P), an issuer-paid agency that obtains private information and may have incentives to cater to issuers; and Egan-Jones Ratings Company (EJR), an investor-paid agency that relies solely on public information to develop its ratings. The differences between these agencies make EJR an effective control group for the identification of the accounting quality effects. I measure the quality of credit ratings by their ability to predict default and measure changes in default risk in a timely and accurate manner. I find that debt issuers with earnings that exhibit more timely loss recognition and asymmetric timely loss recognition have credit ratings that predict default more accurately and are downgraded more promptly. I also find that issuers with upward-managed earnings have less timely rating downgrades. These effects are comparable for both rating agencies for a broad set of firms, but they are more pronounced for EJR ratings relative to S&P ratings for firms near default, when agency reputation costs and information value are high. Conflicts of interest and private information do not predictably modify the effects of accounting quality on credit rating quality. The results support the existence of the news effect of accounting quality but provide limited evidence of the discipline effect or the moderating impact of private information.

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1. Introduction

In this study, I examine how the timeliness and accuracy of credit ratings are influenced by the information available to the credit rating agencies. Rating agencies are sophisticated information intermediaries whose business is the reduction of information asymmetry between debt issuers and market participants. Investors and the general public expect ratings to provide a reliable and timely measure of a debt issuer's "ability and willingness to meet its financial obligations," but empirical and anecdotal evidence suggest that the quality of ratings varies significantly.[1] For example, it was widely acknowledged that the largest agencies failed to predict significant credit events, such as the Asian crisis of the late 1990s, the Enron and Worldcom bankruptcies, and the global financial crisis of the late 2000s. As a result, Congress passed new regulation in the form of the Credit Rating Agency Reform Act of 2006 and the Dodd-Frank Act of 2010 (Langohr et al., 2008). These laws generally sought to improve credit rating quality through increased competition and transparency. These events have also motivated a line of academic research investigating the underlying causes of variation in the quality of credit ratings (e.g. Beaver et al., 2006; Cheng and Neamtiu, 2009; Becker and Milbourn, 2011; Strobl and Xia, 2012; Bruno et al., 2013). The regulators, media, and researchers have focused primarily on agency conflicts of interest or regulatory frictions as drivers of biased or sluggish ratings. However, to my knowledge, this is the first study to examine whether rating quality is a function of the quality of public information available to rating agencies.

[1] "Credit Ratings Definitions & FAQs," Standard & Poor's, Inc., http://www.standardandpoors.com/ratings/definitions-and-faqs/en/us, 2015.

Although rating agencies use many sources of information to generate their ratings, I focus on borrowers' financial accounting information, which is a particularly important source. Rating agencies incorporate information from the financial statements into default prediction models that are critical to the development of ratings. Standard and Poor's states that, "a company's financial reports are the starting point for the financial analysis of a rated entity."[2] The academic literature has also shown that credit rating agencies utilize and adjust accounting information (Kraft, 2012; Altamuro et al., 2012) and that accounting information can be used to predict bond ratings (Kaplan and Urwitz, 1979; Ziebart and Reiter, 1992; Ball et al., 2008). If accounting provides incremental information to rating agencies, then higher quality accounting gives rating agencies better information, enabling them to develop more timely and accurate ratings. I refer to this process as the news effect of accounting quality. Section 2 of the paper focuses on identifying this effect.

I examine two additional effects of accounting quality: the discipline effect and private information overlap. These describe the relationship of rating agencies' conflicts of interest and private information, respectively, with issuer accounting information. Prior analytical and empirical studies suggest rating agencies that are paid by debt issuers may issue inflated ratings and delay rating downgrades in order to satisfy their clients (Becker and Milbourn, 2011; Manso, 2013; Bruno et al., 2013). If this is the case, the public disclosure of high quality financial accounting reports may compel the rating agency to update their ratings with this information to avoid damage to their reputation.

[2] Standard & Poor's, Inc. "2008 Corporate Criteria: Analytical Methodology." April 15, 2008.

Overlap implies that private information and public accounting information act as substitutes. If a rating agency has accurate private information, it may depend less on accounting information to produce high quality ratings. I also examine whether the discipline effect and private information overlap interact to increase the impact of accounting information on credit ratings. These effects are explored primarily in section 3 of the paper.

A key feature of this study is the use of ratings from two nationally-recognized rating agencies – Standard and Poor's (S&P) and Egan-Jones Ratings Company (EJR). S&P is paid for its ratings by the debt issuers, while EJR is paid by outside investors. This difference in the compensation structure of these agencies enables me to explore unique hypotheses and identify the effects described above. Because of their economic relationship with issuers, S&P receives private information directly from management. In contrast, EJR relies solely on public information to develop its ratings. The other major consequence of S&P's fee arrangement is that it may be faced with conflicts of interest that hinder the issuance of accurate ratings, while EJR should be free of such conflicts. Because of these differences, EJR serves as a control group throughout my analysis. By using a sample of firms that are rated by both agencies, I mitigate concerns about correlated omitted variables due to unobservable differences between firms. In addition, I utilize the ratings data from the two agencies to provide novel evidence regarding the overall performance of investor-paid versus issuer-paid rating agencies that is not conditioned on the quality of accounting information.

I measure the quality of credit ratings based on their ability to predict default and measure changes in default risk in a timely and accurate manner. Default prediction is the key purpose of credit ratings and is the basis on which rating agencies assess their own performance. Prior research comparing Big Three[3] agency ratings to EJR ratings evaluates their relative performance based primarily on three criteria: the lead/lag relationship of the agencies' rating changes; stock and bond market responses to rating changes; and the correlation of ratings with initial bond yields (e.g. Beaver et al., 2006; Bruno et al., 2013). I use default prediction accuracy as a better, more direct measure of rating quality that should be less influenced by market liquidity, market efficiency, or investor behavior. I employ a variety of tests that are designed to assess the ability of credit ratings to accurately predict default and measure changes in default risk in a timely manner.

In my analyses to identify the news effect, I define accounting quality using three measures. The first two are timely loss recognition (TLR) and asymmetric timely loss recognition (ATLR), i.e. conservatism (Basu, 1997). Earnings are considered to be timely if they quickly recognize changes in firm value. Timely loss recognition (ATLR) is particularly useful for debt holders (Ahmed et al., 2002; Watts, 2003) whose concave payoff function places a premium on negative information. Accordingly, these attributes should also be important measures of the usefulness of earnings for credit rating agencies, which serve as information intermediaries for firms' current and potential creditors. My third measure of accounting quality is discretionary accruals, a proxy for earnings

[3] Moody's, Standard and Poor's, and Fitch

management. Recent studies by Beaver et al. (2012) and Alissa et al. (2013) suggest that earnings management obscures information used by in default prediction models and may lead to credit rating changes. I extend their analyses to examine whether ratings issued based on managed issuer earnings are less accurate and timely in predicting default. In my analysis to identify the discipline effect of accounting and its overlap with private information, I exploit accounting restatement announcements as public information events and signals of poor previous accounting quality. This provides a powerful setting to identify the distinct effects of accounting quality.

Based on my analysis, I find that more timely accounting contributes to more accurate and timely credit ratings for both EJR and S&P, while upward managed earnings reduces rating quality, consistent with the news effect of accounting quality. The effect of accounting quality on the timeliness of rating downgrades is generally more significant than its impact on the accuracy of the rating level in predicting default. This is not surprising, as my proxies for accounting quality relate specifically to earnings, which itself is a measure of changes in (as opposed to the level of) financial position. I also find, somewhat surprisingly, that the news effect is similar for S&P and EJR in most settings. This implies that S&P is generally not fully exploiting its information advantage, but is instead relying on financial statement information.

I find that both rating agencies tend to issue rating downgrades following adverse accounting restatements, though EJR is more likely to downgrade than S&P. This demonstrates that the agencies do not see through accounting deficiencies or errors and provides further evidence of the news effect. However, I find little evidence to support the discipline effect or the private information overlap of accounting information. Using a variety of measures, I find that the effect of accounting quality does not vary with the level of conflicts of interest or the quality of private information as predicted. While the results of my analyses do not support the effects of conflicts of interest or private information, this may be due to the challenge of identifying clean measures of these constructs. In order to validate the measures, I examine the direct impact of conflicts of interest and private information quality on rating quality without regard to accounting information. Although several of the proxies for conflicts of interest and private information quality have found theoretical and empirical support in prior studies (e.g. Bolton et al., 2012; Strobl and Xia, 2012; Kedia et al., 2014), my validation tests yield mixed results. In several cases, the effects are similar for both S&P and EJR ratings, despite EJR's presumed lack of both conflicts of interest and access to private information. These findings suggest the measures may be too noisy to identify the discipline effect or private information overlap of accounting information. As a result, I analyze firms that are very close to default as an alternative approach to identify the discipline effect. In this setting, information about credit risk is very important to outsiders and the potential costs to S&P's reputation for failing to predict default outweigh its catering incentives. The relationship between earnings quality and rating timeliness is more pronounced for EJR ratings than for S&P ratings in this situation. This suggests that S&P incorporates more private information and/or expends greater monitoring effort for these high risk firms, and is, therefore, less affected by accounting quality when there are fewer conflicts of interest. EJR has a smaller information set and fewer resources, so it is not able to comparably increase its monitoring intensity for these issuers. This finding is consistent with the discipline effect of accounting quality.

In ancillary analysis, I provide unconditional evidence (i.e. without incorporating accounting quality effects) that EJR ratings generally outperform S&P ratings in capturing default risk. This finding adds to the literature that compares these two agencies, which has not thoroughly examined their differential performance in predicting default (Johnson, 2004; Beaver et al., 2006; Strobl and Xia, 2012; Akins, 2013; Bruno et al., 2013; Milidonis, 2013; Berwart et al., 2013). This result also provides a baseline measure of the relative performance of S&P and EJR that helps to assess my primary research agenda: testing the effects of accounting quality on credit ratings.

This study primarily contributes to the literature on the quality of credit ratings. While prior studies focus on conflicts of interest, I examine whether higher quality accounting information provided by the debt issuer contributes to more accurate and timely ratings. Although the primary function of credit rating agencies is to reduce information asymmetry between debt issuers and investors, the agencies themselves are subject to the quality of information provided by the issuers. I also find some limited evidence that more timely earnings can mitigate the negative impact of conflicts of interest on rating quality. The paper also has implications for prior studies that often assume credit ratings are a superior measure of credit risk and that rating agencies can distinguish between high and low quality information and adjust their ratings accordingly (e.g. Ball et al., 2008; Jorion et al., 2009). I relax this assumption and find that rating agencies do not perfectly discern accounting quality, nor do they utilize alternative sources of information to sufficiently offset lower quality accounting.

This study also contributes to the literature on issuer-pay and investor-pay rating agencies. This line of research has focused primarily on the agency problems facing S&P and has examined the relative timeliness of rating changes and capital market reactions to those changes (Strobl et al., 2012; Bruno et al., 2013; Berwart et al., 2013). My study examines how accounting quality affects the properties of S&P and EJR's ratings and shows that, in some settings, S&P's information advantage reduces the impact of borrowers' accounting quality on its ratings. In addition, I provide evidence on ratings' ability to predict default and measure default risk, which are two key objectives of ratings that have not been fully examined in prior studies within this area of research.

Finally, I contribute to the literature on earnings quality in debt markets. Easton et al. (2009) show that earnings are an important source of information for debt market participants. Beaver et al. (2012) demonstrate that poor earnings quality reduces the power of default prediction models that include accounting measures. Other papers have shown that the quality of earnings impacts the design of debt contracts (Ball et al., 2008; Beatty et al., 2008; Zhang, 2008). I add to this stream of literature by showing that borrowers' earnings timeliness and discretionary accruals alter the efficacy of information intermediaries in the debt market.

2. The news effect of accounting quality on credit ratings' default prediction

2.1 Prior literature and hypothesis development

2.1.1 Issuer-paid rating agencies' reliance on accounting information

There are several reasons that accounting can provide incremental information, or news, to S&P or other large, issuer-paid credit rating agencies. Accounting data is an easily-accessible source of information, and rating agencies confirm that it is an important input to the rating process. If the financial statements do a relatively poor job of providing relevant information, rating agencies should place more weight on other information, such as public disclosures, market-based information, or private information. If these alternative sources of information are adequate substitutes for accounting information, then the quality of accounting will not have a significant impact on the rating agencies' output. However, if other information is an inadequate substitute, the agencies' ratings will be affected by the quality of the issuers' financial reporting.

Accounting quality could also modify rating quality if agencies fail to recognize and adjust for the information in accounting. Despite rating agencies' expertise, it is plausible that they could inappropriately rely on low quality accounting information. Costello and Wittenberg-Moerman (2011) finds that banks, which also have significant private information, do not fully distinguish financial reporting quality. It is reasonable to expect that credit rating agencies may have similar difficulty in doing so. Anecdotal evidence also suggests the limited ability of the agencies to accurately interpret accounting information or to utilize alternative sources of information to overcome accounting deficiencies.[4]

Another reason there may be a news effect of accounting information is that issuer-paid rating agencies may shirk on their monitoring responsibility because it is costly to gather information. Prior analytical and empirical studies suggest that rating agencies may choose to exert relatively low levels of monitoring effort for a number of reasons. Cheng and Neamtiu (2009) find that credit rating quality improves following the implementation of the Sarbanes-Oxley Act of 2002 and attribute this to the increased regulatory pressure to improve monitoring and produce better ratings. Doherty et al. (2012) develop an analytical model that shows issuers will continue to pay a monopolistic rating agency for relatively imprecise and inaccurate ratings in order to avoid being pooled with the set of very risky firms that choose not to obtain ratings. In their model, rating agencies' market power allows them to extract rents while expending little effort to improve the accuracy of their ratings. In another analytical paper, Opp et al. (2013) show that the regulatory usage of ratings provides a revenue stream that is not dependent on the accuracy of ratings, allowing the rating agencies to shirk on monitoring effort. If rating agencies are expending suboptimal monitoring effort, as these studies suggest, there will be a news effect of accounting quality because the agencies rely on this readily-available information rather than obtaining private information.

[4] For example, in the wake of the Enron and Worldcom frauds, Moody's established an Accounting Specialist Group to "incorporate accounting, financial reporting and internal control practices more systematically into the credit rating process." Further, S&P acknowledges that accounting changes provide new information that can lead to rating changes. In the 1990s, S&P lowered a number of companies' ratings following new accounting guidance related to postretirement medical benefit liabilities because it previously had insufficient information to value the obligations.

Reliance on accounting as a source of new information implies that accounting quality will affect credit ratings' performance. I specifically analyze timely loss recognition, asymmetric timely loss recognition, and discretionary accruals as measures of earnings quality that may impact credit rating timeliness and accuracy in measuring default risk. In the context of this study, credit rating accuracy describes the ability of the credit rating to capture the level of default risk and to distinguish a firm's risk relative to other firms. Rating timeliness corresponds to the responsiveness of credit rating changes to changes in default risk.

Earnings that recognize losses in a timely manner contain information that is particularly relevant to the firm's credit risk. Due to their concave payoff function, creditors have a disproportionate interest in negative news relative to positive. Prior studies, such as Watts (2003) and Ahmed et al. (2002), argue that earnings exhibiting TLR and ATLR may be optimal for debt holders. If rating agencies rely on accounting information to develop their ratings, then both the timeliness and accuracy of their ratings should be greater when earnings exhibit more TLR. ATLR implies that negative news is reflected in earnings more quickly than positive news. This may contribute to faster downgrades when issuers experience an increase in default risk. However, prior studies (e.g. Givoly and Hayn, 2000) show that ATLR induces a downward bias in earnings that may accumulate on the balance sheet over time. If rating agencies cannot unravel this bias, it may contribute to some erroneous downgrades that result in lower credit rating accuracy. It may also delay the recording of upgrades if good news is concealed by the earnings bias. As a result, I predict the following:

H1a: Issuers with more timely loss recognition (TLR) in earnings will experience more timely rating downgrades conditional on an increase in default risk, and will have ratings that more accurately measure the level of default risk.

H1b: Issuers with more asymmetric timely loss recognition (ATLR) in earnings will experience more (less) timely rating downgrades (upgrades) conditional on an increase (decrease) in default risk. They will also have biased overall ratings that less accurately measure the level of default risk.

Beaver et al. (2012) find that managed earnings reduce the accuracy of accounting-based default prediction models, which suggests that accounting will be a less useful source of information for rating agencies. Two recent studies by Alissa et al. (2013) suggest that firms manage earnings using discretionary accruals to achieve a target credit rating and to reverse rating downgrades. The implication is that rating agencies do not recognize that earnings are over- or understated and improperly issue rating upgrades or downgrades. If this is the case, then managed earnings can impede timely rating changes and result in biased levels of earnings. I formulate the following hypothesis:

H1c: Issuers with more positive discretionary accruals will experience less (more) timely rating downgrades (upgrades) conditional on an increase (decrease) in default risk. Firms with greater positive or negative discretionary accruals will have biased overall ratings that less accurately measure the level of default risk.

2.1.2 Differential effect of accounting quality for EJR and S&P ratings

When evaluating the quality of S&P ratings relative to EJR ratings, the key question is whether greater information or agency problems will dominate. S&P should, in theory, have a distinct information and resource advantage over EJR. S&P is one of the two largest ratings agencies in the world. It is paid by debt issuers who want ratings on their bonds and other debt securities. By virtue of this relationship with issuers, it has direct contact with management and is provided with information that is not publicly disseminated, such as forecasts and business plans.[5] In addition to conducting periodic reviews and inquiries, S&P analysts expect management of the issuing firm to contact them prior to events or actions that may impact their creditworthiness. S&P also employs significant resources in developing ratings, with nearly 1,700 credit analysts and supervisors who are dedicated to specific industries and firms. In contrast, EJR is a relative newcomer, operating since 1995 and becoming one of the ten SEC-designated nationally-recognized statistical rating organizations (NRSROs) in 2007. It is also the only NRSRO that is paid by investors rather than issuers.[6] Unlike S&P, EJR relies solely on public information to determine its rating, and it places particular emphasis on financial statements.[7] Perhaps most remarkable, EJR employs only five credit analysts who combine judgment with proprietary models to develop its credit ratings. Because of the difference in information and resources, I predict:

[5] Credit rating agencies were originally exempted from full disclosure requirements of Regulation Fair Disclosure (Reg FD) when it was implemented in 2000. In the wake of the recent financial crisis, the SEC removed this exemption in 2010. However, it is not clear that this SEC action has significantly impacted private disclosure to rating agencies. A representative from one of the Big Three credit rating agencies informed me that they continue to receive non-public information and that they do so legally, regardless of the explicit exemption from Reg FD. Various reports published by law firms note that the rating agencies often enter into confidentiality agreements, and they are no longer registered as investment advisers, effectively removing the agencies from the set of institutions subject to the disclosure restrictions.
[6] Cohan, William. "SEC Sues the One Rating Firm Not on Wall Street's Take." *Bloomberg.com*, 30 September 2012.
[7] EJR notes in their NRSRO registration form with the SEC that if they receive any non-public information, they will wait until the information is made public before incorporating it into their ratings. A senior analyst at EJR also informed me that the financial statements and accompanying reports are generally the single most important source of information.

H1d: The relationship between accounting quality and credit rating quality predicted in hypotheses H1a-H1c will be stronger for EJR ratings than for S&P ratings.

2.1.3 Overall performance of Egan-Jones and Standard and Poor's ratings

In spite of the ostensible advantages of S&P, extant research suggests that EJR ratings are timelier than those issued by S&P and Moody's (Johnson, 2004; Beaver et al., 2006; Strobl and Xia, 2012; Bruno et al., 2013; Milidonis, 2013; Berwart et al., 2013). This finding is generally attributed to S&P's conflicts of interest that arise because S&P is paid by issuers who have a preference for ratings that are both high and stable (Cantor and Mann, 2007).[8] Further, as an NRSRO, S&P's ratings are used by numerous federal and state regulations (Covitz and Harrison, 2003), perhaps most importantly for determining whether a security is considered to be "investment grade" or "speculative." They are also widely used in the investment policies of large investors, such as pensions, and in debt contract covenants and performance pricing provisions (Asquith et al., 2005; Ball et al., 2008). These additional uses of S&P ratings can increase the real effects of rating changes, which may further compel S&P to maintain rating stability at the expense of timeliness.[9]

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[8] Bonsall (2013) contributes a conflicting finding that both S&P and Moody's ratings became *more* informative after they switched to the issuer-pay model in the 1970s. This result is not entirely surprising, given changes in firms' information environments and the use of credit ratings since that time.

[9] Although EJR became an NRSRO in 2007, the use of its ratings for regulatory and contracting purposes appears to be insignificant relative to S&P. In addition, a representative of EJR noted that they have not made changes to their ratings process or policies since becoming a NRSRO. Consistent with this assertion, Bruno et al. (2013) finds that the properties of EJR ratings did not change significantly following their NRSRO designation.

The primary analyses in my study examine whether accounting quality affects credit ratings' ability to predict default and measure default risk using ratings from S&P and EJR. I supplement these findings and provide a baseline measure of S&P and EJR ratings performance by examining their relative ability to measure default risk without consideration of accounting quality. This additional analysis provides new evidence that contributes to the literature on investor-paid and issuer-paid rating agencies. Prior studies that include both of these agencies generally do not compare the ratings of the two using direct measures of default risk. One exception is Strobl and Xia (2012), which provides some descriptive evidence that the difference between EJR and S&P ratings is a significant predictor of default rates over a five year horizon. The absence of default prediction findings represents a gap in the literature studying these agencies' ratings.

In addition, existing studies generally use measures of rating timeliness or accuracy, but not both. To measure timeliness, these studies often utilize Granger causality tests to examine the lead-lag relationship of both agencies' ratings (Beaver et al., 2006; Berwart et al., 2013; Bruno et al., 2013; Milidonis, 2013). The Granger tests show that EJR rating changes tend to lead S&P changes, but this finding by itself does not imply that EJR ratings more accurately reflect default risk. For example, EJR may record extraneous changes or changes that are too large in magnitude. To measure accuracy, some studies use the correlation between ratings and *initial* bond spreads, which does not provide any information about the relative timeliness of rating changes by the two agencies. In contrast, I provide evidence on the timeliness and accuracy of S&P and EJR ratings before considering how variation in borrowers' accounting quality affects the performance of these ratings. Prior studies' findings lead me to expect that EJR ratings will be more timely and accurate than S&P ratings due to the impact of S&P conflicts of interest, though S&P's information advantage could lead to the opposite result.

2.1.4 Prior literature on credit ratings and accounting information

Extant literature has examined credit ratings and accounting information on a number of dimensions. As Hilscher et al. (2013) note, the "conventional" view has been that credit ratings are generally a superior proxy for the likelihood of default. This assumption is maintained in a number of papers, such as Molina (2005), which uses ratings as an *ex ante* default risk measure in examining firms' optimal use of leverage. Ball et al. (2008) develop a measure of earnings quality based on its ability to predict rating changes, assuming ratings are the most informative measure of default risk.

Another extensive stream of research does not assume credit ratings are a superior measure, but instead compares the ability of market data, accounting information, and credit ratings to predict default or explain bond yields and CDS spreads.[10] Other related studies examine whether credit ratings can be explained or predicted using accounting and market variables (Horrigan, 1966; West, 1970; Kaplan and Urwitz, 1979; Ziebart and Reiter, 1992; Galil, 2003; Hovakimian, 2009). Holthausen et al. (1986) and Hand et al. (1992) provide early evidence that rating changes provide additional information to capital markets despite being partially predictable.

[10] See, for example, Ederington et al. (1987), Shumway (2001), Campbell et al. (2003), Kealhofer (2003), Loffler (2004), Hillegeist et al. (2004), Hull et al. (2004), Norden and Weber (2004), Duffie et al. (2007), Bharath et al. (2008), Das et al. (2009), Hilscher et al. (2013)

More recent studies show that rating agencies adjust reported accounting numbers to make them better reflect credit risk information. Altamuro et al. (2012) shows that rating agencies adjust their ratings to take into account off-balance sheet operating lease liabilities. Kraft (2012) demonstrates that rating agencies make quantitative adjustments to financial statement information, as well as qualitative “soft” adjustments, and that these adjustments contain information about default risk.

Several recent studies consider the effect of information quality on credit ratings under the assumption that credit rating agencies observe and adjust for the information quality. Jorion et al. (2009) find that firms with investment grade debt increased their earnings management activity over time, and that rating agencies reduced their reliance on accounting information over the same period. Ashbaugh-Skaife, Collins, and LaFond (2006) find that firms with more stringent corporate governance, including higher accruals quality and earnings timeliness, have higher credit ratings. Their study views earnings as a disciplining device that contributes to a firm’s governance. If earnings are informative and timely, then managers have less ability to take value-decreasing actions that would increase default risk. Odders-White and Ready (2005) find that higher information asymmetry among equity investors is associated with lower credit ratings. This finding is consistent with the intuition of Duffie and Lando (2001). When information asymmetry is high, credit rating agencies have greater uncertainty. As a result, the rating agencies increase their estimate of default risk and lower their ratings accordingly.

Finally, there are a few studies that hypothesize that rating agencies may be susceptible to poor accounting quality. As described above, there are two papers by Alissa et al. (2013) that find that borrowers can induce rating changes by managing earnings. In addition, Akins (2013) posits that poor accounting quality increases uncertainty in the credit markets and shows that low accounting quality is associated with greater divergence in the ratings issued by various agencies. My study differs from these by examining whether borrowers' accounting quality impacts how well credit ratings predict default and measure default risk.

2.2 Sample and descriptive statistics

My empirical tests use different samples based on the data requirements for each test. I construct my primary sample by matching Compustat to CRSP. CRSP data is required for the earnings timeliness measures, as well as for estimating the Campbell et al. (2008) model. I then match the sample to Mergent FISD, which contains data on debt defaults, using the six-digit CUSIP. Based on default data coverage, I limit the sample years to 1990-2012, which results in a base sample of 128,742 firm-quarter observations. This sample is used to estimate the modified Campbell failure score.

I add information on S&P ratings from S&P RatingsXpress. When I combine this data with the base sample, there are 106,628 observations for which there are active S&P long-term issuer ratings. However, I further limit the sample to include only years 1999 and later, because this is the period for which I have EJR ratings data. For this period, there are 71,659 observations for 2,270 firms rated by S&P. I obtained issuer-level EJR ratings data directly from Egan-Jones Ratings Company. For most tests, I require firms to be rated by both EJR and S&P, which reduces the sample to 37,522 observations for

1,332 firms. Of these 1,332 firms, 148 experience a default at some point during my sample period. Finally, for tests that incorporate both ratings and the modified Campbell model, my sample is reduced to 29,649 firm-quarters for 1,058 firms, of which 106 have a default.

Table 1, Panel A presents descriptive statistics for the primary sample. All variables are defined in Appendix A. The distributions of variables for this sample are very similar to those for the base sample (untabulated). The distributions of EJR and S&P ratings are similar, with nearly identical means. The mean of *ejrmsp*, which is the difference between the EJR rating and the S&P rating for each firm-quarter, is 0.01 and the median is zero. EJR and S&P have identical ratings approximately 30% of the time, and are within one rating notch of each other in 70% of the firm-quarters. In addition, and consistent with prior studies, EJR records both upgrades and downgrades more frequently than does S&P, as shown by the mean of *ejrdown* and *spdown*, which are indicators equal to one if the firm's credit rating is downgraded in the current quarter by EJR and S&P, respectively, and equal to zero otherwise. Panel B presents the distributions of EJR and S&P ratings, which are generally consistent with the data used in prior studies (Beaver et al., 2006; Bruno et al., 2013). I assign numeric values to each letter rating, from 1 for AAA to 21 for C. Panel E presents descriptive statistics for the sample of firms that default, with one observation for each default (with the exception of the statistics for *dahead*, which has one observation for each downgrade in the year prior to default). Note that there are fewer defaults in this table because the sample is limited to those defaults with sufficient data available for testing as of one year prior to default. Note that leverage is much higher and ratings for these firms are much lower than for the main sample.

2.3 Empirical analysis and results

2.3.1 Baseline results for overall accuracy of EJR versus S&P

I estimate a default prediction model to assess both the unconditional accuracy of EJR and S&P ratings, as well as the incremental information each provides relative to the other. I follow Campbell et al. (2008) and Hilscher et al. (2013) and estimate twelve separate logistic regressions that estimate the probability of default over each of the subsequent twelve quarters. Estimating separate models for each horizon allows the coefficients on the independent variables to vary with the prediction horizon and provides a more comprehensive assessment of their predictive power relative to focusing on only a single period. I model the conditional probability of default as:

$$\Pr_t(\mathrm{Def}_{i,t+k} = 1|\mathbf{X}_{i,t}) = \left(1 + \exp\left(-\mathbf{X}_{i,t}\boldsymbol{\beta}_{k}\right)\right)^{-1} \quad (1)$$

where $\mathrm{Def}_{i,t+k}$ is an indicator that equals one if firm i defaults in month $t + k$. Note that the dependent variable relates to default in quarter t+k, not the cumulative default between time t and time t+k. The vector of explanatory variables, $\mathbf{X}_{i,t}$, is defined for each test below.

In the remainder of this section, I discuss my findings regarding the unconditional accuracy of EJR and S&P ratings, before considering the effects of accounting quality. Table 2 presents the results of these twelve regressions with two sets of independent variables. Panel A shows the incremental predictive power of S&P ratings, while Panel B shows the incremental power of EJR ratings. Both panels present estimates for the full sample and the subsample of firms that are classified as speculative (i.e., excluding firm-quarters in which both S&P and EJR issued ratings of BBB- or above). Table 2 reveals several findings. First, the coefficients on *ejrating* in Panel A and *sprating* in Panel B are positive and significant. The interpretation of this coefficient in both models is the association of credit ratings with future default when the S&P rating equals the EJR rating, which is why the coefficients are identical across the panels. The coefficient on *spmejr* in Panel A, which is the difference between the S&P and EJR rating, shows that S&P ratings that diverge from EJR ratings provide some additional explanatory power in estimating default risk, but it is only marginally significant at some horizons for the full sample and is insignificant beyond six quarters in the speculative sample. In contrast, Panel B shows that EJR ratings that diverge from S&P ratings (*ejrmsp*) are significant predictors of default at a 1% level across all horizons in both samples. Thus, EJR ratings that diverge from S&P ratings appear to provide incremental explanatory power more often than S&P ratings that diverge from EJR ratings.[11]

To further assess the accuracy of the ratings, I calculate the accuracy ratio, which measures rating agencies' propensity to assign lower ratings to firms that ultimately default relative to firms that do not. This ratio measures how well credit ratings avoid both Type I errors (granting poor ratings to firms that will not default) and Type II errors (granting relatively high ratings to firms that will default).[12] A benefit of using the

[11] The magnitude of the coefficients represents the marginal effect of the covariates on the log odds-ratio of default at each horizon, which is not very intuitive in and of itself. Marginal effects of each rating on the probability of default can be calculated, though they vary across levels of ratings. It is sufficient for my analysis to analyze statistical significance as a measure of the incremental contribution of the ratings in predicting default.
[12] See Engelmann, Hayden, and Tasche (2003) for more information on calculating the accuracy ratio.

accuracy ratio is that it is non-parametric, so it is not affected by functional form assumptions about the relationship between ratings and default probability. It is also a key metric used by the rating agencies to assess their own performance.

Table 3 presents the accuracy ratios for eight default horizons. Each row represents a different set of independent variables. EJR and S&P show accuracy ratios for models with the agency ratings – *ejrating* and *sprating,* respectively – as the only independent variable. The "both ratings" model includes both *ejrating* and *sprating*. Results are shown for both the full sample (Panels A & C) and the speculative sample (Panels B & D). Figure 1 provides a graphical representation of the data in Table 3, Panels A and B. The modified Campbell row presents the accuracy ratios for the failure score (i.e. predicted probability of default) estimated using a modified version of the default prediction model of Campbell et al. (2008). The superior performance of the modified Campbell model makes it a suitable benchmark measure of default risk that I employ in tests described below. Figure 2 shows the relationship between EJR ratings and S&P ratings across default risk groups. Note that S&P ratings are greater than EJR ratings about 65% of the time for lowest risk group and only 15% of the time for the highest. Of course, the figures for EJR ratings > S&P ratings show the opposite trend. Recall that higher ratings are coded to worse/higher in default risk (AAA = 1, C = 21), so the interpretation of the graph is that EJR ratings capture default risk more effectively.

Several notable results emerge from these tests. Both EJR and S&P perform better in the full sample than in the speculative sample. The accuracy ratios decline monotonically as the prediction horizon increases, which is expected since default is more difficult to predict at longer horizons. Panels C & D present differences in the accuracy ratios and associated z-statistics.[13] These panels show that EJR ratings have a higher accuracy ratio than S&P ratings across all horizons in both samples, and that the magnitude of the difference is larger in the speculative subsample. This result implies that EJR's rating accuracy relative to S&P is even higher among firms that have higher default risk and those for which information is relatively valuable. The statistical significance diminishes at longer prediction horizons, but the overall evidence supports EJR's predictive ability. Additionally, I compare each rating individually to the model with both ratings. There is not a significant difference between the accuracy of EJR ratings and the model with both ratings at any horizon, again supporting the idea that S&P ratings do not provide significant incremental information to EJR ratings for the purpose of predicting default. In contrast, the model with both ratings outperforms S&P ratings alone by a statistically significant margin at nearly all horizons. EJR ratings are more accurate than S&P ratings overall and provide superior incremental predictive power when added to S&P ratings.

2.3.2 Earnings quality and rating accuracy

2.3.2.1 Accuracy ratio tests

To assess the effect of earnings quality on rating accuracy and timeliness, I use measures of timely loss recognition and asymmetric timely loss recognition (Basu, 1997). Both are measured as the estimated coefficients from a piecewise-linear regression of earnings on stock returns. I estimate these measures following the procedure in

[13] Z-statistics for testing the differences in accuracy ratios were formulated using jackknife standard errors for nonparametric statistics. See Newson (2006) for a description of the method.

Wittenberg-Moerman (2008), with two modifications. First, I include controls for lagged firm characteristics, as proposed by Ball et al. (2013). Second, I estimate by industry (three-digit SIC code) rather than industry-year to obtain a measure of a more persistent characteristic of earnings quality that is not affected by particular events that may coincide with changes in default risk.[14] I also hope to avoid capturing earnings management with this measure, as I separately analyze the effect of discretionary accruals.

I examine the impact of earnings management using discretionary accruals estimated using the modified Jones model (Dechow, Sloan, and Sweeney, 1995). This model separates total accruals (operating income minus operating cash flows) into its non-discretionary and discretionary components based on a model of changes in revenue, accounts receivable, and PP&E. The discretionary accruals are the residuals from this estimation. Thus, positive residuals represent positive discretionary accruals, or upward-managed earnings. If discretionary accruals mislead credit rating agencies and cause inappropriate rating changes, then firms with high or low discretionary accruals (i.e. high absolute value of discretionary accruals) will have less accurate ratings.

I divide the sample at the median of each earnings timeliness measure and at the median of the absolute value of discretionary accruals. I then estimate equation (1) on each agency's ratings separately for each earnings quality group and measure rating performance with the accuracy ratio. The results in Table 4, Panel A suggest that EJR is

[14] Results continue to persist for most specifications using industry-year measures of TLR and ATLR. An exception is set of tests performed for the subset of defaulting firms. This is not surprising, as a default may be symptomatic of industry economic events that may influence the estimation of the measures in that particular period.

better at predicting default over most horizons when earnings have more timely loss recognition. This finding is consistent with relevant information being reflected in earnings more rapidly, leading EJR to be more responsive in adjusting its ratings appropriately. When earnings are asymmetrically timely, EJR ratings appear to be less accurate. This is consistent with hypothesis H1b, suggesting that biases in the balance sheet may not be recognized by EJR. The third result in Panel A shows that EJR is more accurate in predicting default up to six quarters ahead when the absolute value of discretionary accruals is lower, but EJR ratings appear to be more accurate when discretionary accruals are high, particularly at longer horizons. As discretionary accruals are temporary and tend to reverse, it could be reasonably expected that the effect of current levels of discretionary accruals will dissipate over time. Overall, these findings are consistent with my hypotheses.

The results for S&P in Panel B show that the effect of earnings timeliness is less pronounced for S&P ratings than for EJR ratings. For each of the timeliness measures, there is a mix of positive and negative differences in accuracy across earnings quality groups. This is not consistent with the prediction that timeliness will increase S&P’s rating accuracy. With the exception of the anomalous results at the one quarter horizon, the effect of discretionary accruals on S&P’s rating accuracy is largely consistent with EJR and with hypothesis H1c. The inference is that S&P uses its private information consistently and, therefore, is not subject to timely loss recognition in earnings, but that it may be temporarily misled by issuer earnings management.

Panel C displays the differences in accuracy ratios between EJR and S&P at each horizon and for each accounting quality group. In column 4 of the first portion of this panel, the 0.056 measures the difference between EJR's and S&P's accuracy ratios for the high TLR group. As expected, EJR performs better than S&P within this group. The 0.022 in the "Low TLR" line shows that EJR also exceeds S&P for firms with less TLR. The "Difference" of 0.034 indicates that the performance of EJR relative to S&P in the high accounting quality group is greater than in the low accounting quality group. This difference-in-differences result is consistent with the expectation that S&P's information advantage will lead it to perform relatively better compared to EJR when accounting quality is low. The difference is positive across most of the horizons for TLR, which supports this prediction. The ATLR results show that when earnings are more asymmetrically timely, EJR performs relatively worse. Again, it appears that EJR rating accuracy suffers from accounting bias more than S&P ratings because S&P has access to other information that limits their reliance on biased earnings, consistent with H1d. The final portion of the table shows the accuracy differences across discretionary accruals groups. These differences vary in sign and are not generally significant (with the exception of the one quarter horizon), indicating that EJR and S&P are similarly impacted by discretionary accruals. This finding is inconsistent with H1d.

Overall, these results suggest that EJR ratings become more accurate when losses are timely, but less accurate when losses are asymmetrically timely. These effects are present both in terms of absolute accuracy and accuracy relative to S&P, in support of my hypotheses that the effect of earnings quality will be greater for EJR than S&P. In addition, the effect of discretionary accruals varies with the prediction horizon. However, these results should be interpreted with caution due to the relatively infrequent incidence of default. The number of defaults is approximately 100 at most horizons.[15] This quantity is likely sufficient for tests involving the full sample, but when it is broken into groups it is possible for noise in the data to significantly impact accuracy ratios calculated with a limited sample of defaults. The problem is increased with the discretionary accruals measure, as data requirements further reduce the number of defaults.

2.3.2.2 Failure score regressions

In order to overcome the lack of defaults in my sample available for use in prediction models, I replace the default indicator with the probability of default as represented by the failure score. The failure score is the predicted value from a logistic regression of default in the subsequent quarter on a set of accounting and market variables. Campbell et al. (2008) shows that this model is a more accurate default predictor than distance-to-default measures (Merton, 1974; Hillegeist et al., 2004) and S&P credit ratings. I create a "modified Campbell" model by adding *cfotlavg* and *tang,* which provide additional explanatory power. *Cfotlavg* is the weighted average cash flow scaled by total liabilities and is included in the well-known Ohlson (1980) bankruptcy prediction model. I add it to the Campbell model to allow for separate coefficients on accruals (represented by *nimtaavg*) and cash flows. *Tang* is asset tangibility, measured as net PP&E divided by total assets. Following Campbell et al. (2008) and Hilscher et al. (2013), I estimate the Campbell model using an "expanding window" approach, where

[15] The actual number varies with horizon due to data availability. For example, data for a given default may be available four quarters prior to the default, but not one or eight quarters.

the model coefficients are re-estimated every year using data from 1990 through the prior year. Thus, the coefficients on the variables change over time. By using coefficients estimated using only past data, I avoid the look-ahead bias of estimation using the full sample. Table 5 provides the coefficients from estimating the model from 1990 – 2012 using the sample of all firms with Mergent and Compustat coverage. The signs of the coefficients are consistent with Campbell et al. (2008) and with predicted relationships of each variable with default risk. Table 3 shows that the accuracy ratios for the modified Campbell score are larger than those for all of the ratings models, and that the differences are statistically significant through at least four quarters. This result supports my use of the failure score as a proxy for default risk.

To test the ability of credit ratings to capture default risk and identify how accounting quality alters this ability, I regress the failure score on credit rating levels interacted with the three accounting quality measures (TLR, ATLR, and DiscAcc). Panel A of Table 6 presents the results for EJR ratings. The first column presents the EJR rating (*ejrating*) and the incremental S&P rating (*spmejr*). The coefficient on *ejrating* is strongly positive, demonstrating that EJR ratings have considerable predictive power. The coefficient on *spmejr* is negative and significant, showing that S&P ratings incremental to EJR ratings has a negative association with the level of credit risk, suggesting that S&P ratings are poor predictors relative to EJR ratings because the incremental S&P rating predicts default risk in the opposite direction. The last three columns present the effects of accounting quality on EJR ratings. Consistent with hypothesis H1a, the interaction (*AQ_EJR*) between TLR and the credit rating is positive, which implies that ratings are better able to predict default risk when firms provide more informative earnings. The interaction term for ATLR is also significantly positive, which suggests that rather than generating biased ratings, earnings with asymmetric loss recognition provide an information signal that helps rating agencies develop better ratings. This is consistent with the idea that this characteristic of accounting may be the equilibrium outcome of firms seeking to meet the demand for information (LaFond and Watts, 2008). The interaction between discretionary accruals (DiscAcc) and *ejrating* is negative, consistent with the idea that upward managed earnings can bias ratings and make them less accurate measures of default risk, but it is not statistically significant. This finding is not entirely surprising, as accruals reverse, so the impact of earnings management may not persist long enough to be reflected in the accuracy of ratings. As discussed in later sections, the effect is stronger when using changes specifications.

The results in Panel B for S&P ratings are consistent with Panel A. The first column shows, without including accounting quality effects, EJR ratings provide significant predictive power incremental to that provided by S&P ratings. In addition, the interaction term in the TLR and ATLR columns is positive and significant, while the interaction with DiscAcc is negative but insignificant.

Panel C presents the differential results of accounting quality on S&P and EJR. In this table, the coefficient of interest is the interaction between accounting quality and the difference between the S&P rating and EJR rating (*AQ_spmejr*). Because accounting quality is predicted to have a less significant impact on S&P ratings than EJR ratings, I expect this interaction to have a negative coefficient. However, it is not significantly different from zero in any of the columns, showing that accounting quality has a comparable impact on both S&P and EJR.

2.3.2.3 Rating change reversal tests

As an additional test of whether accounting bias leads to biased rating levels, I analyze rating change reversals. Specifically, I examine whether rating agencies issue a downgrade (upgrade) within one year following an upgrade (downgrade). It should be noted that a reversal is not necessarily an indication of poor ratings quality. If firms' credit risk fluctuates, then the most timely and accurate rating may be the one that reverses most often. However, if the probability of a rating change reversal is correlated with biases in borrowers' earnings due to earnings management or asymmetric loss recognition, it is more likely that a reversal is the correction of an erroneous rating change that was originally based on poor or inaccurate information.

In order to complete this analysis, I extract all rating changes from the sample of firms rated by both agencies. Table 9 presents estimates from a linear probability model where the dependent variable is *Reverse,* an indicator equal to one if the current rating change for a given agency is followed by a change in the opposite direction within 365 days. The first independent variable is *EJRdum*, an indicator equal to one if the dependent variable relates to EJR ratings and zero for S&P. In this model, *AQ* represents either ATLR or DiscAcc. These are the two earnings quality measures that are predicted to induce bias in hypotheses H1b and H1c. *EJR_AQ* is the interaction between *EJRdum* and *AQ*, representing the incremental impact of accounting quality on EJR rating reversals. *Ratelevel* is included as a control variable equal to the value of the rating prior to the rating change. The columns labeled "Down" relate to downgrades and the "Up" columns are upgrades. The first two columns are baseline specifications that show that EJR rating downgrades and upgrades are both significantly more likely to reverse than S&P rating changes, consistent with Bruno et al. (2013). The last four columns show that the accounting quality results are stronger for downgrades than for upgrades. Prior studies have shown that rating agencies tend to be more conservative in issuing upgrades, which means they tend to lag and are likely less impacted by current earnings (Beaver et al., 2006). Relatively weak results on upgrades persist throughout subsequent testing, as well. The positive and significant coefficient on *AQ* in the ATLR down column indicate that S&P downgrades are more likely to reverse for firms with greater ATLR. It appears that S&P sometimes records overly conservative downgrades when firms' earnings exhibit the negative bias associated with ATLR, and that it tends to reverse those downgrades within one year as the earlier earnings biases are revealed. Interestingly, the coefficient on the *EJR_AQ* interaction term is negative and significant. This coefficient offsets the main effects observed for S&P, so the total effect of ATLR on EJR reversals (*AQ + EJR_AQ)* is not significantly different from zero. The probability of EJR reversal does not depend on the level of earnings ATLR. The reversal results for discretionary accruals are not significant. This is consistent with the findings of our prior accuracy tests that do not provide evidence of bias caused by discretionary accruals.

There are at least two possible explanations for the finding that ATLR increases the probability that S&P downgrades reverse, but it does not appear to affect EJR downgrades. First, EJR may be better than S&P at recognizing potential accounting biases and avoiding inappropriate downgrades that will be soon reversed. This interpretation is at odds with my other results, which show that the effects of earnings quality are generally at least as significant for EJR ratings as they are for S&P ratings. Therefore, a more likely explanation is that EJR, like S&P, records downgrades that are biased by negative discretionary accruals and asymmetric recognition of losses, but that it fails to recognize and reverse those downgrades within one year. Collectively, these effects cause an accumulation of bias in EJR ratings that reduces its accuracy, which is consistent with my results in Table 4.

2.3.3 Earnings quality and rating timeliness

The remainder of my analyses to test the news effect of accounting quality focuses on testing rating timeliness. When a borrower experiences a significant change in default risk, rating agencies should respond with a rating change. A more timely response is a signal of higher rating quality. This is a more powerful setting to test the effects of earnings quality, because earnings itself is a measure of the change in (as opposed to the level of) a company's financial position. To test the responsiveness of credit ratings to changes in default risk, I utilize the modified Campbell failure score as a benchmark measure of default risk.

To test the timely downgrade or upgrade by the rating agencies following a change in default risk, I examine six dependent variables: *ejrdown, spdown, ejrup, spup, downdiff,* and *updiff.* The first two are indicators equal to one if the firm experiences a downgrade from EJR and S&P, respectively. The next two are similar indicators of upgrades. The variable *downdiff (updiff)* is equal to one if the firm is downgraded (upgraded) by EJR and not by S&P, negative one if the firm is downgraded (upgraded) by S&P and not EJR, and zero otherwise. These variables are regressed in a linear probability model on a number of independent variables in Table 8. *AQ* is the accounting quality variable: TLR in Panel A, ATLR in Panel B, and DiscAcc in Panel C. *Csup* is an indicator equal to one if the rated firm experiences an increase in default risk, as measured by the failure score. The key variable in the downgrade specifications is the interaction of these two variables, *AQ_csup*. For TLR and ATLR, I expect a positive coefficient on this interaction. This would indicate that a rated entity with more informative earnings is more likely to be downgraded when their default risk increases. This would be because the increase in default risk is more likely to be reflected in earnings for firms with timely loss recognition. For DiscAcc, I expect a negative coefficient, as upward earnings management can obscure the increase in default risk. In the upgrade specifications, the key variable is *AQ*. This measures the incremental effect of accounting quality on the probability of an upgrade when there is a decrease in default risk. For TLR, there is no directional prediction for this coefficient, as this measure does not capture the timeliness of earnings with respect to good news. For ATLR, the coefficient should be negative because of the downward bias in earnings. For DiscAcc, the coefficient should be positive because upward earnings management may exaggerate the improvement in credit risk. I include as control variables *campscore_lag*, which is the lagged failure score level, and *ejrating_lag, sprating_lag, and ejrmsp_lag*, which are the lagged levels of EJR rating, S&P rating, and the difference between the two, respectively.

Table 6, Panel A presents the results for timely loss recognition. The positive coefficient on *csup* in the ejrdown and spdown columns indicates that, consistent with expectations, rating downgrades are more likely for both rating agencies when the firm experiences an increase in default risk. The positive coefficient on *csup* in the downdiff column indicates that EJR is more likely than S&P to issue a downgrade when default risk increases, consistent with the overall evidence that EJR ratings appears to outperform S&P ratings as measures of default risk. The key coefficient on the interaction term is positive and significant for both EJR and S&P downgrades, indicating that more timely loss recognition increases the probability that the agencies appropriately record a downgrade when default risk increases. The interaction term is not significant in the downdiff column, indicating that the effect of accounting quality on rating timeliness is not significantly different between the two rating agencies.

Panel B presents the results for asymmetric timely loss recognition. For downgrades, the results are similar to those from Panel A and support the hypothesis that ATLR will improve the timeliness of ratings in recording rating downgrades when issuers have an increase in default risk. For upgrades, the effects of ATLR are mostly insignificant, consistent with our earlier finding that upgrades are less timely and, therefore, are less likely to be influenced by the characteristics of current earnings.

Panel C provides results related to discretionary accruals. In the ejrdown and spdown columns, the negative coefficients on the interaction terms show that the probability of a downgrade concurrent with an increase in default risk declines as discretionary accruals become more positive. This is consistent with my hypothesis. As expected, the results for EJR and S&P upgrades are weaker, though it is notable that the interaction term is positive, indicating that firms that manage earnings upward when they experience an increase in default risk are more likely to receive a rating upgrade, which would also be consistent with rating agencies being misled.

2.3.4 Controlling for conflicts of interest and private information

2.3.4.1 The need for additional controls

The results generally support my hypotheses for the news effects of accounting quality. Specifically, it appears that timely loss recognition in earnings and discretionary accruals affect the timeliness of rating downgrades as hypothesized, and timely loss recognition also affects the overall accuracy of ratings. It was somewhat surprising to find that the effects are comparable for both EJR and S&P despite S&P's access to private information. As discussed in section 2.1.1, there are reasons that there may be a news effect of accounting quality for S&P ratings that could match the effect for EJR ratings. For example, S&P may lack adequate, cost-effective substitute information that would either make up for a lack of earnings timeliness or expose the bias in managed earnings. In addition, S&P's market position may allow it to shirk on their monitoring without significantly harming its revenue.

These reasons could explain the observed results, but there is also the possibility that conflicts of interest and private information quality are correlated omitted variables that created an upward bias in the effect of accounting quality for S&P. Because the issuer is the source of their revenue, S&P may feel pressure to provide inflated ratings in order to avoid losing their client and its future revenue to a competing firm. The level of these conflicts may be correlated with the quality of public information provided by rated firms. For example, a firm that puts pressure on the rating agency to inflate its rating may also provide biased accounting information or disclosures. In this case, if I exclude conflict of interest proxies from the models, then the observed effect of good accounting quality may actually be the effect of low conflicts of interest.

Another potential correlated variable is the quality of private information provided to the rating agency. A firm that provides biased or incomplete information to rating agencies may also do the same in their public financial reporting. Again, this positive correlation would create an upward bias in the observed accounting quality effect for a model that excludes a measure of private information.

2.3.4.2 Measures of conflicts of interest

To address the concern about omitted variable bias, I reperform some of the key analyses including controls for conflicts of interest. The conflict of interest measures are intended to capture several constructs, including regulatory pressure on the rating agencies, the likelihood that outside investors will recognize biased ratings, potential real effects of rating changes, expected future revenue from the issuer, and pressure from the issuer based on the CEO's compensation structure. In particular, I include the following:

- *Bbb*: This is an indicator variable equal to one if the firm's S&P credit rating is equal to BBB-, BBB, or BBB+. BBB is the lowest rating a firm can have and still be considered investment grade. If a firm's rating falls below investment grade, it will lose access to a number of institutional investors, such as pensions, who limit their investment to investment grade only (Kraft, 2010). In addition, it is difficult for firms with a long-term rating below BBB to obtain the short-term ratings necessary to access the commercial paper market (Kisgen, 2006). As a result, firms with a BBB rating will be particularly concerned about avoiding downgrades, putting additional pressure on the rating agency to maintain an inflated rating.

- *Financial:* This is an indicator equal to one for financial firms (three digit SIC code between 600 – 641). Kedia et al. (2014) find that Moody's caters to financial firms, which are frequent issuers of debt, including structured debt instruments. S&P may also cater to them in order to preserve the revenue opportunities from rating future securities.
- *Propstd:* This is an indicator equal to one if the firm's ratio of short-term debt to total debt is greater than the sample median. Strobl and Xia (2012) find that S&P's conflicts of interest are more severe for firms with more short-term debt. The motivation behind this measure is that these firms are likely to issue additional debt upon the maturity of their existing debt, which will provide future revenue opportunities for S&P. As a result, they may cater to these firms.
- *Presox:* This is an indicator variable equal to one for observations occurring prior to 2002, when the Sarbanes-Oxley Act was passed. Cheng and Neamtiu (2009) find improvement in the quality of credit ratings after 2002, ostensibly due to the increased regulatory pressure and investor criticism following the Enron and Worldcom debacles. As a result, in the pre-SOX era, rating agencies were more likely to cater to issuers at the expense of accurate ratings.
- *Ewr6:* This is an indicator equal to one for observations occurring following six months of equally-weighted NYSE/AMEX/NASDAQ index returns that are greater than the sample median. Bolton et al. (2012) present an analytical model

showing that rating agencies will tend to cater to investors and inflate ratings during booms when investors are more trusting.

- *Indlevmed:* This indicator is equal to one for firms in an industry where the median leverage is greater than the sample median. This is another proxy for future revenue. Agencies that cover firms in industries that carry more leverage will have more rating business in the future.
- *Ltd:* This is an indicator equal to one if the firm's total long-term debt is greater than the sample median. This is proxy both for large firms, which may feel they can pressure the rating agencies into inflating ratings, as well as for potential future revenue, which will be greater for firms with more debt.

2.3.4.3 Measures of private information quality

The private information measures are designed to capture optimistic bias held by issuer management, the overall accuracy of management's private information, and the information asymmetry between informed and uninformed investors. The measures are:

- *Pin:* This is an indicator equal to one if the Probability of Informed Trade (PIN) is greater than the sample median. PIN is a measure of information asymmetry between informed and uninformed investors in equity markets developed by Easley et al. (2002) and modified by Venter and de Jongh (2006). Although rating agencies operate in debt markets rather than equity markets, I assume that the private information held by informed traders is relevant for valuing both types of securities and that the overall level of asymmetry is positively correlated across markets. In my study, S&P is considered the informed party due to their access to management, while EJR is relatively uninformed, relying solely on public information. Therefore, PIN represents the difference in information available to S&P and EJR.[16]

- *Tenure:* This is an indicator equal to one if the CEO tenure is greater than the sample median. CEO tenure is one of several measures of CEO overconfidence adopted from Schrand and Zechman (2012). A longer-tenured CEO may be overconfident because he over-weights the role of his own ability in prior successes. Overconfident executives will likely communicate optimistically biased private information to rating agencies, so tenure is an inverse measure of the accuracy of private information.
- *Varpay:* This is a measure of the variable portion of CEO compensation, measured as (total compensation – fixed salary)/total compensation from Execucomp. This is a measure of the relationship between CEO compensation and the performance of the form. The stronger this relationship is, the more likely the CEO is to provide biased information to rating agencies or to pressure rating agencies to inflate ratings. The variable is an indicator equal to one if the above ratio is greater than the sample median.
- *Score_oc4:* This is an indicator variable adopted from Schrand and Zechman (2012) that captures executive overconfidence. If the sum of the following four measures is greater than or equal to three, then this variable is equal to one:

[16] I obtained quarterly PIN data from Professor Stephen Brown's web site. The data is that used in Brown and Hillegeist (2007), extended through 2010.

    - Excess investment: the residual from a quarterly cross-sectional regression of total asset growth on sales growth, adjusted for the industry (two-digit SIC) median for that quarter. This is set equal to one if it is greater than zero and zero otherwise.
    - Excess acquisitions: net acquisitions from the statement of cash flows, adjusted for the industry-quarter median. This is set equal to one if it is greater than zero and zero otherwise.
    - Excess leverage: the ratio of current and long-term debt to the sum of current debt, long-term debt, and the book value of shareholders' equity, adjusted for the industry-quarter median. This is set equal to one if it is greater than zero and zero otherwise.
    - Risky debt: an indicator variable equal to one if the firm has convertible debt or preferred stock greater than zero.
- *Score_oc5:* This measure of executive overconfidence is an indicator variable equal to one if the sum of five measures is greater than or equal to three. The first four measures are those described under *score_oc4*, above. The fifth measure is dividend yield, equal to zero if the firm paid dividends on common stock over the prior twelve months and equal to one if it did not.
- *Option_oc*: To calculate this variable, I first obtain the value of in-the-money unexercised exercisable options held by the CEO and scale this amount by the CEO's total holdings. I then multiply this ratio by 100 to get a percentage. If this amount is greater than the industry-quarter median, then this variable is equal to

one. Otherwise, it is equal to zero. The degree to which CEOs delay exercising options is a reflection of their overconfidence (Malmendier and Tate, 2005; Schrand and Zechman, 2012).

- *Purch180*: An indicator variable equal to 1 if the net insider purchases (volume of purchases – volume of sales) divided by shares outstanding over the 180 days prior to the start of the quarter were greater than zero. I limit insider sales and purchases to open market transactions, as in Jagolinzer et al. (2011). This variable is intended to capture executive optimism, as insider purchases imply a belief that the stock will generate positive abnormal returns.
- *Alpha180*: This is a measure of the profitability of insider trades made over the 180 days prior to the start of the quarter. Following Jagolinzer et al. (2011), I net all insider transactions on a given day and treat them as a single transaction. I then measure profitability as the alpha from the Fama and French (1993) and Carhart (1997) model estimated over the 180 days following each transaction. I calculate the average alpha of all transactions over the 180 day period, with each transaction's alpha weighted by the number of shares traded divided by the total volume of insider trades over the period. The measure is an indicator equal to one if the alpha is greater than the sample median. If management makes profitable insider trades, this is an indication that they have accurate private information. If this information is transferred to S&P through its interactions with management, then this will be a proxy for the quality of S&P's private information.

2.3.4.4 Effects of accounting quality after controlling for conflicts of interest and private information

To test the robustness of the rating accuracy results to the inclusion of controls for conflicts of interest and private information, I first reperform the regressions of the modified Campbell failure score on credit ratings and accounting quality originally shown in Table 6. Recall that this test is performed to measure the ability of credit ratings to capture the level of default risk. I add the conflict of interest variables individually to the model, as well as an interaction between the conflict of interest measure and the credit rating of interest. The results are shown in Table 9. Because of the large number of conflict of interest measures, I show only the interaction between the accounting quality measure and the credit rating. Panel A shows the results for Egan-Jones Ratings. The effect of TLR is attenuated somewhat from the original results, but remains fairly consistent overall. The effect of ATLR remains positive and significant, while the impact of discretionary accruals remains insignificant. Panel B provides the comparable results for S&P ratings. The effect of all three accounting quality variables remains consistent with the original analysis. Similarly, Panel C shows the incremental effect of accounting quality on S&P ratings compared to EJR ratings. Based on these robustness tests, it appears that effect of accounting quality on credit rating accuracy is not driven by omitted conflict of interest variables.

Table 10 then presents the original results from Table 6 after adding controls for the quality of private information and private information interacted with credit ratings. The results are comparable to those in Table 9. The effect of accounting quality on the accuracy of EJR ratings is weakened somewhat, particularly for TLR, which is surprising because EJR should not be directly affected by the characteristics of firms' private information. It is possible that these variables are correlated with the quality of other non-earnings public disclosures that provide more information to EJR. Overall, the coefficients remain consistently positive and are significant in enough specifications to suggest that more timely loss recognition does improve rating accuracy. Panel B presents the results for S&P. Interestingly, the effects of earnings timeliness continue to be significant, even though private information should be more relevant for S&P than EJR. Panel C is generally consistent with the original, in that there does not appear to be a significant difference in the news effect of accounting quality between S&P and EJR. It is notable that a few of the coefficients on the interaction with discretionary accruals are now significantly positive, which suggests that the negative effects of earnings management on rating accuracy may be stronger for EJR than for S&P, which is consistent with my initial hypothesis that the news effect should be greater for EJR. However, these results are relatively weak.

I then test the robustness of the rating timeliness results originally presented in Table 8. These tests examine whether higher accounting quality increases the probability that rating agencies record a downgrade when the rated firm has a default risk increase. I reperform these analyses including controls for conflicts of interest and private information interacted with *csup*, the indicator equal to one if the issuer's failure score increases. Table 11 shows the results after controlling for conflicts of interest. Due to the large number of control specifications, I only present the coefficients on the interaction between accounting quality and *csup*. Panels A and B show that the effect of accounting quality persists after controlling for all conflict of interest measures. Panel C shows that the effect continues to be consistent for both S&P and EJR. Table 12 shows similar results after controlling for the private information quality measures. The coefficients on TLR and ATLR continue to be positive and significant for both firms, and the coefficient on discretionary accruals is negative and significant. Panel C shows that the effects are consistent for both agencies. Overall, the results of these robustness tests show that the observed effect of accounting quality on credit rating accuracy and timeliness is not driven by conflicts of interest or the quality of private information.

3. How is credit rating quality impacted by the discipline effect and private information overlap of accounting information?

3.1 Hypothesis development

3.1.1 Conflicts of interest and the discipline effect of accounting quality

Information is the critical tool necessary for investors to monitor a firm. Information asymmetry between the management of debt issuers and investors, combined with their imperfectly aligned incentives, is what creates a market for credit rating agencies, which serve as intermediaries to reduce the information gap between those parties. However, there is also information asymmetry between rating agencies and investors, who do not have perfect insight into the credit rating process. If the rating agencies' only objective is to provide very accurate ratings, then the information asymmetry does not harm investors. Unfortunately, analytical and empirical studies suggest rating agencies that are paid by debt issuers may issue inflated ratings and delay rating downgrades in order to satisfy their clients (Becker and Milbourn, 2011; Manso, 2013; Bruno et al., 2013). Rating agencies are able to issue slow or inflated ratings because it is difficult for investors or regulators to observe this behavior. In order to identify poor ratings, investors need other information signals against which to compare the rating. One clear example of this would be an issuer default or bankruptcy. When an issuer defaults, it is easy to see that rating agencies did a poor job if they had the firm rated as investment grade until one week before the default.

The publicly issued financial statements of the issuer are another information source. If earnings provide an accurate signal of a deterioration in the issuer's creditworthiness, rating agencies may feel compelled to issue a rating downgrade to avoid the appearance that they are ignoring negative information. If earnings accurately and promptly impounds negative news, this will put additional pressure on rating agencies to incorporate the news in their ratings. The result is that higher quality earnings will improve the quality of credit ratings. This is consistent with prior studies that have examined the discipline effect of information in various contexts. For example, Biddle et al. (2009) find that higher financial reporting quality constrains managers' propensity to over- or underinvest, thereby improving firms' efficiency. In another particularly relevant study, Fong et al. (2014) find that equity analyst coverage provides a public information signal that constrains the rating agencies' ability to inflate credit ratings.

Note that the discipline effect is distinct from the news effect discussed in section 2 of the paper. The news effect implies that rating agencies are receiving new information from public financial statements. The discipline effect occurs because the rating agency is privately informed about bad news prior to its public disclosure, but it chooses to ignore that information until it becomes public and becomes a threat to their reputation. The discipline effect also has separate empirical implications, leading to the following hypothesis:

> H2a: If there is a discipline effect of accounting in addition to the news effect, the positive association between timely loss recognition (TLR and ATLR) and credit rating accuracy and timeliness will be more pronounced when the credit rating agency has greater conflicts of interest. The negative relationship between discretionary accruals and credit rating quality will also be stronger when there are greater conflicts of interest.

Because I also use accounting restatements as a public information signal and an inverse measure of past accounting quality, I also predict the following:

> H2b: Firms announcing an adverse accounting restatement will be more likely to receive a credit rating downgrade when the credit rating agency has greater conflicts of interest.

The idea behind this is that a credit rating agency that has private information will likely be able to anticipate the restatement, or will at least have other information that makes it less susceptible to the misstated accounting numbers. If the rating agency incorporates its negative private information into its rating prior to the restatement, it should not need to update its rating based on the information in the restatement itself. However, if the agency chooses to ignore the negative private information until it becomes public, it will be more likely to record a downgrade when the restatement is announced.

3.1.2 Private information overlap

S&P and other issuer-paid rating agencies have direct access to management and expend significant resources developing their ratings. As a result, private information should play a significant role in the development of ratings. If the agency has accurate and precise private information, it should then produce more informative ratings. In this sense, there is a news effect of private information similar to the effect of public accounting information analyzed in section 2. Prior studies have shown that private, soft information improves the quality of agency-issued credit ratings (Kraft, 2012), as well as banks' internal credit ratings (Lehmann, 2003).

If a rating agency has private information, it may utilize less accounting information. Butler and Cornaggia (2012) find that rating agencies that gather more "soft" information rely less on accounting information in developing their ratings. In contrast, if a rating agency has no private information, like EJR, it has no choice but to rely entirely on accounting and other sources of public information. If financial reports are biased or slow to incorporate new information, a rating agency with no access to private information will likely issue biased or slow ratings due to a lack of alternative sources. The agency with private information will be able to consider both sources, and should be less subject to the quality of accounting. In other words, when accounting quality is relatively poor, it will be subsumed by private information. When accounting quality is good, it will still have significant overlap with the privately obtained information.

However, if private information is biased or slow relative to accounting information, then the rating agencies with private information will place more weight on the more reliable accounting data. Again, in this situation, there will be less overlap, or redundancy, between accounting information and private information. Despite its access to private information, the quality of the credit ratings it produces will be a function of accounting quality. Therefore, more information overlap between accounting and private information reduces the impact of accounting quality on rating quality. This is formalized in the following hypothesis:

> H2c: The positive association between timely loss recognition (TLR and ATLR) and credit rating accuracy and timeliness will be more pronounced when the credit rating agency has relatively less private information or more biased private information. The negative relationship between discretionary accruals and credit rating quality will also be stronger when the quality of private information is poor.

In the context of accounting restatements, a rating agency with more accurate private information should be aware of the negative information in an adverse accounting restatement prior to its public release. As a result:

> H2d: Firms announcing an adverse accounting restatement will be more likely to receive a credit rating downgrade when the rating agency has a lower level of private information or if that information is optimistically biased.

3.1.3 Interaction of conflicts of interest and private information

If the discipline and information overlap effects exist individually, then the interaction between the two should also modify the effect of accounting quality on credit rating quality. Recall that the disciplining effect of accounting quality means it will improve rating quality more significantly when the rating agency has relatively high levels of conflicts of interest. In the context of my models, the interaction between conflicts of interest and accounting quality is expected to be positive. However, the existence of the discipline effect also depends on the amount and quality of private information. If the rating agency has very precise negative private information, it will be less likely to fully ignore it, even in the presence of conflicts of interest. On the other hand, if a rating agency is receiving biased or noisy private information, it may not fully recognize the extent of bad news and, therefore, will find it easier to cater to the issuer's wishes. It will then only downgrade its ratings based on negative public information, which it does to protect its reputation, as described earlier. As a result, the impact of conflicts of interest will be stronger when the quality of private information is poor.

Considering now the reverse causal relationship, conflicts of interest can also alter the overlap effect of private information. The overlap effect implies that accounting quality will have a more significant impact on rating quality when there is less overlap with private information, i.e. when private information is relatively limited or biased. This is because when the rating agency incorporates high quality private information, it will depend less on the quality of accounting. However, when the rating agency has significant conflicts of interest, it will choose not to incorporate all (negative) private information into its ratings. Instead, it will wait until that information becomes public through the financial statements, thereby making the quality of its ratings subject to the quality of public information. In other words, when conflicts of interest are severe, the overlap effect of private information is weakened and the effect of accounting quality is strengthened. The overall takeaway is that the accounting quality effect is strongest when conflicts of interest are high and private information quality is low.

To investigate these interactions, I focus on the announcement of accounting restatements as information signals and as indicators of bias in prior periods' financial statements. While my earlier tests have the benefit of testing the usefulness of recognized measures of accounting quality, restatements provide a potentially more powerful setting to identify the interaction between the discipline and private information overlap effects. When a firm restates its financial statements, it publicly acknowledges errors in previously issued statements that may cause those statements to be unreliable. It is one of the cleaner available measures of accounting bias. I also have the advantage of being able to identify the point in time at which the company publicly disclosed the restatement. If a rating agency responds to an unfavorable accounting restatement (one that reduces previously reported earnings and/or net assets) by downgrading the firm's rating, there are two possible reasons. First, the agency may have relied on prior financial statements because it had biased or poor private information, so the restatement came as a surprise. The other possibility is that the agency may have been aware of the optimistic bias in prior financials, but it chose not to correct for this bias because of conflicts of interest that led it to maintain an inflated rating and wait until the financial statements were publicly corrected to issue a downgrade. The interactive effect explained above leads to the following hypothesis:

> H2e: Firms announcing an adverse accounting restatement will be most likely to receive a credit rating downgrade when the rating agency has limited or biased private information *and* relatively severe conflicts of interest.

Recall that EJR, as an investor-paid rating agency, does not have access to private information and should not be subject to the same conflicts of interest faced by S&P.

> H2f: The relationship between accounting quality and EJR rating accuracy and timeliness should not be affected by conflicts of interest and private information in the manner described in H2a – H2e. Those effects should only be observed for S&P.

Because the above hypotheses should not apply to EJR, I include them as a control group to strengthen the interpretation of my findings. In each specification, I compare the results for EJR and S&P. If the findings for S&P are consistent with the hypotheses, but I find the same results apply to EJR, it will cast doubt on the interpretation of the findings as capturing the effects of conflicts of interest or private information. However, if the results are significant for S&P and not EJR, this strengthens their interpretation as such.

3.2 Sample and descriptive statistics

The analysis to identify the discipline and private information overlap effects of accounting quality in this section of the paper utilizes the same core sample of firms rated by S&P and EJR that was used in section 2. However, I focus more on conflicts of interest and private information variables. The conflict of interest variables are obtained from Compustat, CRSP, and S&P Ratings Xpress. Private information variables came from Compustat, Execucomp, and the Thomson Insider database. Accounting restatement data was taken from Audit Analytics. For more detail on individual variables, refer to Appendix A. The descriptive statistics on these additional variables are found in Table 1, Panel A. The correlation matrices for the conflict of interest and private information measures are found in Panels C and D.

3.3 Empirical analysis and results

3.3.1 Direct effects of conflicts of interest and private information

Before testing hypotheses H2a-H2f, I first examine the direct effects of conflicts of interest and private information measures on the accuracy and timeliness of credit ratings. Although I don't formally test any hypotheses regarding the relationship between conflicts of interest, private information and credit rating quality without considering accounting quality, I include this analysis to validate the measures and examine whether they affect credit ratings as I expect.

In order to identify how conflicts of interest and private information quality impact the quality of credit ratings, I reperform two earlier tests, replacing the accounting quality measures with the conflicts and private information variables. In particular, to test the rating accuracy effect, I regress the modified Campbell failure score on the credit ratings, conflict or private information variable, and the interaction of the two. The key coefficient is the interaction term, which signifies how the correlation between the credit rating and default risk varies with conflicts or private information. See sections 2.3.4.2 and 2.3.4.3 for a description of the variables.

The second test I reperform is the rating timeliness test using three dependent variables: *ejrdown, spdown,* and *downdiff.* The first two are indicator variables equal to one if the issuer receives a rating downgrade from EJR and S&P, respectively. The variable *downdiff* is equal to one if the firm is downgraded by EJR and not by S&P, negative one if the firm is downgraded by S&P and not EJR, and zero otherwise. These variables are regressed on *csup*, an indicator equal to one if the firm's failure score increases during the quarter, the measures of conflicts and private information, and the interaction of the measures with *csup*. Again, the interaction term is the key figure, as it describes the incremental effect of conflicts of interest or private information quality on the probability of a downgrade when the firm's default risk increases. I include the lagged failure scores and lagged credit ratings as control variables.

The results of these tests for conflicts of interest are found in Tables 13 and 14. The interaction terms should be equal to zero for EJR, as they should not be subject to conflicts of interest. Panel A of both tables shows that several of the coefficients are significant, suggesting that the measures are likely capturing more than just conflicts of interest. This does not invalidate their use in the study, but calls attention to the importance of considering both the effect on the individual agencies' ratings and the differential effect between S&P and EJR. The coefficients should be negative for S&P, as conflicts of interest would be expected to reduce rating quality (Becker and Milbourn, 2011; Manso, 2013; Bruno et al., 2013). Of course, this would imply that the incremental impact of conflicts of interest on S&P ratings relative to EJR ratings should also be negative. Panel B of both tables shows the results for S&P, while Panel C shows the differential effect between S&P and EJR (*CI_spmejr* in Table 13, *CI_csup* in Table 14).[17] Overall, the results are mixed, but the measures that follow expectations most closely are

[17] Note that the coefficient on *CI_spmejr* in Table 13 represents the effect for S&P incremental to EJR, while *CI_csup* in Table 14 is the effect for EJR incremental to S&P, so the predicted sign should be positive for the former and negative for the latter.

the measures of long-term debt (*ltd*), proximity to the investment grade threshold (*bbb*), financial firms (*financial*), and the proportion of short-term debt (*propstd*).

The results for private information measures are presented in Tables 15 and 16. Again, the coefficients should be zero for EJR. However, the directional prediction for S&P varies across these measures. *Pin* and *alpha180* are measures that capture high quality private information, while the remaining variables capture optimistic bias in private information. The former measures should be positively associated with rating accuracy and timeliness, while the rest should be negatively associated. Panel A of both tables shows that EJR rating quality is associated with several of the private information measures, again indicating that the measures may be capturing multiple constructs. Panels B and C show that a few of the measures show little association with rating quality, and none behave perfectly in line with expectations. However, *score_oc4* and *alpha180* generally outperform the rest.

3.3.2 Rating accuracy tests

To examine whether there is a discipline effect of accounting quality on rating accuracy, I again run regressions with the failure score as the dependent variable. I estimate separate models for each rating agency, in addition to a third specification that includes the difference between the S&P rating and the EJR rating (*spmejr*) to capture the incremental effects for S&P ratings relative to EJR ratings. The independent variables for the EJR and S&P specifications are the credit rating value (*ejrating* / *sprating*), the accounting quality variable, the conflict of interest variable, and the full set of interactions between them. For the third specification, the independent variables include all of those in the EJR specification, plus *spmejr* fully interacted with the accounting quality and conflict of interest measures. The coefficients of interest are the three way interactions between accounting quality, conflicts of interest, and the ratings (*ejrating, sprating,* and *spmejr*, respectively). Each of the three specifications is run for each accounting quality – conflict of interest variable combination. With three accounting quality variables and six conflict variables, this means each of the three specifications is run 18 times.

Table 17 contains the results. For practicality, only the interaction of interest is presented. The results provide limited evidence to support the existence of a discipline effect. The coefficients for the EJR specification are mostly insignificant, as predicted, with the exception of the interactions with *presox*. For the S&P and spmejr models, the coefficients on interactions with TLR and ATLR should be positive and the interaction with DiscAcc should be negative. The coefficients in the S&P models are almost entirely insignificant, meaning the effect of accounting quality on S&P rating accuracy does not appear to vary with the level of conflicts of interest. The incremental impact on S&P compared to EJR, shown in the *spmejr* section, provide some results consistent with predictions for three of the six conflicts of interest variables. This provides some supporting evidence, though the results for these variables do not remain consistent in the timeliness tests discussed in section 3.3.3.

I run the identical test to look for the effect of private information overlap, except I replace the measures of conflicts of interest with private information measures. With three accounting quality measures and eight private information measures, there are 24 estimates for each of the three specifications. As a result, Table 18 shows only the coefficients on the interaction between accounting quality, the credit rating (or incremental rating), and private information. This table shows little evidence of the overlap effect. The interactions between the optimistic private information measures and TLR/ATLR should be positive for S&P and spmejr, while the interactions with DiscAcc should be negative. *Pin* and *alpha180*, which measure private information quality, have the opposite predictions. Table 18 contains relatively few statistically significant coefficients. The two exceptions are *score_oc5* and *purch180*, which show some evidence that optimistic private information makes accounting quality a more important factor in determining the accuracy of credit ratings. On the whole, however, the evidence to support the effect of private information is limited.

3.3.3 Rating timeliness tests

3.3.3.1 Downgrades in response to increases in default risk

To determine whether accounting quality has a discipline effect on rating timeliness, I again utilize the timeliness test with three dependent variables: *ejrdown, spdown,* and *downdiff*, as defined in previous sections and in Appendix A. The independent variables are *csup* (the indicator for a failure score increase), the accounting quality variables, and the conflict of interest variables. These variables are fully interacted, and I include the lagged failure scores and lagged credit ratings as control variables. The coefficients of interest are the three way interactions between accounting quality, conflicts of interest, and *csup*. Each of the three specifications is run for each accounting quality – conflict of interest variable combination. The coefficients on the interaction term are displayed in Table 19. It is immediately apparent that very few are statistically different from zero. In addition, half of those that are significant are in the wrong direction. Based on the preponderance of coefficients that don't meet expectations, there appears to be little evidence for a discipline effect of earnings quality.

To test the impact of private information quality on the accounting quality effect, I perform the same analysis, replacing the conflict of interest variables with private information measures. The coefficients on the interaction between *csup*, the accounting quality variables, and the private information measures are shown in Table 20. Similar to Table 19, the majority of interactions do not load. Interestingly, only *purch180* appears to interact with accounting quality to affect S&P rating timelines as expected. The positive and significant coefficients on the interaction with TLR and ATLR are consistent with the notion that timely loss recognition more significantly improves timeliness of downgrades for firms that have optimistic private information based on the balance of insider trades. The negative coefficient on the interaction with DiscAcc implies that the combination of earnings management and optimistic private information reduce the timeliness of downgrades more than either of these biases do individually. However, these findings are outweighed by the lack of evidence found for other measures, so this analysis does not strongly support hypothesis H2c.

3.3.3.2 Rating timeliness near default

After failing to find support for the discipline effect of accounting quality using the above specifications and measures of conflicts of interest, I use an alternative approach and focus on the subset of firms that experience a default. This is a powerful research setting where the potential reputational cost of failing to predict defaults should outweigh the incentives to cater to the issuers. This is particularly true because defaulting issuers often enter bankruptcy and are unlikely to be a significant source of revenue in the near future. As a result, S&P should utilize its information advantage and be less reliant on accounting quality relative to the more general setting analyzed in previous tests. In those tests, I observed a similar effect of accounting quality on the timeliness of both S&P's and EJR's ratings. Using EJR as a benchmark, if I find that S&P ratings are affected by accounting quality less than EJR ratings in this low conflict of interest setting, this would be evidence that accounting quality has a greater impact on S&P ratings when it is facing higher conflicts of interest (i.e. when rating the broad set of firms as compared to firms close to default).

I employ two measures of rating timeliness from Cheng and Neamtiu (2009) to assess how each agency performs within one year of default. For these tests, my sample is limited to those firms that ultimately experience a default. The first measure is *dahead*, which is the number of days prior to default that the agency downgrades the firm's rating, so a larger value indicates a more timely downgrade. The sample is composed of one observation for each rating downgrade by an individual agency that takes place within 360 days prior to default. So, if a firm that defaults has EJR downgrades at 200 days and 100 days prior to default and S&P downgrades at 175 days and 90 days, there will be 4 observations related to that default. In this way, each agency is given credit for its early downgrades, but penalized for the later ones.

The second measure is *wrate*, which is the weighted average rating during the year leading up to default. This measure complements the first one, similar to performing levels versus changes analyses. Assuming that new information regarding the decline in default risk is yet to be incorporated in ratings one year prior to default, *dahead* captures how quickly the rating agencies recognize the increasing default risk and issue downgrades. *Wrate* measures the overall level of the rating, so it is affected by not only the timeliness of rating changes, but also the rating as of the beginning of the year and the magnitude of the rating changes during the year. Using OLS, I regress *dahead* and *wrate* on the accounting quality variables and *EJRdum,* an indicator equal to one if the dependent variable relates to EJR ratings and zero for S&P. I also include the interaction of the two, which measures the incremental impact of accounting quality on the timeliness of EJR ratings relative to S&P. $Controls$ for the *wrate* specification include log_size_adj, $cfotl$, and $tlta$, all defined in Appendix A and measured as of one year prior to the default. The *dahead* specification includes the same controls plus $begyrrate$, the credit rating level as of one year prior to default.

The results for *dahead* are shown in Table 21. For TLR and ATLR, the coefficient on AQ is positive and significant at a 10% level, which indicates that S&P rating downgrades are more timely for firms with more timely loss recognition. The coefficient on the interaction term is also positive and significant, indicating that the impact of TLR and ATLR on rating timeliness is greater for EJR than for S&P. This is consistent with hypothesis H2c and the existence of a discipline effect of accounting. However, the results for DiscAcc are not significant. This may be due to the misspecification of the modified Jones model for firms in significant financial distress.

Table 22 presents the results for the weighted average ratings, *wrate,* in the year leading to default. The coefficients on AQ for TLR and ATLR are positive but not significant. This indicates that earnings timeliness does not significantly impact the timeliness of S&P ratings in the year prior to default. The interaction term, *EJRdum_AQ*, is positive and significant, suggesting that EJR ratings timeliness continues to benefit from more timely loss recognition. This is further evidence in support of the discipline effect of accounting quality. However, consistent with the *dahead* analysis, the effect of discretionary accruals continues to be insignificant.

3.3.3.3 Accounting restatement analysis

As discussed in section 3.1.3, accounting restatements provide a powerful setting to examine the effects of accounting information, conflicts of interest, and private information, as well as the interaction of the three. Accounting restatements are signals of prior accounting bias, as well as a public disclosure event that is easily observed by the public. Restatements are often announced separately in an 8-K filing, though they may also be included with other information in a 10-K or 10-Q. There are approximately 454 adverse accounting restatements in the sample and 100 favorable restatements, representing approximately 1.5% and 0.35% of the main sample, respectively. Similar to earlier tests, I use *ejrdown*, *spdown*, and *downdiff* as dependent variables. In my first test, I regress them on *res_adv*, an indicator variable equal to one if the rated firm announces an adverse accounting restatement during the quarter. As control variables, I initially include *res_fav*¸ which is an indicator equal to one if the firm announces a favorable restatement, and the lagged credit rating. The results of this specification are shown in the first three columns of Table 23. The coefficients on *res_adv* is positive and significant for both EJR and S&P, indicating that both are more likely to record downgrades when the firm announces a restatement. This coefficient is also significant when *downdiff* is the dependent variable, implying that EJR is more likely than S&P to record a downgrade when a restatement is announced. This is consistent with the hypothesis that EJR ratings are more reliant on public information, and thus a restatement is more likely to be news to them. In the last three columns, I include controls for the lagged failure score and the change in the failure score during the quarter. This has the potential to bias the coefficient on *res_adv* toward zero because the change in failure score will incorporate at least some portion of the negative impact of the restatement. However, it is critical to include this control to show that the effect of the restatement is not just reflecting the change in default risk, but that it incrementally increases the probability of a downgrade, implying that the upward bias in the prior financial statements was not fully accounted for by the rating agencies. For EJR, this would be due to the news effect of the restatement. For S&P, it could be due to any combination of the news effect, discipline effect, and the overlap of accounting information with private information. The coefficients on *res_adv* in the last three columns are weaker, but remain positive and significant.

In Table 24, I revise the baseline model from Table 23 to include conflicts of interest measures interacted with the restatement indicator. If there is a discipline effect of the restatement announcement, then the probability of an S&P rating downgrade concurrent with the announcement will be greater when S&P has greater conflicts of interest. As before, I also present results for EJR and compare them to S&P. Panel A shows the results for EJR. Consistent with hypothesis H2f, the interaction between conflicts of interest and *res_adv* is not significant in most of the specifications. Panel B shows that the results for S&P are generally not significant and are comparable to those for EJR. The interaction in the second column is positive and significant, meaning firms with a greater proportion of short-term debt are more likely to be downgraded due to a restatement. This is consistent with the discipline effect, but the interaction with *financial* is negative and significant, which is contrary to expectations. Panel C similarly lacks evidence to support the discipline effect. The coefficients on the interaction term here represent the incremental impact of conflicts of interest on EJR compared to S&P. Because EJR should not be affected, these coefficients should be negative. Yet, most are insignificant and only one is significantly negative.

To explore the mitigating effect of private information overlap on the accounting restatement, I re-run the model from Table 24 replacing the conflict of interest measures with private information variables. The coefficients on *resadv_PI* in Panel A of Table 25 show that private information measures generally do not alter the effect of accounting restatements on the probability of an EJR downgrade, consistent with my hypotheses. The interactions in Panel B for S&P rating downgrades are also largely insignificant. Only the interaction with *score_oc4* is significant in the hypothesized direction. With a row of almost completely insignificant interaction terms, Panel C shows that there is no difference in the private information effects between S&P and EJR, contrary to expectations. Overall, the evidence in Table 25 does not support the idea that high quality private information reduces the importance of accounting information in determining ratings.

Although I find limited support for the discipline and private information overlap effects of accounting information, I test the conjecture in H2e that firms with more severe conflicts of interest and poor or biased private information will be most likely to experience a downgrade from S&P in response to an adverse accounting restatement. To test this hypothesis, I include both conflicts of interest and private information in the model used in Tables 24 and 25. I fully interact these variables with each other and with *res_adv*. The coefficient of interest is the interaction of all three variables, which should be negative when interacting conflicts of interest and *res_adv* with measures of private information quality (i.e. *pin* and *alpha180*) and positive when using measures of optimism/bias in private information (all other private information measures) in the S&P downgrade specification. For *downdiff*, the coefficients should have the opposite sign, and they should all be zero for EJR downgrades. I run the model separately for each conflict of interest – private information variable pair, resulting in 56 sets of results for each of the dependent variables. As a result, Table 26 presents only the coefficients on the key interaction. Consistent with expectations, Panel A shows that the effect is generally insignificant for EJR, with the exception of some inconsistently significant coefficients on interactions with *financial*. The coefficients in Panel B that are significant are generally the correct sign, but they are not sufficient to support hypothesis H2e. Panel C similarly provides little support for hypothesis H2e. Overall, the positive effect of a restatement on the probability of a downgrade for both firms appears to be consistent with the news effect of accounting information, as the effect does not vary consistently with measures of conflicts of interest or private information.

4. Conclusion

The extant literature studying the quality of credit ratings focuses on the incentives and pressures facing credit rating agencies (Cheng and Neamtiu, 2009;

Bonsall, 2013; Opp et al., 2013). This study takes a different perspective and examines whether credit rating quality is driven by the quality of the information rating agencies use to develop their ratings. I investigate whether credit ratings are better predictors of default for rated borrowers with high quality earnings, characterized by timely loss recognition and low earnings management. If rating agencies rely on accounting information because of its low cost or inadequate alternative information sources, then the quality of accounting will determine the timeliness and accuracy of the credit ratings. This is what I call the news effect of accounting quality on credit ratings.

I also consider whether accounting quality may improve rating quality by disciplining credit rating agencies that would otherwise issue inflated ratings to cater to their clients. Financial statements provide information that is easily observable to investors and is relevant for evaluating the credit risk of the issuer. Rating agencies may feel compelled to incorporate this information into their ratings to avoid the appearance that they are ignoring important information. In this way, accounting information may constrain the agencies' ability to inflate ratings and will, therefore, improve the quality of the ratings through the discipline effect.

I exploit the differences between two rating agencies: EJR, which relies entirely on public information in developing its ratings, and S&P, which has access to both public and private information. The use of both rating agencies is a significant advantage of this study, as EJR operates as a control group for a number of tests. It also enables me to test additional hypotheses that contribute to the literature on issuer-paid and investor-paid rating agencies.

I find that higher earnings quality improves the accuracy and timeliness of credit ratings. I also find that both rating agencies are more likely to issue a rating downgrade when a firm has an adverse accounting restatement, providing further evidence of rating agencies' reliance on the accuracy of accounting information. This evidence supports the news effect of accounting quality. However, when incorporating measures of conflicts of interest and private information, I find that the impact of accounting quality does not vary predictably with rating agencies' incentives and ability to inflate ratings. As such, the discipline effect of accounting information is not supported by my findings. However, this may be due to difficulty in obtaining reliable measures of rating agency conflicts. Future researchers may revisit the discipline effect of accounting using superior measures of conflicts of interest and private information quality.

Appendix: Variable Definitions

Variable Name	Description
alpha180	This is a measure of the profitability of insider trades made over the 180 days prior to the start of the quarter. Following Jagolinzer et al. (2011), I net all insider transactions on a given day and treat them as a single transaction. I then measure profitability as the alpha from the Fama and French (1993) and Carhart (1997) model estimated over the 180 days following each transaction. I calculate the average alpha of all transactions over the 180 day period, with each transaction's alpha weighted by the number of shares traded divided by the total volume of insider trades over the period. The measure is an indicator equal to one if the alpha is greater than the sample median.
atq	Total assets (in millions)
ATLR	Asymmetric timely loss recognition, equal to β3 from the specification described in the definition of TLR
bbb	Indicator variable equal to one if the firm's S&P credit rating is equal to BBB-, BBB, or BBB+
begyrrate	The credit rating level one year prior to default
campscore	Measure of default risk adopted from Campbell et al. (2008). The estimation of this measure is described in section 2.3.1.
cashmta	Cash and short-term investments divided by the market value of assets.
cfotl	Quarterly operating cash flows divided by total liabilities
cfotlavg	The weighted average of quarterly operating cash flows divided by total liabilities over the prior 12 months. The weights are such that each quarter's ratio has twice the weight of the previous quarter.
clca	Current liabilities divided by current assets
csup	Indicator equal to one if the default risk (modified Campbell failure score) of the firm increases during the quarter.
dahead	Number of days prior to default that the agency downgrades the firm's rating, limited to rating downgrades within 360 days of default
defaultX	Indicator variables equal to 1 in quarter t if the firm will default in quarter $t + X$.
DiscAcc	Discretionary accruals equal to the residuals from the modified Jones model (Dechow, Sloan, and Sweeney 1995) estimated at the two-digit SIC and year level.

downdiff	Equal to *ejrdown – spdown.*
ejrating	Egan-Jones Ratings Company long-term issuer credit rating, converted to a numerical scale from 1 to 23. See Table 1, Panel B for the mapping from letter to numerical rating.
ejrdown	Indicator variable equal to 1 if EJR downgrades the firm in the current quarter.
ejrmsp	The difference between the EJR rating and S&P rating, *ejrating - sprating*
ejrup	Indicator variable equal to 1 if EJR upgrades the firm in the current quarter.
ewr6	Indicator equal to one for observations occurring following six months of equally-weighted NYSE/AMEX/NASDAQ index returns that are greater than the sample median.
exretavg_sp	The weighted average of excess returns over the prior twelve months. Excess returns are calculated as the monthly raw returns minus the return on the S&P 500. The weight on each monthly excess return monotonically declines with each monthly lag within the 12 month average such that the weight is halved every three months.
financial	Indicator equal to one for financial firms (three digit SIC code between 600 – 641)
indlevmed	Indicator is equal to one for firms in an industry where the median leverage is greater than the sample median.
log_rsize	The natural log of the ratio of the market value of equity to the total market value of the S&P 500
log_size_adj	The natural log of total assets divided by the consumer price index level
ltd	Indicator equal to one if the firm's total long-term debt is greater than the sample median.
ltd_total	Total long-term debt, including the current portion (in millions)
nimtaavg	The weighted average of net income divided by the market value of assets over the prior 12 months. The weights are such that each quarter's ratio has twice the weight of the previous quarter. The market value of assets is calculated as the market value of equity plus the book value of liabilities.

nita	Net income divided by the book value of total assets
option_oc	To calculate this variable, I first obtain the value of in-the-money unexercised exercisable options held by the CEO and scale this amount by the CEO's total holdings. I multiply this ratio by 100 to get a percentage. If this amount is greater than the industry-quarter median, then this variable is equal to one. Otherwise, it is equal to zero.
pin	Indicator equal to one if the Probability of Informed Trade (PIN) is greater than the sample median. PIN is a measure of information asymmetry between informed and uninformed investors in equity markets developed by Easley et al. (2002) and modified by Venter and de Jongh (2006).
presox	Indicator variable equal to one for observations occurring prior to 2002, when the Sarbanes-Oxley Act was passed.
price	The stock price of the firm is winsorized at $15 for all values above $15. This variable is then calculated as the natural log of the winsorized price.
propstd	Indicator equal to one if the firm's ratio of short-term debt to total debt is greater than the sample median.
purch180	Indicator variable equal to 1 if the net insider purchases (volume of purchases – volume of sales) divided by shares outstanding over the 180 days prior to the start of the quarter were greater than zero.
ratediff	The difference in the ratings of EJR and S&P at the beginning of the period, calculated as the beginning *ejrating* - *sprating*.
ratelevel	The level of the credit rating for EJR or S&P at the beginning of the period.
res_adv	Indicator equal to one if the firm announces an adverse accounting restatement during the quarter.
res_fav	Indicator equal to one if the firm announces a favorable accounting restatement during the quarter.
reverse	Indicator variable equal to 1 if the current rating change for a given agency is followed by a change in the opposite direction (e.g. a downgrade followed by an upgrade) within 365 days.
score_oc4	This is an indicator variable adopted from Schrand and Zechman (2012) that captures executive overconfidence. If the sum of the following four measures is greater than or equal to three, then this variable is equal to one:

	- Excess investment: the residual from a quarterly cross-sectional regression of total asset growth on sales growth, adjusted for the industry (two-digit SIC) median for that quarter. This is set equal to one if it is greater than zero and zero otherwise. - Excess acquisitions: net acquisitions from the statement of cash flows, adjusted for the industry-quarter median. This is set equal to one if it is greater than zero and zero otherwise. - Excess leverage: the ratio of current and long-term debt to the sum of current debt, long-term debt, and the book value of shareholders' equity, adjusted for the industry-quarter median. This is set equal to one if it is greater than zero and zero otherwise. - Risky debt: an indicator variable equal to one if the firm has convertible debt or preferred stock greater than zero.
score_oc5	This measure of executive overconfidence is an indicator variable equal to one if the sum of five measures is greater than or equal to three. The first four measures are those described under *score_oc4*, above. The fifth measure is dividend yield, equal to zero if the firm paid dividends on common stock over the prior twelve months and equal to one if it did not.
sigma	The standard deviation of daily stock returns over the prior three months
spdown	Indicator variable equal to 1 if S&P downgrades the firm in the current quarter.
spmejr	The difference between the S&P rating and EJR rating, *sprating - ejrating*
sprating	Standard & Poor's long-term issuer credit rating, converted to a numerical scale from 1 to 23. See Table 1, Panel B for the mapping from letter to numerical rating.
spup	Indicator variable equal to 1 if S&P upgrades the firm in the current quarter.
tang	Asset tangibility, calculated as net property, plant, and equipment divided by total assets
tenure	Indicator equal to one if the CEO tenure is greater than the sample median.
tlmta	Total liabilities divided by the market value of assets

TLR	I estimate a modified version of the piece-wise linear regression of earnings on stock returns from Basu (1997), adding control variables suggested by Ball, Kothari, and Nikolaev (2013): $NI_{i,t} = \alpha + \beta_1 Neg_{i,t} + \beta_2 R_{i,t} + \beta_3 Neg_{i,t} * R_{i,t} + \boldsymbol{\gamma} Controls_{i,t-1} + \varepsilon_{i,t}$ $NI_{i,t}$ is net income for the quarter scaled by the market value of equity as of the end of the prior quarter. $Neg_{i,t}$ is an indicator equal to one if the market-adjusted stock return in the period is negative. $R_{i,t}$ is the nominal return for the quarter minus the index return. $Controls_{i,t-1}$ include lagged values of the market value of equity, market-to-book ratio, leverage and stock price volatility. I estimate this model cross-sectionally for each three digit SIC code. *TLR* is the sum of the estimated β_1 and β_3. See Wittenberg-Moerman (2008) for more details on estimation.
tlta	Total liabilities divided by total assets
updiff	Equal to *ejrup* - *spup*, so it is 1 if EJR upgrades and S&P doesn't, 0 if neither upgrades, and -1 if S&P upgrades and EJR doesn't.
varpay	The variable portion of CEO compensation is measured as (total compensation – fixed salary)/total compensation from Execucomp. The variable is an indicator equal to one if this ratio is greater than the sample median.
wrate	The weighted average rating over the year leading up to default for a given agency (EJR or S&P)

Table 1
Descriptive Statistics

Panel A presents descriptive statistics for the main sample of firm-quarters that have the data necessary to calculate the modified Campbell failure score and ratings from both S&P and EJR. Panel B shows the distribution of S&P and EJR ratings for the main sample. Panels C and D provide correlation matrices for the measures of conflicts of interest and private information, respectively. Panel E describes the sample of firm defaults, with most variables measured as of one year prior to the default date. All variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Some variables that are converted to indicators for use in the empirical analysis are included here in their original form.

Panel A: Firm quarter characteristics – main sample

Variable	N	Mean	Std Dev	25%	Median	75%
alpha180	22,349	0.0125	0.1677	-0.0753	0.0042	0.0890
ATLR	29,649	0.1260	0.0800	0.0946	0.1299	0.1607
atq	29,647	11778.37	18209.23	2149.10	5052.30	13029.60
bbb	29,589	0.3629	0.4809	0	0	1
campscore	29,649	-10.3155	2.5041	-12.1489	-10.5803	-8.8306
cashmta	29,649	0.0513	0.0579	0.0110	0.0296	0.0691
cfotlavg	29,649	0.0431	0.0380	0.0192	0.0364	0.0601
clca	29,649	0.7631	0.3503	0.5018	0.6932	0.9601
csup	29,405	0.4590	0.4983	0	0	1
default4	29,649	0.0025	0.0496	0	0	0
downdiff	28,719	0.0537	0.3298	0	0	0
DiscAcc	28,471	0.0291	0.1002	-0.0213	0.0171	0.0659
ejrating	29,649	9.9719	3.5136	7	9	12
ejrdown	28,757	0.1022	0.3030	0	0	0
ejrmsp	29,649	0.0171	1.6953	-1	0	1
ejrup	28,757	0.1006	0.3008	0	0	0
ewr6	29,649	0.1785	0.4342	-0.1039	0.1517	0.3039
exretavg_sp	29,649	0.0068	0.0344	-0.0127	0.0067	0.0267
financial	29,649	0.0186	0.1352	0	0	0
indlevmed	27,151	0.4332	0.1192	0.3444	0.4218	0.5387
log_rsize	29,649	-8.0307	1.4294	-8.9221	-7.9678	-6.8976
ltd	29,356	3287.58	4715.65	611.56	1406.00	3853.05
nimtaavg	29,649	0.0046	0.0110	0.0023	0.0073	0.0107
option_oc	24,486	9.3803	23.80	-6.53	2.00	23.93
pin	25,506	0.1104	0.0586	0.0731	0.1007	0.1373
presox	29,649	0.1612	0.3677	0	0	0
price	29,649	2.5388	0.4645	2.7081	2.7081	2.7081
purch180	22,349	-0.1552	0.3977	-0.1437	-0.0318	-0.0026
propstd	29,320	0.1227	0.1609	0.0100	0.0623	0.1717

Panel A: Firm quarter characteristics – main sample (continued)

Variable	N	Mean	Std Dev	25%	Median	75%
res_adv	29,649	0.0153	0.1228	0	0	0
res_fav	29,649	0.0034	0.0580	0	0	0
score_oc4	29,649	0.3687	0.4825	0	0	1
score_oc5	29,649	0.5048	0.5000	0	1	1
sigma	29,649	0.3977	0.2188	0.2385	0.3375	0.4877
spdown	29,589	0.0490	0.2159	0	0	0
sprating	29,649	9.9548	3.2098	8	10	12
spup	29,589	0.0276	0.1640	0	0	0
tang	29,649	0.3628	0.2367	0.1559	0.3156	0.5545
tenure	24,625	6.1529	6.0927	2	4	8
tlmta	29,649	0.4709	0.2086	0.3100	0.4528	0.6198
TLR	29,649	0.1419	0.0688	0.0999	0.1395	0.1766
updiff	28,719	0.0733	0.3269	0	0	0
varpay	25,111	0.7798	0.1818	0.7347	0.8374	0.8935

Panel B: Distribution of credit ratings

		Egan-Jones Ratings			S&P Ratings		
Rating	Number	N	%	Cum %	N	%	Cum %
AAA	1	16	0.05	0.05	160	0.54	0.54
AA+	2	86	0.29	0.34	2	0.01	0.55
AA	3	271	0.91	1.26	368	1.24	1.79
AA-	4	563	1.90	3.16	420	1.42	3.20
A+	5	1,130	3.81	6.97	1,128	3.80	7.01
A	6	2,407	8.12	15.09	2,475	8.35	15.36
A-	7	3,080	10.39	25.47	2,337	7.88	23.24
BBB+	8	3,622	12.22	37.69	3,035	10.24	33.47
BBB	9	3,876	13.07	50.76	4,195	14.15	47.62
BBB-	10	3,031	10.22	60.99	3,541	11.94	59.57
BB+	11	2,489	8.39	69.38	2,180	7.35	66.92
BB	12	2,388	8.05	77.44	2,479	8.36	75.28
BB-	13	1,872	6.31	83.75	2,716	9.16	84.44
B+	14	1,635	5.51	89.26	2,036	6.87	91.31
B	15	1,212	4.09	93.35	1,431	4.83	96.13
B-	16	799	2.69	96.05	785	2.65	98.78
CCC+	17	117	0.39	96.44	223	0.75	99.53
CCC	18	473	1.60	98.04	93	0.31	99.85
CCC-	19	15	0.05	98.09	22	0.07	99.92
CC	20	338	1.14	99.23	23	0.08	100.00
C	21	229	0.77	100.00			
Total		29,649	100.00		29,649	100.00	

Panel C: Correlation of conflict of interest measures

	bbb	propstd	presox	financial	ewr6	indlevmed	ltd
bbb	1.000						
propstd	0.020***	1.000					
presox	-0.022***	0.073***	1.000				
financial	0.070***	0.007	-0.030***	1.000			
ewr6	0.003	-0.033***	-0.085***	0.001	1.000		
indlevmed	0.008	-0.039***	0.112***	-0.131***	0.010	1.000	
ltd	0.010*	0.067***	-0.064***	-0.025***	0.002	0.174***	1.000

Panel D: Correlation of private information measures

	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
pin	1.000							
tenure	-0.002	1.000						
varpay	-0.310***	-0.052***	1.000					
score_oc4	-0.031***	0.030***	0.042***	1.000				
score_oc5	0.069***	0.037***	0.000	0.757***	1.000			
option_oc	-0.117***	-0.031***	0.118***	0.038***	0.015**	1.000		
purch180	-0.088***	-0.079***	0.020***	0.007	-0.017**	-0.050***	1.000	
alpha180	0.042***	0.011	-0.029***	0.013*	0.040***	-0.006	0.081***	1.000

Panel E: Characteristics of defaulting firms

Variable	N	Mean	Std Dev	25%	Median	75%
ATLR	85	0.1475	0.0998	0.1060	0.1528	0.1866
cfotl	83	0.0055	0.0429	-0.0098	0.0055	0.0211
DiscAcc	79	-0.0023	0.1498	-0.0441	0.0017	0.0466
log_size_adj	85	8.4020	1.2780	7.4653	8.3983	9.4144
TLR	85	0.1531	0.0804	0.1215	0.1395	0.1896
tlta	85	0.8006	0.1578	0.7131	0.8282	0.9233
wrate-S&P	86	14.6136	2.8246	13.5889	15.2444	16.4972
wrate-EJR	86	16.6498	3.1430	15.2889	16.8292	19.1083
dahead	392	145.8903	104.8947	49.0000	126.0000	233.5000

Table 2
Incremental Predictive Value of Ratings

This table presents the results from logistic regressions of default indicators for defaults in quarter *t+1, t+2,…, t+12* on rating variables (results for some default horizons excluded for brevity). Panel A includes the EJR rating and the difference between the S&P rating and the EJR rating to demonstrate the incremental information in S&P ratings. Panel B runs the same regressions with the incremental EJR ratings. Both panels include tests on the full sample of firm quarters with ratings from both credit rating agencies, and the subsample of firm-quarters for which at least one of the agencies has the firm rated as BB+ or below. All variables are defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Incremental value of S&P ratings over EJR ratings

Rating Sample

VARIABLES	default1	default2	default3	default4	default6	default8	default10	default12
ejrating	0.850***	0.574***	0.542***	0.493***	0.478***	0.395***	0.387***	0.355***
	(8.48)	(10.20)	(10.46)	(9.41)	(11.10)	(9.23)	(7.58)	(6.07)
spmejr	0.463***	0.224**	0.186*	0.216*	0.285***	0.146**	0.179**	0.183*
	(3.65)	(2.55)	(1.82)	(1.93)	(3.21)	(1.97)	(2.21)	(1.68)
Constant	-18.217***	-13.733***	-13.185***	-12.315***	-12.034***	-11.073***	-11.019***	-10.738***
	(-11.05)	(-15.44)	(-18.04)	(-17.12)	(-19.01)	(-17.61)	(-15.47)	(-13.93)
Observations	29,651	29,651	29,651	29,651	29,651	29,651	29,651	29,651
Log Pseudo-likelihood	-279.2	-358.8	-386.7	-414.8	-409.6	-375.1	-348.4	-305.3
Pseudo R-Squared	0.363	0.245	0.235	0.189	0.159	0.132	0.117	0.0943

Panel A (continued)

Speculative Sample

VARIABLES	default1	default2	default3	default4	default6	default8	default10	default12
ejrating	0.883***	0.585***	0.556***	0.472***	0.435***	0.336***	0.306***	0.286***
	(8.96)	(10.40)	(9.54)	(7.99)	(8.40)	(5.55)	(4.13)	(3.27)
spmejr	0.489***	0.246***	0.203**	0.197*	0.242**	0.095	0.112	0.132
	(4.16)	(2.99)	(1.99)	(1.76)	(2.56)	(1.14)	(1.17)	(1.03)
Constant	-18.790***	-13.870***	-13.401***	-11.985***	-11.375***	-10.184***	-9.789***	-9.686***
	(-11.32)	(-15.24)	(-15.41)	(-14.16)	(-14.69)	(-11.23)	(-9.35)	(-8.06)
Observations	13,448	13,448	13,448	13,448	13,448	13,448	13,448	13,448
Log Pseudo-likelihood	-267.8	-339.3	-358.8	-386.3	-381.4	-338.9	-319.2	-268.5
Pseudo R-Squared	0.304	0.175	0.171	0.118	0.0847	0.0659	0.0478	0.0359

Panel B: Incremental value of EJR ratings over S&P ratings

Rating Sample

VARIABLES	default1	default2	default3	default4	default6	default8	default10	default12
sprating	0.850***	0.574***	0.542***	0.493***	0.478***	0.395***	0.387***	0.355***
	(8.48)	(10.20)	(10.46)	(9.41)	(11.10)	(9.23)	(7.58)	(6.07)
ejrmsp	0.387***	0.350***	0.356***	0.277***	0.193***	0.249***	0.208***	0.173***
	(5.93)	(6.36)	(5.50)	(3.60)	(3.05)	(5.62)	(4.61)	(2.85)
Constant	-18.217***	-13.733***	-13.185***	-12.315***	-12.034***	-11.073***	-11.019***	-10.738***
	(-11.05)	(-15.44)	(-18.04)	(-17.12)	(-19.01)	(-17.61)	(-15.47)	(-13.93)
Observations	29,651	29,651	29,651	29,651	29,651	29,651	29,651	29,651
Log Pseudo-likelihood	-279.2	-358.8	-386.7	-414.8	-409.6	-375.1	-348.4	-305.3
Pseudo R-Squared	0.363	0.245	0.235	0.189	0.159	0.132	0.117	0.0943

Panel B (continued)

Speculative Sample

VARIABLES	default1	default2	default3	default4	default6	default8	default10	default12
sprating	0.883***	0.585***	0.556***	0.472***	0.435***	0.336***	0.306***	0.286***
	(8.96)	(10.40)	(9.54)	(7.99)	(8.40)	(5.55)	(4.13)	(3.27)
ejrmsp	0.394***	0.339***	0.353***	0.275***	0.193***	0.242***	0.194***	0.154***
	(5.43)	(5.88)	(5.07)	(3.50)	(3.10)	(5.60)	(4.55)	(2.66)
Constant	-18.790***	-13.870***	-13.401***	-11.985***	-11.375***	-10.184***	-9.789***	-9.686***
	(-11.32)	(-15.24)	(-15.41)	(-14.16)	(-14.69)	(-11.23)	(-9.35)	(-8.06)
Observations	13,448	13,448	13,448	13,448	13,448	13,448	13,448	13,448
Log Pseudo-likelihood	-267.8	-339.3	-358.8	-386.3	-381.4	-338.9	-319.2	-268.5
Pseudo R-Squared	0.304	0.175	0.171	0.118	0.0847	0.0659	0.0478	0.0359

Table 3
Default Prediction Accuracy of Models

This table presents the accuracy ratios for four default predictors for defaults at quarter *t+1, t+2,…,t+12* (results for some default horizons excluded for brevity). The first predictor is the failure score from the modified Campbell model (Campbell et al. 2008), which is the predicted value from a logistic regression of defaults at each horizon on a set of market and accounting variables. The second predictor is the EJR credit rating. The third predictor is the S&P credit rating. The fourth predictor is the predicted value from a logistic regression of defaults at each horizon on both the S&P rating and the EJR rating. Panel A contains the results for the full sample of firm quarters with ratings from both credit rating agencies. Panel B contains the results for the subsample of firm-quarters for which at least one of the agencies has the firm rated as BB+ or below. Panel C contains the comparative differences in the accuracy ratios for each pair of predictors for the full sample. Panel D contains the differences for the speculative grade sample. Panels C and D show z-statistics in parentheses, calculated using jackknife standard errors for nonparametric statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Accuracy ratios for firms rated by both EJR and S&P

	Default prediction horizon (quarters)							
Model	**1**	**2**	**3**	**4**	**6**	**8**	**10**	**12**
Modified Campbell	96.89%	94.49%	91.37%	86.34%	78.19%	73.84%	71.58%	67.43%
EJR	90.50%	85.20%	83.29%	79.15%	77.20%	73.73%	71.12%	65.21%
S&P	84.85%	77.63%	78.06%	75.67%	74.71%	68.19%	65.81%	60.41%
Both ratings	89.64%	84.36%	83.51%	80.16%	77.63%	73.77%	70.85%	64.81%

Panel B: Accuracy ratios for speculative grade firms

	Default prediction horizon (quarters)							
Model	**1**	**2**	**3**	**4**	**6**	**8**	**10**	**12**
Modified Campbell	93.87%	89.97%	86.56%	79.42%	65.21%	58.63%	53.74%	50.48%
EJR	82.74%	73.05%	72.40%	64.25%	59.29%	54.79%	46.16%	38.84%
S&P	74.66%	61.48%	63.07%	57.83%	54.62%	44.77%	38.85%	33.82%
Both ratings	81.86%	72.43%	73.55%	66.53%	60.23%	55.28%	46.26%	40.80%

Panel C: Comparison of accuracy ratios across models for all rated firms

Model differences	**1**	**2**	**3**	**4**	**6**	**8**	**10**	**12**
Mod Campbell – EJR	6.39%***	9.28%***	8.07%***	7.19%**	0.99%	0.11%	0.46%	2.22%
	(3.18)	(4.16)	(3.25)	(2.43)	(0.30)	(0.03)	(0.11)	(0.39)
Mod Campbell - S&P	12.04%***	16.86%***	13.31%***	10.67%***	3.48%	5.65%	5.77%	7.01%
	(3.26)	(4.42)	(3.95)	(2.93)	(0.87)	(1.16)	(1.01)	(1.01)
Mod Campbell - Both ratings	7.25%***	10.12%***	7.86%***	6.18%**	0.56%	0.07%	0.72%	2.61%
	(2.63)	(3.76)	(2.95)	(2.04)	(0.16)	(0.02)	(0.15)	(0.42)
EJR - S&P	5.65%**	7.57%***	5.24%**	3.48%	2.49%	5.54%**	5.31%*	4.80%
	(2.37)	(3.11)	(2.43)	(1.43)	(1.12)	(1.98)	(1.92)	(1.47)
EJR - Both ratings	0.86%	0.84%	-0.21%	-1.01%	-0.43%	-0.04%	0.26%	0.40%
	(0.78)	(1.03)	(-0.3)	(-1.08)	(-0.36)	(-0.04)	(0.25)	(0.24)
S&P - Both ratings	-4.79%***	-6.73%***	-5.45%***	-4.49%***	-2.92%***	-5.58%***	-5.04%***	-4.40%**
	(-3.46)	(-4.00)	(-3.56)	(-2.83)	(-2.74)	(-2.83)	(-2.86)	(-2.48)

Panel D: Comparison of accuracy ratios across models for speculative-grade firms

Model differences	**1**	**2**	**3**	**4**	**6**	**8**	**10**	**12**
Mod Campbell – EJR	11.13%***	16.92%***	14.16%***	15.18%***	5.92%	3.85%	7.58%	11.63%
	(3.53)	(4.09)	(3.48)	(3.56)	(1.28)	(0.74)	(1.35)	(1.35)
Mod Campbell - S&P	19.22%***	28.49%***	23.49%***	21.60%***	10.60%*	13.86%*	14.89%*	16.65%*
	(3.5)	(4.75)	(4.48)	(3.98)	(1.68)	(1.87)	(1.88)	(1.66)
Mod Campbell - Both ratings	12.01%***	17.54%***	13.01%***	12.90%***	4.98%	3.36%	7.48%	9.68%
	(2.62)	(3.73)	(3.09)	(3.05)	(0.94)	(0.61)	(1.19)	(1.09)
EJR - S&P	8.09%**	11.57%***	9.33%**	6.42%	4.67%	10.01%*	7.31%	5.02%
	(2.07)	(2.85)	(2.25)	(1.29)	(1.06)	(1.75)	(1.46)	(0.73)
EJR - Both ratings	0.88%	0.62%	-1.14%	-2.28%	-0.94%	-0.49%	-0.10%	-1.95%
	(0.39)	(0.38)	(-0.88)	(-1.17)	(-0.38)	(-0.36)	(-0.06)	(-0.72)
S&P - Both ratings	-7.21%***	-10.95%***	-10.47%***	-8.70%***	-5.62%***	-10.50%**	-7.41%**	-6.97%
	(-3.26)	(-4.08)	(-3.36)	(-2.62)	(-2.62)	(-2.28)	(-2.15)	(-1.49)

Table 4
Accounting Quality and Rating Accuracy

This table presents the accuracy ratios for Egan-Jones ratings and S&P ratings for the prediction of default at quarter *t+1, t+2,…,t+12* (results for some default horizons excluded for brevity). The sample is partitioned at the median using three different accounting quality variables: TLR, ATLR, and DiscAcc, as defined in Appendix A, except that this analysis uses abs(DiscAcc) rather than the signed magnitude. Panel A shows the difference in the accuracy ratios for EJR ratings across the subsamples for each of the three accounting quality variables. Panel B shows comparable results for S&P ratings. Panel C displays the differences between the EJR and S&P accuracy ratios for each accounting quality subsample and default prediction horizon.

Panel A: Egan-Jones Ratings

		Accuracy Ratio by Default Horizon							
	N	**1**	**2**	**3**	**4**	**6**	**8**	**10**	**12**
High TLR	18,422	0.882	0.824	0.798	0.774	0.734	0.714	0.674	0.584
Low TLR	19,100	0.888	0.842	0.790	0.738	0.700	0.674	0.606	0.590
Difference		-0.006	-0.018	0.008	0.036	0.034	0.04	0.068	-0.006
High ATLR	18,148	0.858	0.786	0.776	0.732	0.686	0.65	0.614	0.586
Low ATLR	19,374	0.922	0.894	0.808	0.776	0.748	0.758	0.67	0.588
Difference		-0.064	-0.108	-0.032	-0.044	-0.062	-0.108	-0.056	-0.002
Low Disc Acc	16,672	0.94	0.876	0.826	0.79	0.728	0.658	0.576	0.598
High Disc Acc	16,677	0.842	0.784	0.74	0.684	0.674	0.72	0.648	0.548
Difference		0.098	0.092	0.086	0.106	0.054	-0.062	-0.072	0.05

Panel B: Standard and Poor's

	Accuracy Ratio by Default Horizon								
	N	**1**	**2**	**3**	**4**	**6**	**8**	**10**	**12**
High TLR	18,422	0.830	0.742	0.734	0.718	0.688	0.626	0.576	0.456
Low TLR	19,100	0.788	0.750	0.748	0.716	0.704	0.644	0.572	0.586
Difference		0.042	-0.008	-0.014	0.002	-0.016	-0.018	0.004	-0.13
High ATLR	18,148	0.802	0.734	0.746	0.718	0.7	0.614	0.542	0.498
Low ATLR	19,374	0.812	0.752	0.712	0.694	0.66	0.654	0.612	0.538
Difference		-0.01	-0.018	0.034	0.024	0.04	-0.04	-0.07	-0.04
Low Disc Acc	16,672	0.74	0.756	0.764	0.754	0.716	0.63	0.536	0.528
High Disc Acc	16,677	0.816	0.702	0.68	0.63	0.652	0.626	0.598	0.498
Difference		-0.076	0.054	0.084	0.124	0.064	0.004	-0.062	0.03

Panel C: Difference between EJR and S&P

	Difference in Accuracy Ratio by Default Horizon								
	N	**1**	**2**	**3**	**4**	**6**	**8**	**10**	**12**
High TLR	18,422	0.052	0.082	0.064	0.056	0.046	0.088	0.098	0.128
Low TLR	19,100	0.100	0.092	0.042	0.022	-0.004	0.030	0.034	0.004
Difference		-0.048	-0.01	0.022	0.034	0.05	0.058	0.064	0.124
High ATLR	18,148	0.056	0.052	0.03	0.014	-0.014	0.036	0.072	0.088
Low ATLR	19,374	0.11	0.142	0.096	0.082	0.088	0.104	0.058	0.05
Difference		-0.054	-0.09	-0.066	-0.068	-0.102	-0.068	0.014	0.038
Low Disc Acc	16,672	0.2	0.12	0.062	0.036	0.012	0.028	0.04	0.07
High Disc Acc	16,677	0.026	0.082	0.06	0.054	0.022	0.094	0.05	0.05
Difference		0.174	0.038	0.002	-0.018	-0.01	-0.066	-0.01	0.02

Table 5
Modified Campbell Score Variable Weights

This table presents the weights for the modified Campbell failure score estimated from 1990-2012. The weights are coefficients from the logistic regression of an indicator variable equal to 1 for default in quarter *t+1* on a set of market and accounting variables (Campbell et al. 2008). The weights vary by year, as the failure score is estimated annually using expanding windows starting in 1990 to allow out-of-sample prediction. t-statistics are shown in parentheses, calculated using standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Weight
log_rsize	0.072
	(0.89)
tlmta	9.337***
	(10.30)
clca	0.328**
	(2.18)
nimtaavg	-18.686***
	(-3.95)
cfotlavg	-11.349***
	(-5.98)
exretavg_sp	-7.814***
	(-5.09)
sigma	2.873***
	(6.36)
cashmta	-4.152***
	(-3.90)
tang	0.560**
	(2.17)
price	-0.367***
	(-5.49)
Constant	-14.503***
	(-12.72)
Observations	128,742

Table 6
Accounting Quality and Default Risk Prediction

This table presents the results from linear regressions of the modified Campbell failure score on S&P and EJR credit ratings interacted with three accounting quality variables: TLR, ATLR, and DiscAcc. Panel A includes the results for EJR ratings; Panel B for S&P ratings; and Panel C for the incremental effect of S&P ratings over EJR ratings. All variables are defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR ratings

		AQ =		
VARIABLES	Overall	TLR	ATLR	DiscAcc
ejrating	0.4363***	0.4187***	0.4157***	0.4636***
	(26.39)	(15.26)	(17.14)	(31.16)
spmejr	-0.1575***			
	(-4.67)			
AQ		-3.3353**	-4.6885***	1.0280
		(-2.25)	(-3.35)	(1.37)
AQ_EJR		0.2540*	0.3125**	-0.0717
		(1.92)	(2.51)	(-1.13)
Constant	-14.6674***	-13.6283***	-13.5099***	-14.2201***
	(-94.09)	(-44.42)	(-49.64)	(-82.55)
Observations	29,649	29,649	29,649	28,471
R-squared	0.430	0.465	0.468	0.471
Year FE	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P ratings

		AQ =		
VARIABLES	Overall	TLR	ATLR	DiscAcc
sprating	0.4363***	0.3459***	0.3541***	0.4285***
	(26.39)	(10.33)	(12.00)	(22.00)
ejrmsp	0.5938***			
	(19.72)			
AQ		-4.6254**	-5.5587***	1.3600
		(-2.38)	(-2.98)	(1.34)
AQ_SP		0.5041***	0.4966***	-0.1339
		(2.66)	(2.76)	(-1.48)
Constant	-14.6674***	-12.9681***	-12.9167***	-13.7669***
	(-94.09)	(-36.54)	(-41.05)	(-66.39)
Observations	29,649	29,649	29,649	28,471
R-squared	0.430	0.353	0.354	0.356
Year FE	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Incremental effect of S&P ratings over EJR ratings

	AQ =		
VARIABLES	TLR	ATLR	DiscAcc
ejrating	0.4009***	0.3987***	0.4422***
	(13.56)	(15.36)	(25.86)
spmejr	-0.1263*	-0.1110*	-0.1103***
	(-1.89)	(-1.82)	(-3.46)
AQ	-3.5054**	-4.7467***	0.5467
	(-2.15)	(-3.00)	(0.61)
AQ_EJR	0.2612*	0.3104**	-0.0292
	(1.70)	(2.11)	(-0.36)
AQ_spmejr	0.2212	0.1184	0.0825
	(0.64)	(0.35)	(0.50)
Constant	-13.4611***	-13.3567***	-14.0343***
	(-41.72)	(-46.66)	(-74.50)
Observations	29,649	29,649	28,471
R-squared	0.468	0.471	0.475
Year FE	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 7
Rating Change Reversals

This table presents the results from linear probability models with *reverse* as the dependent variable. *Reverse* is an indicator equal to one if the rating change is followed by a rating change in the opposite direction (e.g. a downgrade followed by an upgrade) within 365 days. The sample includes all rating downgrades for both EJR and S&P in columns labeled "Down," and all upgrades in columns labeled "Up." *EJRdum* is an indicator variable equal to one if the rating change is from EJR and zero if it is S&P. *AQ* represents the accounting quality variables – ATLR or DiscAcc. All other variables are as defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

			AQ = ATLR		AQ = DiscAcc	
VARIABLES	Down	Up	Down	Up	Down	Up
EJRdum	0.136***	0.111***	0.195***	0.140***	0.152***	0.146***
	(8.74)	(8.82)	(12.45)	(7.60)	(9.46)	(9.00)
AQ			0.148***	0.085	-0.028	0.006
			(3.41)	(1.08)	(-0.60)	(0.10)
EJRDUM_AQ			-0.285***	0.019	0.028	-0.071
			(-4.25)	(0.20)	(0.36)	(-0.80)
Ratelevel			0.004***	-0.004**	0.004***	-0.004**
			(3.18)	(-2.17)	(2.83)	(-2.53)
Constant	0.028***	0.045***	0.022	0.183***	0.034	0.195***
	(6.49)	(5.47)	(0.75)	(3.99)	(1.19)	(6.36)
Observations	6,886	4,926	6,368	4,600	5,710	4,182
R-squared	0.039	0.018	0.097	0.072	0.094	0.072
Year FE	No	No	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 8
Accounting Quality and Rating Responses to Default Risk Changes

This table presents the results from linear probability models for six dependent variables: *ejrdown*, *spdown*, *ejrup*, *spup*, *downdiff*, and *updiff*, all defined in Appendix A. One of the key independent variables is the change in the modified Campbell failure score during the quarter. The change is represented by the indicator variable *csup*, which equals one when the failure score increases during the quarter. *AQ* represents the accounting quality variable: TLR in Panel A, ATLR, in Panel B, and DiscAcc in Panel C, all of which are defined in Appendix A. All other variables are also defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effects of timely loss recognition (TLR)

VARIABLES	ejrdown	ejrup	spdown	spup	downdiff	updiff
AQ	0.090**	0.029	0.022	0.033	0.093**	-0.014
	(2.24)	(0.62)	(0.96)	(1.47)	(2.52)	(-0.29)
campscore_lag	0.029***	-0.024***	0.022***	-0.009***	0.007***	-0.009***
	(11.17)	(-12.10)	(12.77)	(-12.23)	(5.54)	(-6.37)
csup	0.049***	-0.045***	0.014**	-0.005	0.035***	-0.035***
	(4.25)	(-5.30)	(2.12)	(-1.09)	(3.42)	(-3.90)
AQ_csup	0.174**	0.027	0.114***	-0.041	0.066	0.057
	(2.46)	(0.61)	(2.80)	(-1.35)	(1.08)	(1.07)
ejrating_lag	-0.010***	0.020***				
	(-7.58)	(12.75)				
sprating_lag			-0.007***	0.009***		
			(-8.56)	(13.54)		
ejrmsp_lag					-0.024***	0.031***
					(-10.82)	(8.49)
Constant	0.446***	-0.359***	0.339***	-0.143***	0.074***	-0.042**
	(13.20)	(-10.17)	(15.13)	(-10.87)	(4.96)	(-2.24)
Observations	28,528	28,528	29,349	29,349	28,492	28,492
R-squared	0.061	0.065	0.051	0.027	0.029	0.044
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: Effects of asymmetric timely loss recognition (ATLR)

VARIABLES	ejrdown	ejrup	spdown	spup	downdiff	updiff
AQ	0.110***	0.028	0.034	0.034*	0.093***	0.000
	(3.00)	(0.63)	(1.59)	(1.91)	(2.76)	(0.00)
campscore_lag	0.029***	-0.024***	0.022***	-0.009***	0.007***	-0.009***
	(11.29)	(-12.14)	(12.81)	(-12.26)	(5.60)	(-6.41)
csup	0.056***	-0.041***	0.017***	-0.005	0.039***	-0.030***
	(5.40)	(-5.32)	(3.09)	(-1.51)	(4.03)	(-3.70)
AQ_csup	0.139**	-0.002	0.105***	-0.042	0.038	0.026
	(2.23)	(-0.04)	(2.78)	(-1.58)	(0.66)	(0.48)
ejrating_lag	-0.010***	0.020***				
	(-7.77)	(12.75)				
sprating_lag			-0.007***	0.009***		
			(-8.63)	(13.55)		
ejrmsp_lag					-0.024***	0.031***
					(-10.85)	(8.49)
Constant	0.451***	-0.358***	0.340***	-0.142***	0.076***	-0.044**
	(13.58)	(-10.47)	(15.38)	(-11.15)	(5.52)	(-2.49)
Observations	28,528	28,528	29,349	29,349	28,492	28,492
R-squared	0.061	0.065	0.051	0.027	0.029	0.044
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Effects of discretionary accruals

VARIABLES	ejrdown	ejrup	spdown	spup	downdiff	updiff
AQ	0.008	-0.008	0.027	-0.006	-0.017	-0.022
	(0.39)	(-0.29)	(1.47)	(-0.39)	(-0.80)	(-0.69)
campscore_lag	0.029***	-0.024***	0.022***	-0.009***	0.008***	-0.010***
	(11.22)	(-11.99)	(12.82)	(-12.33)	(5.72)	(-6.36)
csup	0.078***	-0.043***	0.034***	-0.012***	0.044***	-0.027***
	(9.38)	(-7.97)	(6.88)	(-6.23)	(8.10)	(-4.94)
AQ_csup	-0.090**	0.062*	-0.130***	0.044*	0.045	0.011
	(-2.21)	(1.77)	(-3.42)	(1.93)	(0.99)	(0.27)
ejrating_lag	-0.010***	0.021***				
	(-7.44)	(12.79)				
sprating_lag			-0.007***	0.009***		
			(-8.50)	(13.23)		
ejrmsp_lag					-0.025***	0.033***
					(-10.67)	(8.60)
Constant	0.465***	-0.361***	0.344***	-0.136***	0.091***	-0.046***
	(13.79)	(-10.68)	(15.37)	(-11.04)	(6.63)	(-3.03)
Observations	27,403	27,403	28,190	28,190	27,368	27,368
R-squared	0.061	0.066	0.052	0.027	0.029	0.045
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 9
Accounting Quality and Default Risk Prediction, Controlling for Conflicts of Interest

This table presents the results from linear regressions of the modified Campbell failure score on S&P and EJR credit ratings interacted with three accounting quality variables: TLR, ATLR, and DiscAcc. The model is the same as that presented in Table 6, with two control variables added: a conflict of interest (CI) indicator and the CI indicator interacted with the credit rating. The CI variables are defined in the text and in Appendix A. The purpose of this table is to examine whether the effect of accounting quality on the credit ratings persists after controlling for conflicts of interest. For brevity, only the coefficients on the interaction of accounting quality and credit ratings are shown. Panel A includes the results for EJR ratings; Panel B for S&P ratings; and Panel C for the incremental effect of S&P ratings over EJR ratings. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Egan-Jones Ratings

	Conflicts of Interest =					
VARIABLES	financial	propstd	presox	ewr6	indlevmed	ltd
EJR_TLR	0.2535*	0.2013	0.2509*	0.2483*	0.2708*	0.1623
	(1.91)	(1.54)	(1.87)	(1.86)	(1.87)	(1.32)
EJR_ATLR	0.3068**	0.2763**	0.3098**	0.3067**	0.3074**	0.2300**
	(2.46)	(2.27)	(2.46)	(2.45)	(2.39)	(2.00)
EJR_DiscAcc	-0.0723	-0.0238	-0.0444	-0.0653	-0.0474	-0.0275
	(-1.14)	(-0.39)	(-0.66)	(-1.04)	(-0.76)	(-0.44)
Year FE	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: Standard & Poor's

	Conflicts of interest =					
VARIABLES	financial	propstd	presox	ewr6	indlevmed	ltd
SP_TLR	0.5062***	0.4404**	0.5036***	0.5003***	0.5253***	0.4470**
	(2.68)	(2.43)	(2.66)	(2.64)	(2.65)	(2.54)
SP_ATLR	0.4849***	0.4476***	0.5126***	0.4920***	0.4467***	0.4223**
	(2.70)	(2.62)	(2.85)	(2.73)	(2.63)	(2.45)
SP_DiscAcc	-0.1312	-0.0703	-0.1233	-0.1282	-0.0769	-0.0832
	(-1.46)	(-0.82)	(-1.33)	(-1.45)	(-0.87)	(-0.94)
Year FE	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: S&P ratings minus EJR ratings

	Conflicts of interest =					
VARIABLES	financial	propstd	presox	ewr6	indlevmed	ltd
spmejr_TLR	0.2313	0.1318	0.2247	0.2238	0.4695	0.3116
	(0.68)	(0.40)	(0.64)	(0.65)	(1.47)	(1.00)
spmejr_ATLR	0.1052	0.0400	0.1552	0.1185	0.1904	0.1173
	(0.31)	(0.12)	(0.45)	(0.35)	(0.66)	(0.39)
spmejr_DiscAcc	0.0752	0.1190	0.0491	0.0798	0.1303	0.1160
	(0.45)	(0.74)	(0.28)	(0.48)	(0.79)	(0.72)
Year FE	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 10
Accounting Quality and Default Risk Prediction,
Controlling for Private Information Quality

This table presents the results from linear regressions of the modified Campbell failure score on S&P and EJR credit ratings interacted with three accounting quality variables: TLR, ATLR, and DiscAcc. The model is the same as that presented in Table 6, with two control variables added: a private information quality (PI) indicator and the PI indicator interacted with the credit rating. The PI variables are defined in the text and in Appendix A. The purpose of this table is to examine whether the effect of accounting quality on the credit ratings persists after controlling for private information quality. For brevity, only the coefficients on the interaction of accounting quality and credit ratings are shown. Panel A includes the results for EJR ratings; Panel B for S&P ratings; and Panel C for the incremental effect of S&P ratings over EJR ratings. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Egan-Jones Ratings

	Private Information Quality =							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
EJR_TLR	0.2594**	0.1592	0.1668	0.2446*	0.2618**	0.1469	0.1581	0.1494
	(1.99)	(1.10)	(1.15)	(1.85)	(1.98)	(1.04)	(1.12)	(1.05)
EJR_ATLR	0.3082**	0.2045	0.2051	0.3107**	0.3092**	0.1774	0.2483*	0.2351*
	(2.54)	(1.55)	(1.57)	(2.49)	(2.50)	(1.39)	(1.91)	(1.76)
EJR_DiscAcc	-0.0566	-0.0471	-0.0690	-0.0681	-0.0698	-0.0568	-0.0887	-0.0953
	(-0.90)	(-0.66)	(-0.97)	(-1.09)	(-1.11)	(-0.82)	(-1.38)	(-1.41)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: Standard and Poor's

	Private Information Quality =							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
SP_TLR	0.4819***	0.4492**	0.4416**	0.4846**	0.5308***	0.4091**	0.3188*	0.3127
	(2.68)	(2.09)	(2.09)	(2.56)	(2.83)	(1.99)	(1.69)	(1.63)
SP_ATLR	0.4779***	0.4629**	0.4416**	0.4896***	0.4993***	0.4146**	0.3873**	0.3646*
	(2.85)	(2.26)	(2.23)	(2.72)	(2.81)	(2.12)	(2.20)	(1.96)
SP_DiscAcc	-0.1076	-0.0518	-0.0961	-0.1248	-0.1372	-0.0472	-0.1680*	-0.1873**
	(-1.26)	(-0.51)	(-0.92)	(-1.40)	(-1.55)	(-0.46)	(-1.90)	(-1.99)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: S&P ratings minus EJR ratings

	Private Information Quality =							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
spmejr_TLR	0.0808	0.3116	0.3438	0.2118	0.2520	0.3321	-0.0069	0.0036
	(0.24)	(0.97)	(1.13)	(0.62)	(0.73)	(1.04)	(-0.02)	(0.01)
spmejr_ATLR	-0.0052	0.2430	0.2468	0.1118	0.1244	0.2855	0.0463	0.0478
	(-0.02)	(0.80)	(0.86)	(0.33)	(0.37)	(0.97)	(0.15)	(0.15)
spmejr_DiscAcc	0.0677	0.3268*	0.3079*	0.0908	0.0775	0.3801**	0.0972	0.0828
	(0.40)	(1.76)	(1.65)	(0.54)	(0.47)	(1.99)	(0.54)	(0.46)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 11
Accounting Quality and Rating Responses to Default Risk Changes, Controlling for Conflicts of Interest

This table presents the results from linear probability models for three dependent variables: *ejrdown*, *spdown*, and *downdiff*, all defined in Appendix A. One of the key independent variables is the change in the modified Campbell failure score during the quarter. The change is represented by the indicator variable *csup*, which equals one when the failure score increases during the quarter. The model is the same as that presented in Table 8, with two control variables added: a conflict of interest (CI) indicator and the CI indicator interacted with *csup*. For brevity, only the coefficients on the interaction of accounting quality and *csup* are shown, and results for upgrades are excluded. Panel A includes the results for EJR downgrades; Panel B for S&P downgrades; and Panel C for the difference, *downdiff*. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR Downgrades

	Conflicts of Interest =						
VARIABLES	bbb	financial	propstd	presox	ewr6	indlevmed	ltd
TLR_csup	0.163**	0.165**	0.166**	0.163**	0.161**	0.167**	0.172***
	(2.53)	(2.54)	(2.53)	(2.47)	(2.49)	(2.42)	(2.62)
ATLR_csup	0.135**	0.135**	0.134**	0.134**	0.133**	0.133**	0.141**
	(2.30)	(2.29)	(2.26)	(2.23)	(2.26)	(2.12)	(2.39)
DiscAcc_csup	-0.090**	-0.092**	-0.096**	-0.087**	-0.087**	-0.063	-0.096**
	(-2.36)	(-2.40)	(-2.47)	(-2.13)	(-2.29)	(-1.60)	(-2.50)
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Downgrades

	Conflicts of Interest =						
VARIABLES	bbb	financial	propstd	presox	ewr6	indlevmed	ltd
TLR_csup	0.096**	0.099**	0.105***	0.097**	0.098**	0.106**	0.099**
	(2.45)	(2.52)	(2.63)	(2.49)	(2.51)	(2.55)	(2.51)
ATLR_csup	0.093**	0.098***	0.097***	0.095**	0.097***	0.092**	0.093**
	(2.54)	(2.63)	(2.58)	(2.56)	(2.63)	(2.57)	(2.51)
DiscAcc_csup	-0.102***	-0.103***	-0.104***	-0.097***	-0.101***	-0.087***	-0.102***
	(-3.45)	(-3.47)	(-3.46)	(-3.23)	(-3.43)	(-3.08)	(-3.44)
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Difference between EJR and S&P downgrades (*downdiff*)

	Conflicts of Interest =						
VARIABLES	bbb	financial	propstd	presox	ewr6	indlevmed	ltd
TLR_csup	0.073	0.072	0.069	0.071	0.069	0.064	0.080
	(1.31)	(1.29)	(1.22)	(1.29)	(1.22)	(1.05)	(1.43)
ATLR_csup	0.046	0.043	0.043	0.042	0.041	0.042	0.052
	(0.85)	(0.78)	(0.79)	(0.78)	(0.75)	(0.71)	(0.98)
DiscAcc_csup	0.016	0.015	0.011	0.016	0.018	0.029	0.008
	(0.39)	(0.38)	(0.26)	(0.39)	(0.45)	(0.72)	(0.20)
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 12
Accounting Quality and Rating Responses to Default Risk Changes,
Controlling for Private Information Quality

This table presents the results from linear probability models for three dependent variables: *ejrdown*, *spdown*, and *downdiff*, all defined in Appendix A. One of the key independent variables is the change in the modified Campbell failure score during the quarter. The change is represented by the indicator variable *csup*, which equals one when the failure score increases during the quarter. The model is the same as that presented in Table 8, with two control variables added: a private information quality (PI) indicator and the PI indicator interacted with *csup*. For brevity, only the coefficients on the interaction of accounting quality and *csup* are shown, and results for upgrades are excluded. Panel A includes the results for EJR downgrades; Panel B for S&P downgrades; and Panel C for the difference, *downdiff*. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR Downgrades

	Private Information Quality =							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
TLR_csup	0.142*	0.175***	0.174***	0.165**	0.166**	0.175***	0.162**	0.175**
	(1.96)	(2.86)	(2.85)	(2.54)	(2.55)	(2.82)	(2.39)	(2.49)
ATLR_csup	0.125*	0.150***	0.150***	0.135**	0.132**	0.147***	0.126**	0.132**
	(1.80)	(2.68)	(2.69)	(2.28)	(2.24)	(2.60)	(2.04)	(2.09)
DiscAcc_csup	-0.065	-0.103**	-0.108***	-0.091**	-0.089**	-0.088**	-0.090**	-0.098**
	(-1.61)	(-2.53)	(-2.64)	(-2.39)	(-2.34)	(-2.17)	(-2.20)	(-2.31)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Downgrades

	Private Information Quality =							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
TLR_csup	0.087**	0.098**	0.088**	0.097**	0.099**	0.101**	0.099***	0.109***
	(2.25)	(2.39)	(2.24)	(2.47)	(2.51)	(2.54)	(2.83)	(2.95)
ATLR_csup	0.084**	0.088**	0.086**	0.098***	0.097***	0.084**	0.090***	0.096***
	(2.33)	(2.31)	(2.27)	(2.64)	(2.62)	(2.31)	(2.73)	(2.81)
DiscAcc_csup	-0.102***	-0.088***	-0.099***	-0.103***	-0.103***	-0.090**	-0.125***	-0.130***
	(-3.33)	(-2.68)	(-2.83)	(-3.46)	(-3.45)	(-2.41)	(-4.16)	(-4.20)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Difference between EJR and S&P downgrades (*downdiff*)

	Private Information Quality =							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
TLR_csup	0.065	0.088	0.097*	0.075	0.073	0.079	0.068	0.071
	(1.01)	(1.59)	(1.76)	(1.32)	(1.29)	(1.46)	(1.07)	(1.11)
ATLR_csup	0.049	0.071	0.073	0.042	0.040	0.065	0.042	0.043
	(0.80)	(1.39)	(1.43)	(0.77)	(0.74)	(1.29)	(0.69)	(0.70)
DiscAcc_csup	0.041	-0.010	-0.003	0.015	0.017	0.008	0.040	0.037
	(0.94)	(-0.24)	(-0.08)	(0.39)	(0.44)	(0.16)	(1.04)	(0.96)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 13
Direct Effect of Conflicts of Interest on Rating Accuracy

This table presents the results from linear regressions of the modified Campbell failure score on S&P and EJR credit ratings interacted with measures of conflicts of interest (CI). The measures are defined in the text and Appendix A. Panel A includes the results for EJR ratings; Panel B for S&P ratings; and Panel C for the incremental effect of S&P ratings over EJR ratings. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Egan-Jones Ratings

VARIABLES	financial	propstd	presox	ewr6	indlevmed	ltd
ejrating	0.4569***	0.5074***	0.4530***	0.4912***	0.4303***	0.5108***
	(30.98)	(32.84)	(26.90)	(30.49)	(21.86)	(27.92)
CI	2.8802**	1.2082***	-0.0495	0.3594***	0.8473***	1.6937***
	(2.13)	(7.07)	(-0.24)	(2.79)	(3.34)	(7.59)
CI_EJR	-0.3966***	-0.0544***	0.0747***	-0.0714***	0.0209	-0.0317
	(-2.75)	(-3.43)	(3.59)	(-4.57)	(0.89)	(-1.55)
Constant	-14.1137***	-14.9613***	-14.9459***	-14.1331***	-14.6286***	-15.2497***
	(-86.21)	(-85.30)	(-98.40)	(-79.44)	(-72.70)	(-75.21)
Observations	29,651	29,322	29,651	29,651	27,152	29,356
R-squared	0.466	0.484	0.432	0.470	0.503	0.536
Year FE	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Ratings

VARIABLES	financial	propstd	presox	ewr6	indlevmed	ltd
sprating	0.4230***	0.5028***	0.4025***	0.4610***	0.3745***	0.5064***
	(22.15)	(24.24)	(19.63)	(22.39)	(15.54)	(19.09)
CI	4.4126***	1.6346***	0.1648	0.4318***	0.7033**	1.9645***
	(3.66)	(7.04)	(0.61)	(2.70)	(2.24)	(6.42)
CI_SP	-0.5730***	-0.0878***	0.0817***	-0.0810***	0.0550*	-0.0418
	(-4.74)	(-3.75)	(3.03)	(-4.72)	(1.84)	(-1.45)
Constant	-13.6587***	-14.8530***	-14.4744***	-13.7089***	-14.1160***	-15.1417***
	(-68.96)	(-66.89)	(-71.67)	(-65.13)	(-58.50)	(-53.51)
Observations	29,651	29,322	29,651	29,651	27,152	29,356
R-squared	0.357	0.376	0.294	0.358	0.403	0.438
Year FE	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Incremental effect of S&P ratings over EJR ratings

VARIABLES	financial	propstd	presox	ewr6	indlevmed	ltd
ejrating	0.4406***	0.5061***	0.4258***	0.4755***	0.4111***	0.5082***
	(26.37)	(27.53)	(23.32)	(26.59)	(19.11)	(22.17)
CI	3.4950***	1.3284***	-0.1072	0.3892***	0.7586***	1.6393***
	(2.58)	(6.54)	(-0.49)	(2.95)	(2.72)	(5.97)
CI_EJR	-0.4461***	-0.0694***	0.0712***	-0.0740***	0.0273	-0.0260
	(-3.15)	(-3.48)	(3.33)	(-4.93)	(1.03)	(-1.02)
spmejr	-0.0870***	-0.0077	-0.1339***	-0.0813**	-0.1133***	-0.0101
	(-2.65)	(-0.21)	(-3.57)	(-2.49)	(-2.91)	(-0.22)
CI_spmejr	-0.3320***	-0.0787**	-0.0437	-0.0191	0.0405	0.0275
	(-3.10)	(-2.04)	(-0.76)	(-0.65)	(0.84)	(0.54)
Constant	-13.9740***	-14.9636***	-14.6655***	-14.0079***	-14.4415***	-15.2206***
	(-79.17)	(-75.08)	(-84.61)	(-74.48)	(-66.75)	(-61.44)
Observations	29,651	29,322	29,651	29,651	27,152	29,356
R-squared	0.470	0.485	0.440	0.473	0.507	0.536
Year FE	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 14
Direct Effect of Conflicts of Interest on Rating Timeliness

This table presents the results from linear probability models for three dependent variables: *ejrdown*, *spdown*, and *downdiff*, all defined in Appendix A. One of the key independent variables is the change in the modified Campbell failure score during the quarter. The change is represented by the indicator variable *csup*, which equals one when the failure score increases during the quarter. *CI* represents the conflict of interest variable. *CI_csup* is the interaction of these terms. All other variables are also defined in Appendix A. Panel A includes the results for EJR downgrades; Panel B for S&P downgrades; and Panel C for the difference, *downdiff*. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR Downgrades

VARIABLES	bbb	financial	propstd	presox	ewr	indlevmed	ltd
csup	0.076***	0.075***	0.074***	0.074***	0.084***	0.067***	0.069***
	(8.50)	(8.94)	(10.19)	(7.16)	(7.81)	(7.62)	(9.48)
CI	-0.006	0.022	0.004	0.001	-0.014	-0.038***	-0.013**
	(-1.31)	(1.12)	(0.64)	(0.05)	(-1.09)	(-5.57)	(-2.08)
CI_csup	-0.005	-0.025	-0.000	0.050***	-0.026**	0.013	0.012
	(-0.60)	(-0.73)	(-0.04)	(3.18)	(-2.17)	(1.22)	(1.62)
campscore_lag	0.028***	0.028***	0.028***	0.029***	0.028***	0.031***	0.029***
	(11.10)	(11.07)	(11.12)	(8.55)	(11.45)	(10.89)	(10.78)
ejrating_lag	-0.010***	-0.010***	-0.009***	-0.010***	-0.009***	-0.010***	-0.010***
	(-7.81)	(-7.37)	(-7.19)	(-6.72)	(-7.63)	(-7.60)	(-7.06)
Constant	0.460***	0.454***	0.454***	0.462***	0.474***	0.504***	0.475***
	(14.06)	(13.70)	(13.45)	(9.04)	(12.69)	(12.87)	(12.48)
Observations	28,492	28,528	28,218	28,528	28,528	26,100	28,249
R-squared	0.059	0.059	0.059	0.048	0.061	0.062	0.059
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Downgrades

VARIABLES	bbb	financial	propstd	presox	ewr6	indlevmed	ltd
csup	0.037***	0.030***	0.034***	0.028***	0.037***	0.026***	0.034***
	(6.74)	(6.80)	(6.82)	(6.20)	(6.22)	(4.99)	(7.52)
CI	0.000	0.014	0.003	-0.010	0.009**	-0.025***	-0.025***
	(0.01)	(1.04)	(1.14)	(-1.57)	(2.28)	(-4.74)	(-6.08)
CI_csup	-0.019***	-0.006	-0.009*	0.024***	-0.015**	0.008	-0.007
	(-3.73)	(-0.47)	(-1.74)	(3.06)	(-2.25)	(1.11)	(-1.30)
campscore_lag	0.022***	0.022***	0.022***	0.022***	0.022***	0.024***	0.025***
	(12.74)	(12.75)	(12.83)	(12.94)	(12.81)	(12.30)	(13.36)
sprating_lag	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.009***
	(-8.58)	(-8.44)	(-8.34)	(-8.54)	(-8.49)	(-8.51)	(-10.20)
Constant	0.344***	0.342***	0.342***	0.327***	0.338***	0.378***	0.395***
	(15.53)	(15.49)	(15.67)	(13.92)	(15.03)	(14.80)	(15.87)
Observations	29,349	29,349	29,026	29,349	29,349	26,878	29,059
R-squared	0.051	0.050	0.050	0.049	0.050	0.054	0.053
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Difference between EJR and S&P downgrades (*downdiff*)

VARIABLES	bbb	financial	propstd	presox	ewr6	indlevmed	ltd
csup	0.041***	0.045***	0.041***	0.045***	0.047***	0.040***	0.036***
	(6.86)	(7.73)	(7.56)	(5.01)	(5.20)	(5.99)	(6.70)
CI	-0.004	0.004	0.008*	0.017	-0.024**	-0.011**	0.018***
	(-0.89)	(0.16)	(1.78)	(1.21)	(-2.24)	(-2.05)	(3.11)
CI_csup	0.011	-0.019	0.009	0.026	-0.009	0.009	0.019**
	(1.40)	(-0.74)	(0.98)	(1.52)	(-0.85)	(0.94)	(2.04)
campscore_lag	0.007***	0.007***	0.007***	0.008***	0.007***	0.008***	0.007***
	(5.54)	(5.56)	(5.65)	(4.87)	(5.33)	(5.78)	(5.02)
ejrmsp_lag	-0.024***	-0.024***	-0.024***	-0.025***	-0.023***	-0.025***	-0.024***
	(-10.61)	(-10.61)	(-10.76)	(-11.15)	(-10.41)	(-10.64)	(-11.07)
Constant	0.089***	0.087***	0.086***	0.115***	0.112***	0.096***	0.075***
	(6.59)	(6.50)	(6.26)	(5.48)	(7.22)	(6.27)	(5.51)
Observations	28,492	28,492	28,184	28,492	28,492	26,068	28,214
R-squared	0.029	0.029	0.029	0.021	0.030	0.030	0.031
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 15
Direct Effect of Private Information Quality on Rating Accuracy

This table presents the results from linear regressions of the modified Campbell failure score on S&P and EJR credit ratings interacted with measures of private information quality (PI). The measures are defined in the text and Appendix A. Panel A includes the results for EJR ratings; Panel B for S&P ratings; and Panel C for the incremental effect of S&P ratings over EJR ratings. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Egan-Jones Ratings

VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
ejrating	0.3966***	0.4441***	0.4376***	0.4643***	0.4404***	0.4658***	0.4112***	0.4494***
	(19.57)	(26.42)	(23.68)	(29.35)	(23.71)	(26.96)	(23.99)	(23.13)
PI	-0.5743***	-0.1537	-0.1998	0.2954	-0.3244*	0.3484*	0.1038	0.4799***
	(-2.79)	(-0.99)	(-0.89)	(1.57)	(-1.65)	(1.80)	(0.49)	(4.04)
PI_EJR	0.0784***	0.0019	0.0020	-0.0232	0.0292	-0.0640***	0.0706***	-0.0009
	(3.92)	(0.12)	(0.09)	(-1.31)	(1.51)	(-3.43)	(3.74)	(-0.07)
Constant	-13.6989***	-14.0142***	-13.9680***	-14.2256***	-13.9526***	-14.1454***	-13.9156***	-14.2925***
	(-67.48)	(-78.57)	(-72.13)	(-81.12)	(-72.76)	(-73.96)	(-86.23)	(-79.56)
Observations	25,506	24,625	25,111	29,649	29,649	24,486	22,349	22,349
R-squared	0.466	0.447	0.448	0.464	0.465	0.450	0.481	0.472
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Ratings

VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
sprating	0.3173***	0.4104***	0.3859***	0.4338***	0.3950***	0.4394***	0.3511***	0.3925***
	(13.59)	(17.81)	(14.77)	(20.67)	(16.64)	(17.91)	(17.45)	(17.17)
PI	-0.9796***	-0.0027	-0.3327	0.4246**	-0.4387*	0.6599***	-0.3076	0.2625**
	(-4.05)	(-0.01)	(-1.21)	(1.97)	(-1.76)	(2.80)	(-1.29)	(2.12)
PI_SP	0.1416***	-0.0197	-0.0052	-0.0364*	0.0442*	-0.1126***	0.1405***	0.0257*
	(5.96)	(-0.88)	(-0.19)	(-1.77)	(1.74)	(-4.78)	(6.42)	(1.85)
Constant	-12.9585***	-13.5210***	-13.2748***	-13.8120***	-13.4158***	-13.6881***	-13.2991***	-13.6441***
	(-57.09)	(-61.43)	(-52.97)	(-64.05)	(-58.03)	(-56.41)	(-73.03)	(-68.80)
Observations	25,506	24,625	25,111	29,649	29,649	24,486	22,349	22,349
R-squared	0.360	0.323	0.327	0.352	0.352	0.331	0.384	0.358
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Incremental effect of S&P ratings over EJR ratings

VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
ejrating	0.3797***	0.4231***	0.3937***	0.4458***	0.4181***	0.4386***	0.3928***	0.4255***
	(17.98)	(21.72)	(17.61)	(24.90)	(20.50)	(21.28)	(21.74)	(21.52)
PI	-0.5070**	-0.0686	-0.5128**	0.2621	-0.3607	0.3044	-0.0713	0.3794***
	(-2.20)	(-0.38)	(-2.10)	(1.26)	(-1.55)	(1.45)	(-0.32)	(3.15)
PI_EJR	0.0745***	-0.0055	0.0332	-0.0199	0.0360	-0.0595***	0.0888***	0.0091
	(3.33)	(-0.29)	(1.41)	(-1.01)	(1.55)	(-2.92)	(4.39)	(0.72)
spmejr	-0.1233***	-0.1044**	-0.1999***	-0.0917***	-0.1068***	-0.1257***	-0.1200***	-0.1391***
	(-3.31)	(-2.48)	(-5.08)	(-2.71)	(-2.94)	(-3.01)	(-3.46)	(-3.35)
PI_spmejr	0.0360	-0.0494	0.1194***	-0.0019	0.0241	-0.0217	0.1177***	0.0613*
	(0.82)	(-1.12)	(2.74)	(-0.05)	(0.55)	(-0.47)	(2.82)	(1.73)
Constant	-13.5697***	-13.8824***	-13.6138***	-14.0664***	-13.7767***	-13.9360***	-13.7556***	-14.0960***
	(-65.47)	(-71.46)	(-61.36)	(-74.28)	(-67.40)	(-65.62)	(-81.95)	(-78.55)
Observations	25,506	24,625	25,111	29,649	29,649	24,486	22,349	22,349
R-squared	0.470	0.453	0.456	0.467	0.468	0.456	0.485	0.477
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 16
Direct Effect of Private Information Quality on Rating Timeliness

This table presents the results from linear probability models for three dependent variables: *ejrdown*, *spdown*, and *downdiff*, all defined in Appendix A. One of the key independent variables is the change in the modified Campbell failure score during the quarter. The change is represented by the indicator variable *csup*, which equals one when the failure score increases during the quarter. *PI* represents the private information variable. *PI_csup* is the interaction of these terms. All other variables are also defined in Appendix A. Panel A includes the results for EJR downgrades; Panel B for S&P downgrades; and Panel C for the difference, *downdiff*. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR Downgrades

VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
csup	0.067***	0.077***	0.079***	0.071***	0.067***	0.083***	0.062***	0.062***
	(7.17)	(7.40)	(8.76)	(8.47)	(7.54)	(8.46)	(8.45)	(6.55)
PI	-0.017***	0.001	0.018***	-0.002	-0.009**	-0.002	-0.009	0.003
	(-2.65)	(0.26)	(3.07)	(-0.33)	(-2.02)	(-0.50)	(-1.16)	(0.68)
PI_csup	0.012	-0.007	-0.013*	0.007	0.015**	-0.019**	0.067***	0.020**
	(1.29)	(-0.89)	(-1.71)	(1.00)	(2.15)	(-2.16)	(4.45)	(2.55)
campscore_lag	0.027***	0.029***	0.029***	0.028***	0.028***	0.029***	0.027***	0.028***
	(10.79)	(9.75)	(9.74)	(11.07)	(11.07)	(9.54)	(10.43)	(10.17)
ejrating_lag	-0.009***	-0.009***	-0.009***	-0.010***	-0.009***	-0.009***	-0.010***	-0.010***
	(-7.36)	(-6.31)	(-5.96)	(-7.36)	(-7.29)	(-6.29)	(-7.56)	(-7.37)
Constant	0.450***	0.474***	0.456***	0.455***	0.458***	0.477***	0.460***	0.463***
	(13.52)	(12.07)	(11.71)	(13.54)	(13.63)	(12.04)	(12.97)	(12.76)
Observations	24,432	23,820	24,269	28,527	28,527	23,683	22,193	22,193
R-squared	0.056	0.058	0.058	0.059	0.059	0.059	0.062	0.060
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Downgrades

VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
csup	0.022***	0.027***	0.032***	0.034***	0.030***	0.031***	0.019***	0.025***
	(4.70)	(4.77)	(5.46)	(6.68)	(5.86)	(4.23)	(5.51)	(5.43)
PI	0.002	0.002	-0.001	0.003	-0.005	-0.010**	0.011*	-0.000
	(0.47)	(0.57)	(-0.21)	(0.74)	(-1.37)	(-2.28)	(1.75)	(-0.13)
PI_csup	0.013**	-0.003	-0.013**	-0.009*	0.001	-0.012*	0.042***	0.002
	(1.99)	(-0.56)	(-2.53)	(-1.88)	(0.20)	(-1.71)	(4.51)	(0.51)
campscore_lag	0.023***	0.021***	0.021***	0.022***	0.022***	0.020***	0.019***	0.020***
	(12.36)	(11.61)	(11.33)	(12.74)	(12.74)	(11.51)	(10.84)	(11.19)
sprating_lag	-0.008***	-0.006***	-0.006***	-0.007***	-0.007***	-0.006***	-0.006***	-0.006***
	(-8.95)	(-7.20)	(-7.50)	(-8.46)	(-8.34)	(-7.42)	(-7.91)	(-7.60)
Constant	0.353***	0.331***	0.329***	0.341***	0.343***	0.331***	0.339***	0.357***
	(14.45)	(13.61)	(13.10)	(15.44)	(15.31)	(13.96)	(16.31)	(16.43)
Observations	25,225	24,417	24,890	29,348	29,348	24,281	22,193	22,193
R-squared	0.050	0.045	0.046	0.050	0.050	0.045	0.052	0.048
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Difference between EJR and S&P downgrades (*downdiff*)

VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
csup	0.045***	0.051***	0.048***	0.038***	0.038***	0.051***	0.041***	0.036***
	(5.12)	(6.55)	(7.19)	(6.55)	(5.52)	(7.11)	(6.70)	(5.12)
PI	-0.022***	-0.003	0.019***	-0.005	-0.010*	0.007	-0.019**	0.004
	(-3.56)	(-0.45)	(3.26)	(-0.84)	(-1.95)	(1.17)	(-2.40)	(0.77)
PI_csup	-0.000	-0.004	-0.001	0.017**	0.014*	-0.003	0.025*	0.016*
	(-0.01)	(-0.57)	(-0.09)	(2.28)	(1.83)	(-0.30)	(1.92)	(1.92)
campscore_lag	0.007***	0.009***	0.010***	0.007***	0.007***	0.010***	0.008***	0.007***
	(4.90)	(5.60)	(5.98)	(5.55)	(5.50)	(5.88)	(5.72)	(5.26)
ejrmsp_lag	-0.026***	-0.024***	-0.023***	-0.024***	-0.024***	-0.023***	-0.022***	-0.022***
	(-10.77)	(-9.54)	(-9.68)	(-10.65)	(-10.63)	(-9.35)	(-9.21)	(-9.09)
Constant	0.097***	0.098***	0.095***	0.088***	0.093***	0.103***	0.082***	0.069***
	(6.29)	(5.48)	(5.44)	(6.41)	(6.23)	(5.69)	(5.32)	(4.69)
Observations	24,398	23,794	24,240	28,491	28,491	23,657	22,193	22,193
R-squared	0.030	0.030	0.030	0.029	0.029	0.030	0.029	0.029
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 17
The Discipline Effect of Accounting Quality on Rating Accuracy

This table presents the results from linear regressions of the modified Campbell failure score on S&P and EJR credit ratings, conflicts of interest, and accounting quality. The base model is the same as that presented in Table 6, but it includes all interactions between credit ratings, conflicts of interest (CI), and accounting quality (AQ) measures. The CI and AQ variables are defined in the text and in Appendix A. The key coefficient is on the triple interaction between ratings, conflicts of interest, and accounting quality. For brevity, only the coefficients on these interactions are shown. The table has three sections – one for EJR, one for S&P, and one for the incremental S&P rating (S&P rating – EJR rating). t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

		CI					
RATING	AQ	financial	propstd	presox	ewr6	indlevmed	ltd
EJR	TLR	0.4567	0.1853	-0.3321**	-0.0097	0.0752	0.2052
		(0.08)	(1.03)	(-2.00)	(-0.12)	(0.25)	(0.92)
	ATLR	-12.7121	0.1454	-0.3528**	-0.0173	-0.0865	0.2630
		(-0.64)	(0.92)	(-2.37)	(-0.25)	(-0.35)	(1.22)
	DiscAcc	-0.5591	-0.0721	-0.0111	0.0191	-0.1525	-0.0019
		(-1.57)	(-0.65)	(-0.09)	(0.31)	(-1.36)	(-0.02)
SP	TLR	-0.6967	0.4509*	-0.1260	-0.1348	0.2651	0.4846
		(-0.14)	(1.71)	(-0.53)	(-1.61)	(0.65)	(1.37)
	ATLR	-0.2818	0.3054	-0.2970	-0.1421	-0.0012	0.4123
		(-0.03)	(1.26)	(-1.32)	(-1.63)	(-0.00)	(1.18)
	DiscAcc	-0.2841	-0.0351	-0.0287	0.0536	-0.1417	-0.0103
		(-0.99)	(-0.22)	(-0.14)	(0.71)	(-0.88)	(-0.06)
spmejr	TLR	-4.1319	1.0724**	0.7435	-0.1023	1.0821*	0.7369
		(-0.98)	(2.27)	(1.17)	(-0.40)	(1.85)	(1.36)
	ATLR	1.1588	0.8293*	0.1942	-0.1640	1.0953**	1.0388**
		(0.13)	(1.90)	(0.34)	(-0.69)	(2.05)	(2.01)
	DiscAcc	0.2933	-0.0985	-0.3120	-0.0963	-0.0068	-0.6959**
		(0.36)	(-0.34)	(-0.64)	(-0.64)	(-0.03)	(-2.19)

Table 18
Information Overlap and the Effect of Accounting Quality on Rating Accuracy

This table presents the results from linear regressions of the modified Campbell failure score on S&P and EJR credit ratings, private information quality, and accounting quality. The base model is the same as that presented in Table 6, but it includes all interactions between credit ratings, private information (PI), and accounting quality (AQ) measures. The PI and AQ variables are defined in the text and in Appendix A. The key coefficient is on the triple interaction between ratings, private information, and accounting quality. For brevity, only the coefficients on these interactions are shown. The table has three sections – one for EJR, one for S&P, and one for the incremental S&P rating (S&P rating – EJR rating). t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

		PI							
RATING	AQ	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
EJR	TLR	-0.1946	0.0820	0.0563	0.0980	0.2254	-0.0860	-0.3930*	-0.1118
		(-1.06)	(0.42)	(0.24)	(0.54)	(1.20)	(-0.38)	(-1.96)	(-0.85)
	ATLR	-0.0712	0.0819	0.0487	0.2147	0.4425**	-0.0238	-0.3615**	-0.1590
		(-0.44)	(0.44)	(0.25)	(1.26)	(2.49)	(-0.12)	(-2.01)	(-1.28)
	DiscAcc	0.1863*	-0.1276	-0.1476	-0.0903	-0.0733	0.0037	0.1508	0.1700*
		(1.75)	(-1.17)	(-1.17)	(-0.87)	(-0.62)	(0.03)	(1.26)	(1.80)
SP	TLR	0.1207	0.0354	0.0909	0.2412	0.5625**	-0.0662	-0.2779	0.1258
		(0.50)	(0.13)	(0.27)	(0.97)	(2.06)	(-0.23)	(-1.17)	(0.83)
	ATLR	0.2471	0.1253	-0.0903	0.4065*	0.8104***	-0.1051	-0.2041	0.0340
		(1.20)	(0.47)	(-0.31)	(1.74)	(3.19)	(-0.42)	(-0.97)	(0.23)
	DiscAcc	0.1264	-0.2077	-0.0521	0.0329	-0.0017	0.2029	0.0972	0.0935
		(0.90)	(-1.20)	(-0.29)	(0.23)	(-0.01)	(1.10)	(0.60)	(0.80)
spmejr	TLR	0.6227	-0.4776	-0.4977	-0.1807	0.4286	0.2549	0.6592*	0.3722
		(1.20)	(-0.99)	(-1.02)	(-0.39)	(0.91)	(0.52)	(1.66)	(1.03)
	ATLR	0.6600	-0.3404	-0.6275	0.3281	0.8692**	0.0653	0.7677**	0.3842
		(1.34)	(-0.80)	(-1.61)	(0.80)	(2.09)	(0.16)	(2.15)	(1.11)
	DiscAcc	-0.2854	-0.2224	0.0525	0.5886**	0.2296	0.3027	-0.3874	-0.3164
		(-0.98)	(-0.72)	(0.17)	(2.18)	(0.77)	(0.83)	(-1.34)	(-1.14)

Table 19
The Discipline Effect of Accounting Quality on Rating Timeliness

This table presents the results from linear probability models for three dependent variables: *ejrdown*, *spdown*, and *downdiff*, all defined in Appendix A. These variables are regressed on *csup* (indicator variable equal to one when the failure score increases during the quarter), accounting quality (AQ), and conflict of interest (CI) measures. The CI and AQ variables are defined in the text and in Appendix A. The key coefficient is on the triple interaction between csup, conflicts of interest, and accounting quality. For brevity, only the coefficients on these interactions are shown. The table has three sections - one for EJR downgrades, one for S&P downgrades, and one for the difference, *downdiff*. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

		CI						
DOWNGRADE	AQ	bbb	financial	propstd	presox	ewr6	indlevmed	ltd
EJR	TLR	0.086	-1.551*	0.062	0.162	0.001	0.030	0.116
		(0.71)	(-1.80)	(0.53)	(0.65)	(0.01)	(0.24)	(0.84)
	ATLR	-0.016	-1.040	0.039	0.137	0.054	-0.008	0.140
		(-0.17)	(-1.60)	(0.37)	(0.61)	(0.50)	(-0.07)	(1.34)
	DiscAcc	-0.036	-0.419	-0.050	0.188*	0.048	-0.253***	-0.036
		(-0.39)	(-1.26)	(-0.63)	(1.78)	(0.66)	(-3.13)	(-0.47)
S&P	TLR	-0.116	-0.939*	-0.064	-0.097	0.053	-0.015	0.126*
		(-1.33)	(-1.77)	(-0.79)	(-0.82)	(0.71)	(-0.19)	(1.70)
	ATLR	-0.099	-0.586***	-0.062	-0.048	0.041	-0.033	0.102*
		(-1.29)	(-4.76)	(-0.88)	(-0.44)	(0.53)	(-0.52)	(1.72)
	DiscAcc	-0.075	-0.042	0.039	0.021	0.067	-0.124**	-0.006
		(-1.51)	(-0.22)	(0.62)	(0.25)	(1.30)	(-2.31)	(-0.12)
DOWNDIFF	TLR	0.207*	-0.590	0.114	0.196	-0.061	0.037	-0.006
		(1.95)	(-1.18)	(1.09)	(0.81)	(-0.50)	(0.28)	(-0.05)
	ATLR	0.085	-0.518	0.079	0.094	0.005	0.015	0.034
		(0.98)	(-0.86)	(0.75)	(0.46)	(0.04)	(0.13)	(0.31)
	DiscAcc	0.033	-0.318*	-0.082	0.176	-0.022	-0.132	-0.027
		(0.38)	(-1.77)	(-1.00)	(1.19)	(-0.27)	(-1.37)	(-0.34)

Table 20
Information Overlap and the Effect of Accounting Quality on Rating Timeliness

This table presents the results from linear probability models for three dependent variables: *ejrdown*, *spdown*, and *downdiff*, all defined in Appendix A. These variables are regressed on *csup* (indicator variable equal to one when the failure score increases during the quarter), accounting quality (AQ), and private information (PI) measures. The PI and AQ variables are defined in the text and in Appendix A. The key coefficient is on the triple interaction between csup, private information, and accounting quality. For brevity, only the coefficients on these interactions are shown. The table has three sections - one for EJR downgrades, one for S&P downgrades, and one for the difference, *downdiff*. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

		PI							
DOWNGRADE		pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
EJR	TLR	-0.005	0.083	0.048	-0.015	0.048	-0.257*	0.351*	0.154
		(-0.04)	(0.76)	(0.40)	(-0.18)	(0.49)	(-1.96)	(1.86)	(1.55)
	ATLR	-0.055	0.055	0.037	-0.010	0.067	-0.150	0.029	0.147*
		(-0.53)	(0.61)	(0.37)	(-0.14)	(0.84)	(-1.32)	(0.16)	(1.67)
	DISCACC	-0.012	-0.027	-0.073	0.040	-0.048	-0.038	0.073	-0.023
		(-0.21)	(-0.38)	(-1.01)	(0.68)	(-0.82)	(-0.46)	(0.70)	(-0.32)
SP	TLR	0.079	-0.011	0.002	-0.010	0.035	-0.100	0.382**	-0.048
		(0.78)	(-0.11)	(0.03)	(-0.09)	(0.39)	(-1.22)	(2.44)	(-0.67)
	ATLR	0.018	-0.009	0.000	-0.021	0.063	-0.094	0.328**	-0.084
		(0.21)	(-0.11)	(0.01)	(-0.23)	(0.77)	(-1.28)	(2.20)	(-1.48)
	DiscAcc	0.007	0.048	0.049	0.082	0.095*	0.054	-0.277**	0.000
		(0.13)	(0.76)	(0.78)	(1.38)	(1.71)	(0.73)	(-2.54)	(0.01)
DOWNDIFF	TLR	-0.083	0.091	0.061	0.007	0.012	-0.186	-0.009	0.200*
		(-0.66)	(0.64)	(0.51)	(0.07)	(0.10)	(-1.56)	(-0.06)	(1.77)
	ATLR	-0.068	0.064	0.051	0.019	-0.000	-0.065	-0.276	0.229**
		(-0.59)	(0.56)	(0.52)	(0.19)	(-0.00)	(-0.56)	(-1.54)	(2.38)
	DiscAcc	-0.013	-0.083	-0.121	-0.041	-0.138**	-0.100	0.351***	-0.019
		(-0.19)	(-0.93)	(-1.42)	(-0.55)	(-2.03)	(-1.03)	(2.71)	(-0.23)

Table 21
Accounting Quality and the Time Between Downgrade and Default

This table presents the results from OLS regressions using the sample of all rating changes within 360 days prior to a default. The dependent variable, *dahead*, is a measure of rating timeliness and is defined in Appendix A. AQ represents the accounting quality measure included as an independent variable. *EJRdum* is an indicator variable equal to one for changes in Egan-Jones ratings and zero for S&P rating changes. All control variables are as defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent var = *dahead*		
VARIABLES	TLR	ATLR	DiscAcc
EJRdum	-18.097	-14.056	12.464*
	(-1.15)	(-1.05)	(2.08)
AQ	231.943*	143.823*	20.109
	(1.89)	(1.92)	(0.86)
EJRdum_AQ	202.974*	175.615*	-40.244
	(1.83)	(1.86)	(-0.81)
begyrrate	6.457**	6.931**	7.446***
	(2.75)	(2.66)	(5.33)
log_size_adj	-9.277	-8.436	-7.073
	(-1.26)	(-1.14)	(-1.11)
cfotl	-96.403	-61.407	-95.293
	(-1.06)	(-0.80)	(-0.82)
tlta	139.316***	137.008***	118.167**
	(4.33)	(4.08)	(2.50)
Constant	-61.638	-55.877	52.123
	(-0.60)	(-0.54)	(0.61)
Observations	350	350	327
R-squared	0.185	0.175	0.158
Year FE	Yes	Yes	Yes
Cluster	Year	Year	Year

Table 22
Accounting Quality and the Average Credit Rating Prior to Default

This table presents the results from OLS regressions using the sample of all firms that default. Each defaulting firm has two observations – one for its S&P rating and one for its EJR rating. The dependent variable, *wrate*, is a measure of rating timeliness and is defined in Appendix A. AQ represents the accounting quality measure included as an independent variable. *EJRdum* is an indicator variable equal to one for the weighted average Egan-Jones ratings and zero for the S&P ratings. All control variables are as defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent var = *wrate*		
VARIABLES	TLR	ATLR	DiscAcc
EJRdum	1.403***	1.571***	1.891***
	(5.02)	(7.30)	(12.08)
log_size_adj	-0.912***	-0.906***	-0.979***
	(-4.18)	(-4.17)	(-4.38)
cfotl	-11.533*	-11.316*	-12.703**
	(-1.94)	(-1.88)	(-3.01)
tlta	2.558	2.584	1.782
	(1.41)	(1.45)	(0.86)
AQ	3.296	1.942	-1.645
	(1.32)	(1.18)	(-0.93)
EJRdum_AQ	3.892**	2.899**	-0.846
	(2.60)	(2.16)	(-0.50)
Constant	20.057***	20.303***	22.331***
	(12.12)	(13.24)	(10.12)
Observations	166	166	154
R-squared	0.407	0.401	0.439
Year FE	Yes	Yes	Yes
Cluster	Year	Year	Year

Table 23
Rating Responses to Accounting Restatements

This table presents the results from linear probability models for three dependent variables: *ejrdown*, *spdown*, and *downdiff*, all defined in Appendix A. These variables are regressed on *res_adv* and *res_fav*, indicator variables equal to one when the rated firm announces an adverse or favorable accounting restatement, respectively. Control variables are defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	ejrdown	spdown	downdiff	ejrdown	spdown	downdiff
res_adv	0.092***	0.044***	0.052***	0.063***	0.029*	0.032*
	(4.32)	(2.77)	(2.81)	(3.39)	(1.72)	(1.67)
res_fav	-0.019	0.014	-0.022	-0.031	0.003	-0.036
	(-0.77)	(0.66)	(-0.74)	(-1.27)	(0.15)	(-1.36)
campscore_chg				0.058***	0.025***	0.033***
				(11.01)	(8.74)	(8.13)
campscore_lag				0.031***	0.023***	0.008***
				(11.77)	(13.06)	(6.30)
ejrating_lag	0.003***			-0.010***		
	(4.62)			(-7.61)		
sprating_lag		0.002***			-0.007***	
		(5.27)			(-8.71)	
ejrmsp_lag			-0.020***			-0.024***
			(-10.37)			(-10.64)
Constant	0.100***	0.049***	0.048***	0.514***	0.366***	0.112***
	(15.49)	(9.61)	(26.11)	(13.85)	(15.60)	(8.25)
Observations	36,185	37,384	36,127	28,526	29,347	28,490
R-squared	0.025	0.011	0.024	0.077	0.058	0.033
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 24
Conflicts of Interest and the Discipline Effect of Restatements

This table presents the results from linear probability models for three dependent variables: *ejrdown* (Panel A), *spdown* (Panel B), and *downdiff* (Panel C), all defined in Appendix A. These variables are regressed on *res_adv* and *res_fav*, indicator variables equal to one when the rated firm announces an adverse or favorable accounting restatement, respectively. The model also includes measures of conflicts of interest (CI) interacted with *res_adv*. Control variables are defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR Downgrades

	CI						
VARIABLES	bbb	propstd	presox	financial	ewr6	indlevmed	ltd
res_adv	0.052***	0.019	0.055***	0.064***	0.096***	0.065**	0.039*
	(2.71)	(1.06)	(3.08)	(3.42)	(3.12)	(2.24)	(1.87)
res_fav	-0.031	-0.032	-0.029	-0.031	-0.031	-0.034	-0.030
	(-1.28)	(-1.29)	(-1.14)	(-1.28)	(-1.26)	(-1.28)	(-1.24)
resadv_CI	0.039	0.102**	0.110	-0.102**	-0.053	0.007	0.058
	(0.87)	(2.37)	(1.56)	(-2.39)	(-1.53)	(0.16)	(1.30)
CI	-0.009*	0.000	0.022	0.013	-0.020*	-0.036***	-0.015**
	(-1.91)	(0.01)	(1.55)	(0.74)	(-1.86)	(-4.98)	(-2.47)
campscore_chg	0.058***	0.057***	0.059***	0.058***	0.057***	0.057***	0.058***
	(11.03)	(11.00)	(10.41)	(11.01)	(10.89)	(10.70)	(11.01)
campscore_lag	0.031***	0.031***	0.031***	0.031***	0.031***	0.033***	0.032***
	(11.79)	(11.87)	(9.35)	(11.76)	(12.12)	(11.73)	(11.69)
ejrating_lag	-0.011***	-0.010***	-0.011***	-0.010***	-0.010***	-0.011***	-0.011***
	(-8.08)	(-7.56)	(-6.93)	(-7.61)	(-7.81)	(-7.95)	(-7.63)
Constant	0.520***	0.517***	0.530***	0.514***	0.529***	0.568***	0.546***
	(14.36)	(13.96)	(9.86)	(13.85)	(13.14)	(13.45)	(13.24)
Observations	28,490	28,216	28,526	28,526	28,526	26,098	28,248
R-squared	0.078	0.078	0.068	0.078	0.078	0.081	0.078
Year FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Downgrades

	CI						
VARIABLES	bbb	propstd	presox	financial	ewr6	indlevmed	ltd
res_adv	0.031	0.009	0.030*	0.030*	0.015	0.024	0.008
	(1.37)	(0.55)	(1.65)	(1.75)	(0.63)	(1.19)	(0.42)
res_fav	0.003	0.003	0.006	0.003	0.003	-0.001	0.004
	(0.14)	(0.12)	(0.26)	(0.15)	(0.14)	(-0.06)	(0.21)
resadv_CI	-0.006	0.043**	0.017	-0.062***	0.024	0.010	0.044
	(-0.18)	(2.02)	(0.30)	(-2.90)	(0.66)	(0.38)	(1.44)
CI	-0.008***	-0.002	0.000	0.013	0.005	-0.024***	-0.032***
	(-2.65)	(-0.80)	(0.02)	(0.91)	(1.43)	(-5.67)	(-8.15)
campscore_chg	0.025***	0.025***	0.025***	0.025***	0.026***	0.025***	0.026***
	(8.75)	(8.63)	(9.34)	(8.74)	(8.92)	(7.64)	(9.03)
campscore_lag	0.023***	0.023***	0.023***	0.023***	0.023***	0.025***	0.026***
	(13.06)	(13.15)	(13.33)	(13.07)	(13.12)	(12.49)	(13.79)
sprating_lag	-0.008***	-0.007***	-0.007***	-0.007***	-0.007***	-0.008***	-0.010***
	(-8.84)	(-8.62)	(-8.77)	(-8.68)	(-8.73)	(-8.66)	(-10.45)
Constant	0.371***	0.369***	0.355***	0.366***	0.362***	0.403***	0.427***
	(15.56)	(15.69)	(14.25)	(15.58)	(15.12)	(14.65)	(16.12)
Observations	29,347	29,024	29,347	29,347	29,347	26,876	29,058
R-squared	0.059	0.058	0.056	0.058	0.058	0.061	0.062
Year FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Difference between EJR and S&P downgrades (*downdiff*)

	CI						
VARIABLES	bbb	propstd	presox	financial	ewr6	indlevmed	ltd
res_adv	0.017	0.010	0.020	0.032*	0.079***	0.037	0.033
	(0.80)	(0.49)	(1.01)	(1.67)	(3.23)	(1.28)	(1.40)
res_fav	-0.036	-0.034	-0.038	-0.036	-0.035	-0.036	-0.035
	(-1.36)	(-1.26)	(-1.44)	(-1.36)	(-1.34)	(-1.42)	(-1.31)
resadv_CI	0.050	0.056	0.108*	-0.040	-0.078**	-0.002	0.007
	(1.09)	(1.44)	(1.85)	(-1.07)	(-2.27)	(-0.05)	(0.15)
CI	0.001	0.012**	0.027**	-0.004	-0.024***	-0.008	0.024***
	(0.15)	(2.50)	(2.30)	(-0.20)	(-2.90)	(-1.54)	(4.99)
campscore_chg	0.033***	0.033***	0.034***	0.033***	0.032***	0.033***	0.032***
	(8.15)	(8.10)	(6.15)	(8.14)	(7.58)	(7.48)	(7.88)
campscore_lag	0.008***	0.008***	0.009***	0.008***	0.008***	0.009***	0.007***
	(6.33)	(6.39)	(5.63)	(6.33)	(6.04)	(6.51)	(5.76)
ejrmsp_lag	-0.024***	-0.024***	-0.025***	-0.024***	-0.023***	-0.025***	-0.024***
	(-10.61)	(-10.77)	(-11.00)	(-10.62)	(-10.42)	(-10.65)	(-11.04)
Constant	0.113***	0.109***	0.146***	0.112***	0.134***	0.122***	0.097***
	(8.29)	(7.99)	(6.79)	(8.27)	(8.64)	(7.71)	(7.01)
Observations	28,490	28,182	28,490	28,490	28,490	26,066	28,213
R-squared	0.033	0.034	0.026	0.033	0.035	0.035	0.035
Year FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 25
Restatements and Private Information Overlap

This table presents the results from linear probability models for three dependent variables: *ejrdown* (Panel A), *spdown* (Panel B), and *downdiff* (Panel C), all defined in Appendix A. These variables are regressed on *res_adv* and *res_fav*, indicator variables equal to one when the rated firm announces an adverse or favorable accounting restatement, respectively. The model also includes measures of private information (PI) interacted with *res_adv*. PI variables are defined in the text and Appendix A. Control variables are defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR Downgrades

	PI							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
res_adv	0.075***	0.063**	0.091***	0.035	0.055*	0.120***	0.077***	0.031
	(2.80)	(2.07)	(2.71)	(1.47)	(1.69)	(3.49)	(3.52)	(1.17)
res_fav	-0.020	-0.018	-0.018	-0.031	-0.031	-0.026	-0.023	-0.021
	(-0.77)	(-0.54)	(-0.52)	(-1.27)	(-1.27)	(-0.78)	(-0.71)	(-0.67)
resadv_PI	-0.005	0.021	-0.028	0.074*	0.015	-0.075*	-0.041	0.068*
	(-0.14)	(0.56)	(-0.61)	(1.85)	(0.38)	(-1.84)	(-0.95)	(1.90)
PI	-0.012**	-0.002	0.012**	-0.003	-0.006	-0.010**	0.023***	0.007
	(-2.06)	(-0.40)	(2.48)	(-0.74)	(-1.48)	(-2.06)	(2.64)	(1.50)
campscore_chg	0.060***	0.059***	0.058***	0.058***	0.058***	0.058***	0.058***	0.057***
	(11.61)	(10.31)	(10.28)	(10.99)	(11.03)	(10.34)	(10.49)	(10.43)
campscore_lag	0.030***	0.032***	0.032***	0.031***	0.031***	0.032***	0.030***	0.031***
	(11.46)	(10.46)	(10.38)	(11.75)	(11.74)	(10.17)	(11.01)	(10.84)
ejrating_lag	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.011***	-0.011***
	(-7.52)	(-6.56)	(-6.24)	(-7.60)	(-7.49)	(-6.59)	(-7.92)	(-7.77)
Constant	0.509***	0.534***	0.518***	0.515***	0.516***	0.540***	0.515***	0.523***
	(13.67)	(12.32)	(12.06)	(13.84)	(13.83)	(12.35)	(13.53)	(13.04)
Observations	24,431	23,819	24,268	28,526	28,526	23,682	22,192	22,192
R-squared	0.077	0.076	0.077	0.078	0.078	0.078	0.078	0.078
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel B: S&P Downgrades

	PI							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
res_adv	0.044*	0.020	0.027	0.004	0.001	0.064**	0.028	0.020
	(1.67)	(0.84)	(1.40)	(0.23)	(0.07)	(2.32)	(1.27)	(0.90)
res_fav	-0.005	0.007	0.008	0.003	0.003	0.011	-0.011	-0.010
	(-0.25)	(0.27)	(0.30)	(0.16)	(0.16)	(0.42)	(-0.53)	(-0.49)
resadv_PI	-0.017	0.020	0.015	0.065**	0.049	-0.065**	-0.041	-0.003
	(-0.55)	(0.85)	(0.47)	(2.04)	(1.56)	(-2.05)	(-1.23)	(-0.11)
PI	0.008*	0.000	-0.007**	-0.004	-0.006**	-0.014***	0.030***	-0.001
	(1.94)	(0.06)	(-1.96)	(-1.59)	(-2.05)	(-4.06)	(5.52)	(-0.43)
campscore_chg	0.026***	0.023***	0.023***	0.025***	0.025***	0.022***	0.023***	0.023***
	(8.87)	(7.42)	(7.03)	(8.79)	(8.81)	(6.87)	(8.36)	(8.25)
campscore_lag	0.024***	0.022***	0.022***	0.023***	0.023***	0.021***	0.020***	0.021***
	(12.73)	(11.95)	(11.60)	(13.06)	(13.06)	(11.80)	(11.06)	(11.43)
sprating_lag	-0.008***	-0.006***	-0.007***	-0.007***	-0.007***	-0.006***	-0.006***	-0.006***
	(-9.10)	(-7.56)	(-7.84)	(-8.73)	(-8.55)	(-7.71)	(-8.13)	(-7.78)
Constant	0.374***	0.352***	0.352***	0.367***	0.367***	0.352***	0.359***	0.381***
	(14.62)	(14.09)	(13.61)	(15.68)	(15.63)	(14.14)	(16.44)	(16.47)
Observations	25,224	24,416	24,889	29,347	29,347	24,280	22,192	22,192
R-squared	0.059	0.052	0.053	0.059	0.059	0.051	0.058	0.055
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Panel C: Difference between EJR and S&P downgrades (*downdiff*)

	PI							
VARIABLES	pin	tenure	varpay	score_oc4	score_oc5	option_oc	purch180	alpha180
res_adv	0.026	0.037	0.060**	0.028	0.049*	0.050	0.046*	0.006
	(0.95)	(0.94)	(2.26)	(1.05)	(1.73)	(1.57)	(1.89)	(0.19)
res_fav	-0.016	-0.027	-0.026	-0.036	-0.036	-0.040	-0.015	-0.015
	(-0.58)	(-0.82)	(-0.76)	(-1.36)	(-1.35)	(-1.24)	(-0.54)	(-0.53)
resadv_PI	0.018	0.005	-0.039	0.010	-0.031	-0.004	-0.001	0.072*
	(0.46)	(0.13)	(-0.86)	(0.24)	(-0.83)	(-0.09)	(-0.01)	(1.91)
PI	-0.023***	-0.005	0.020***	0.001	-0.005	0.005	-0.007	0.008**
	(-4.40)	(-1.01)	(4.37)	(0.26)	(-1.39)	(1.23)	(-0.86)	(2.03)
campscore_chg	0.035***	0.036***	0.036***	0.033***	0.033***	0.037***	0.034***	0.033***
	(8.99)	(8.64)	(8.58)	(8.17)	(8.18)	(8.53)	(7.64)	(7.56)
campscore_lag	0.008***	0.010***	0.011***	0.008***	0.008***	0.011***	0.009***	0.008***
	(5.80)	(6.39)	(6.75)	(6.30)	(6.28)	(6.58)	(6.34)	(5.99)
ejrmsp_lag	-0.026***	-0.024***	-0.024***	-0.024***	-0.024***	-0.023***	-0.022***	-0.022***
	(-10.85)	(-9.51)	(-9.64)	(-10.64)	(-10.64)	(-9.35)	(-9.18)	(-9.11)
Constant	0.125***	0.126***	0.123***	0.112***	0.117***	0.132***	0.106***	0.094***
	(8.05)	(7.10)	(7.05)	(8.24)	(7.95)	(7.31)	(6.77)	(6.23)
Observations	24,397	23,793	24,239	28,490	28,490	23,656	22,192	22,192
R-squared	0.036	0.035	0.036	0.033	0.033	0.035	0.033	0.034
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter	Firm & Quarter

Table 26
Conflicts of Interest, Private Information, and the Rating Response to Restatements

This table presents the results from linear probability models for three dependent variables: *ejrdown* (Panel A), *spdown* (Panel B), and *downdiff* (Panel C), all defined in Appendix A. These variables are regressed on *res_adv* and *res_fav*, indicator variables equal to one when the rated firm announces an adverse or favorable accounting restatement, respectively. It is the same model as that shown in Table 23, augmented with measures of private information (PI) and conflicts of interest (CI) as independent variables, both interacted with *res_adv*. For my hypothesis, the key coefficient is the triple interaction of the CI measure, PI measure, and *res_adv*. For brevity, only this coefficient is shown in the table. PI and CI variables are defined in the text and Appendix A. Control variables are defined in Appendix A. t-statistics are shown in parentheses and are calculated using standard errors clustered by firm and quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EJR downgrades

	CI						
PI	ltd	bbb	financial	propstd	presox	ewr6	indlevmed
pin	0.130	0.080	0.175***	0.042	0.082	-0.041	-0.070
	(1.57)	(1.21)	(3.81)	(0.45)	(0.61)	(-0.57)	(-0.82)
varpay	-0.042	0.026	-0.012	-0.098	-0.088	0.087	-0.024
	(-0.53)	(0.25)	(-0.20)	(-1.07)	(-0.56)	(0.96)	(-0.26)
tenure	0.102	0.065	-0.171***	-0.011	-0.144	0.189**	0.093
	(1.43)	(0.83)	(-3.09)	(-0.15)	(-1.51)	(2.48)	(1.01)
score_oc4	0.014	0.003	-0.113*	-0.012	0.030	0.124	0.250***
	(0.18)	(0.03)	(-1.68)	(-0.15)	(0.25)	(1.35)	(2.92)
score_oc5	0.007	0.094	-0.049	-0.024	-0.111	0.163*	0.130
	(0.09)	(0.98)	(-0.68)	(-0.36)	(-0.74)	(1.89)	(1.48)
option_oc	0.163**	0.046	0.001	-0.027	-0.080	0.107	-0.166**
	(2.00)	(0.58)	(0.02)	(-0.36)	(-0.52)	(1.31)	(-1.99)
purch180	-0.054	0.110	0.201***	-0.152*	0.249*	-0.116	0.112
	(-0.51)	(1.13)	(3.61)	(-1.78)	(1.85)	(-1.23)	(1.03)
alpha180	-0.056	-0.016	-0.219***	0.159*	-0.090	0.111	0.018
	(-0.72)	(-0.20)	(-4.30)	(1.84)	(-0.56)	(1.55)	(0.22)

Panel B: S&P Downgrades

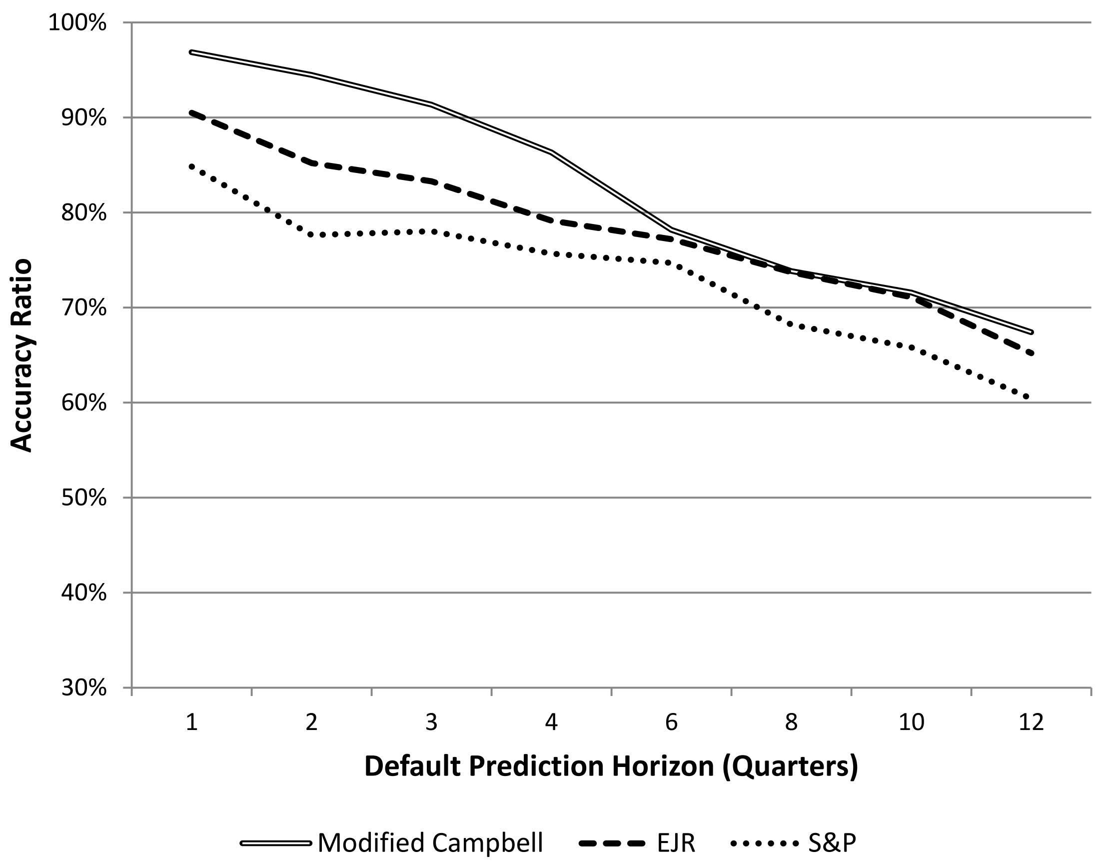
	CI						
PI	ltd	bbb	financial	propstd	presox	ewr6	indlevmed
pin	0.050	0.053	0.043	0.021	0.086	0.053	0.055
	(0.69)	(0.77)	(1.18)	(0.38)	(0.67)	(0.78)	(0.82)
varpay	-0.071	0.012	-0.011	-0.045	0.150	0.138***	-0.022
	(-1.30)	(0.26)	(-0.26)	(-0.73)	(0.98)	(2.61)	(-0.33)
tenure	0.026	0.097*	-0.064**	0.035	0.037	0.042	0.134**
	(0.42)	(1.86)	(-2.01)	(0.61)	(0.39)	(0.76)	(2.00)
score_oc4	0.082	0.048	-0.080**	0.002	0.145	0.086	0.024
	(1.46)	(0.91)	(-2.44)	(0.03)	(1.00)	(1.30)	(0.34)
score_oc5	0.036	0.018	-0.050	0.018	0.181*	0.085	0.039
	(0.76)	(0.33)	(-1.28)	(0.37)	(1.74)	(1.36)	(0.75)
option_oc	-0.039	0.031	0.054	-0.031	0.304*	0.057	0.017
	(-0.56)	(0.51)	(1.22)	(-0.70)	(1.86)	(0.89)	(0.25)
purch180	0.051	0.062	0.052	0.054	0.045	-0.061	-0.064
	(0.81)	(0.68)	(1.04)	(0.72)	(0.64)	(-0.92)	(-0.97)
alpha180	-0.016	0.048	-0.047	-0.004	0.109*	-0.029	-0.135***
	(-0.29)	(0.99)	(-1.45)	(-0.06)	(1.82)	(-0.56)	(-2.79)

Panel C: Difference between EJR and S&P downgrades (*downdiff*)

	CI						
PI	ltd	bbb	financial	propstd	presox	ewr6	indlevmed
pin	0.084	0.005	0.107*	0.019	0.030	-0.086	-0.107
	(1.06)	(0.06)	(1.91)	(0.21)	(0.22)	(-1.06)	(-1.05)
varpay	0.004	0.015	0.027	-0.065	-0.182	-0.050	0.012
	(0.05)	(0.15)	(0.41)	(-0.70)	(-1.64)	(-0.59)	(0.12)
tenure	0.076	-0.041	-0.087	-0.050	-0.160	0.161*	-0.037
	(0.79)	(-0.53)	(-1.56)	(-0.66)	(-1.30)	(1.89)	(-0.34)
score_oc4	-0.081	-0.046	-0.034	-0.017	-0.092	0.037	0.228**
	(-0.96)	(-0.56)	(-0.62)	(-0.19)	(-0.67)	(0.39)	(2.42)
score_oc5	-0.042	0.072	-0.000	-0.044	-0.277*	0.079	0.092
	(-0.63)	(0.95)	(-0.01)	(-0.70)	(-1.79)	(0.92)	(1.09)
option_oc	0.192**	0.004	-0.032	-0.006	-0.334***	0.070	-0.170*
	(2.10)	(0.05)	(-0.61)	(-0.07)	(-4.24)	(0.82)	(-1.75)
purch180	-0.108	0.043	0.105*	-0.209**	0.194	-0.057	0.172*
	(-1.27)	(0.44)	(1.86)	(-2.19)	(1.32)	(-0.49)	(1.95)
alpha180	-0.040	-0.061	-0.139***	0.168*	-0.207	0.136	0.154*
	(-0.50)	(-0.89)	(-3.07)	(1.75)	(-1.54)	(1.64)	(1.81)

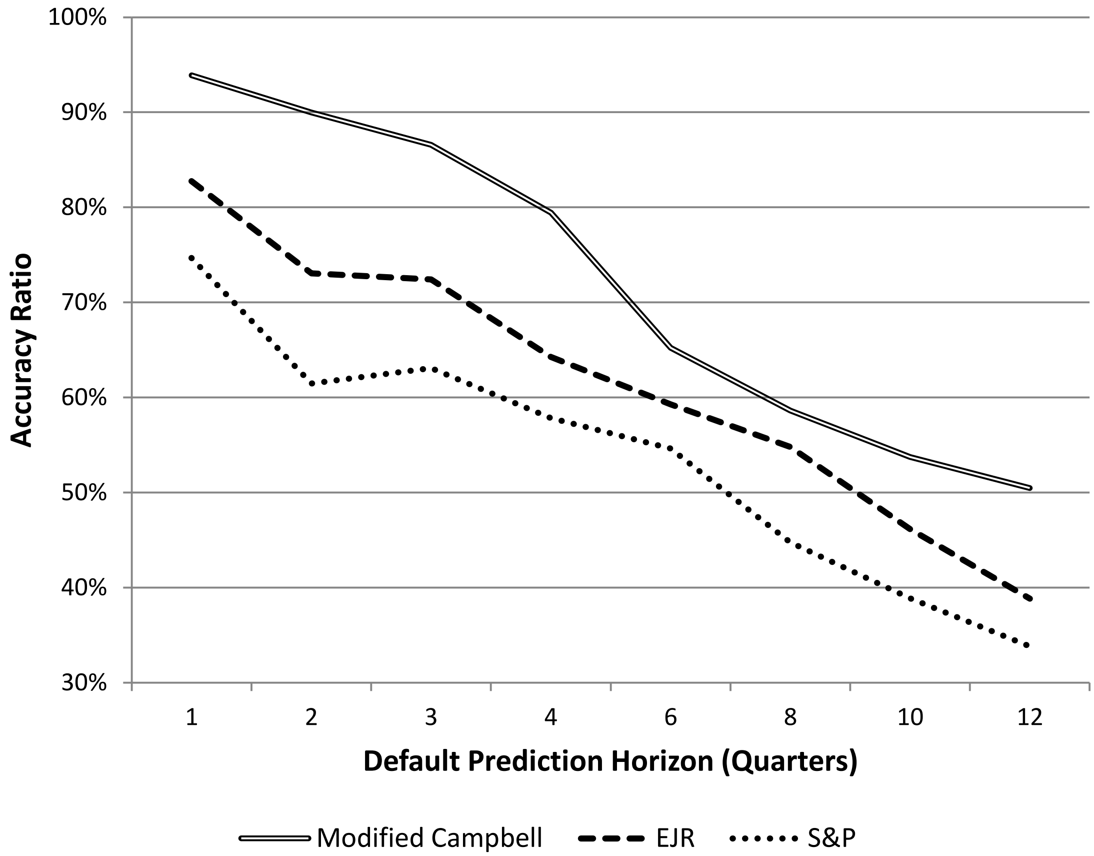
Figure 1
Accuracy Ratios for Default Prediction

Panel A: All rated firms



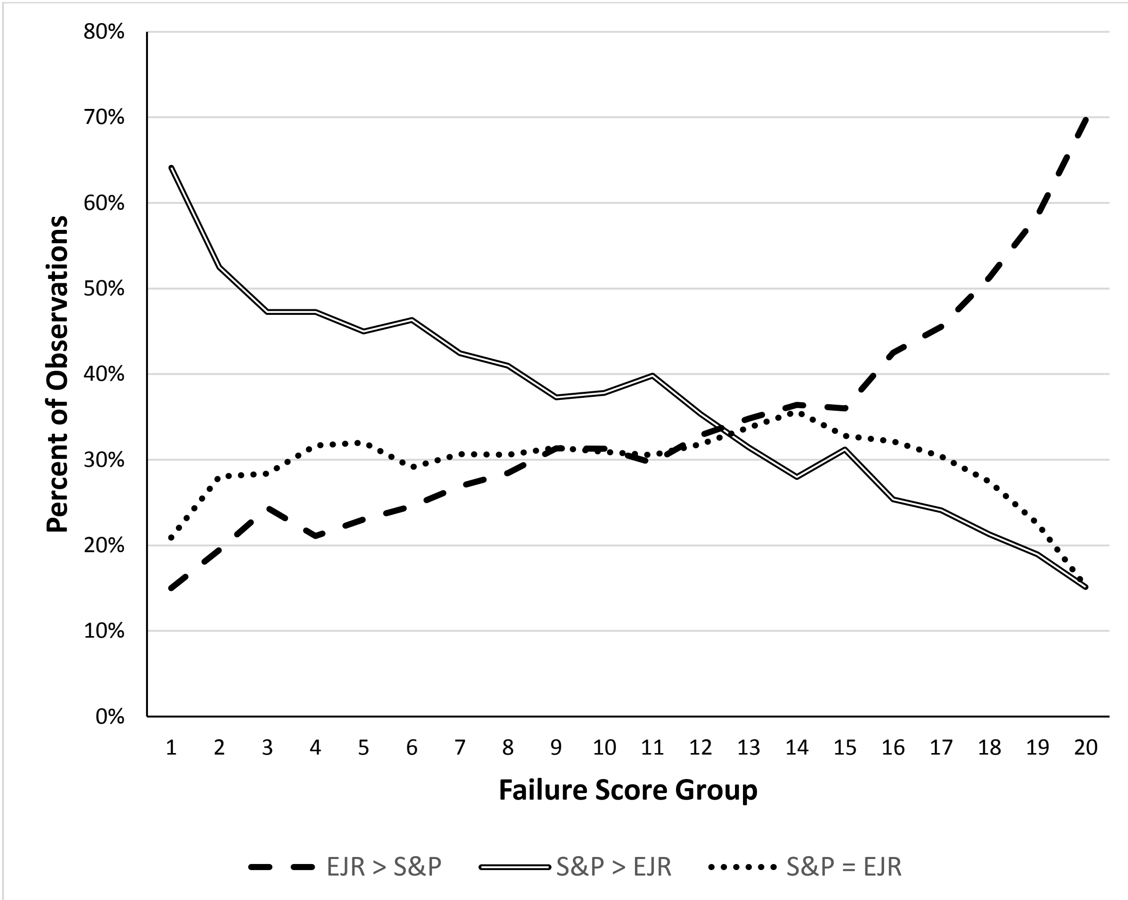
This figure graphs the accuracy ratios for the modified Campbell failure score, Egan-Jones ratings, and S&P ratings over default prediction horizons up to 12 quarters for the full sample of firms rated by both agencies. The data for this figure is found in Table 3.

Panel B: Speculative grade firms



This figure graphs the accuracy ratios for the modified Campbell failure score, Egan-Jones ratings, and S&P ratings over default prediction horizons up to 12 quarters for the sample of firms rated below investment grade by both agencies. The data for this figure is found in Table 3.

Figure 2
S&P and Egan-Jones Ratings Across Default Risk Groups



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