THE IMPACT OF THE DODD-FRANK ACT ON THE INFORMATINAL CONTENT OF CREDIT RATINGS

Abstract

In 2010, U.S. Congress passed the Dodd-Frank Act (Dodd-Frank) which outlined a series of regulatory reforms to the credit rating industry. We examine the extent to which the withdrawal of an exemption allowing the disclosure of nonpublic information to credit rating agencies affects the consensus across Moody's and S&P. As Fitch typically provides a third opinion after Moody's and S&P, we then test whether the elimination of ratings from regulatory requirements impacts the demand for Fitch ratings. Lastly, we quantify the informational content of Fitch ratings following Dodd-Frank by examining the market's response to ratings issued by Fitch. We find that the passage of Dodd-Frank leads to an increase in the issuance of split ratings for newly issued corporate bonds. Further, firms are less likely to seek a Fitch rating for newly issued bonds and Fitch ratings are less informative following Dodd-Frank with a smaller market impact on credit spreads.

1. Introduction

Credit ratings are widely used by investors and financial institutions in assessing firms' creditworthiness, compliance with investment mandates, and determining regulatory capital requirements. However, a large number of unanticipated credit rating downgrades of corporations and structured securities by credit rating agencies (CRAs) during the financial crisis has raised concerns about their objectivity and quality. As a result, there has been strong pressure on policy makers to regulate the credit rating industry, which has mostly relied on self-regulation. In response, in July 2010, U.S. Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) which outlined several reforms to the industry. We argue that a number of these reforms including increased penalties for issuing inaccurate ratings, prohibition of selective disclosure of material information to CRAs and the elimination of regulatory reliance on credit ratings have had a profound effect on the consensus of opinion across the CRAs and the demand for obtaining multiple ratings.

While studies have shown that regulatory reforms such as the Regulation Fair Disclosure (RegFD) Act, the Sarbanes-Oxley Act (SOX), and the Dodd-Frank Act change the behavior of CRAs and affect the informativeness, accuracy and timeliness of credit ratings (Jorion, Liu and Shi, 2005; Cheng and Neamtiu, 2009; Dimitrov, Palia and Tang, 2015) little is known about the effect of these regulatory changes on the consensus of opinion across CRAs. We hypothesize that forbidding the selective disclosure of material information to CRAs stipulated by the Dodd-Frank act will reduce the amount of private information available to CRAs and thus increase the dispersion of their ratings. Similarly, although extant literature examines the motivation for obtaining multiple ratings (see, for example Cantor and Packer, 1997; Jewell and Livingston, 1999;

Bongaerts, Cremers and Goetzmann, 2012; Chen and Wang, 2015), the impact of Dodd-Frank on the changes in the demand for multiple ratings remains relatively unexplored. We conjecture that eliminating the regulatory reliance on credit ratings reduces the demand for multiple ratings, particularly ratings issued by Fitch, which generally provides a third rating.

Using a database of newly issued bond ratings from 2006 to 2015, we show that following Dodd-Frank, Standard & Poor's (S&P) and Moody's are more likely to provide split ratings. These results are robust to numerous asset opaqueness proxies, market conditions, outliers and different measures of split ratings. These results are consistent with an increase in the dispersion of equity analysts' forecasts following the removal of selective disclosure of material information to equity analysts by the passage of the RegFD (Heflin, Subramanyam and Zhang, 2003; Bailey et al., 2003). Our findings complement those of Dimitrov, Palia and Tang (2015) who conclude that Dodd-Frank has an adverse effect on the quality of credit ratings.

In relation to our second hypothesis we find that firms are less likely to seek a Fitch rating following the passage of Dodd-Frank, and the decrease is more pronounced for firms with split ratings. We further show that Fitch ratings are less informative following Dodd-Frank with a smaller market impact on credit spreads.

Our results are of interest to regulators as they present early evidence of the effectiveness of the Dodd-Frank act and its impact on the demand for CRAs and in particular Fitch. These results are also relevant to firms and investors since split ratings affect bond yields and prices, which in turn influence a firm's investment policy (Livingston, Naranjo and Zhou, 2007).

The remainder of the paper is organized as follows. Section 2 reviews existing literature and formulates the hypotheses. Section 3 describes the data while Section 4 outlines the methodologies including the probit regressions and an event study. Section 5 presents empirical results. Concluding remarks are provided in Section 6.

2. Related Studies and Hypotheses Development

2.1 Impact of Dodd-Frank on the Consensus of opinion across CRAs

In July 2010 the U.S. Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) which enhanced the regulation of the credit rating industry. Dodd-Frank increased the legal and regulatory penalties for issuing inaccurate ratings (Section 932), eliminated regulatory reliance on credit ratings by financial institutions in determining capital adequacy ratios (Section 939A), and the extended the Regulation Fair Disclosure (Reg FD) Act to encompass CRAs (Section 939B).[1]

We hypothesize that removing the selective disclosure exemption granted to CRAs will impair the flow of information to CRAs and increase uncertainty about the creditworthiness of firms. Increased uncertainty will create more disagreements among CRAs, and lead to higher issuance of split ratings between Moody's and Standard & Poor's (S&P). This is consistent with Ederington (1986) who finds that credit analysts' subjectivity is one of the drivers of split ratings. Our hypothesis is motivated by the removal of selective nonpublic disclosure of material

[1] On October 23, 2000, the Securities and Exchange Commission (SEC) passed Reg FD that prohibits selective disclosure of material information to analysts and other investment professionals (SEC 2000). CRAs received blanket exemption from Reg FD (SEC 2000). Dodd-Frank revised Reg FD and removed the exemption for CRAs.

information to equity analysts mandated by the RegFD which decreased the informativeness of equity analysts' forecasts. Jorion, Liu and Shi (2005) show that the passage of RegFD strengthened the stock price response to bond credit rating changes while earnings became more difficult to forecast (Irani and Karamanou, 2003) and the dispersion of forecasts increased (Bailey et al., 2003). In effect RegFD provided CRAs, which were exempt, with an informational advantage which was removed by the passage of Dodd-Frank. Formally, our first hypothesis can be written as follows:

> **H_1**: The passage of Dodd-Frank increases the proportion of newly issued bonds with split ratings between Moody's and S&P.

2.2 The Impact of Dodd Frank on the Demand for Multiple Ratings

There are three commonly cited reasons why firms demand multiple ratings (see, for example Cantor and Packer, 1997; Bongaerts, Cremers and Goetzmann, 2012). First, the information production hypothesis states that an additional rating may reduce uncertainty about the credit quality of firms' bonds. Second, the rating shopping hypothesis argues that issuers will shop for a better rating if they receive a disappointing one. Lastly, the regulatory certification hypothesis proposes that a third rating plays the role of a tiebreaker that will differentiate between high yield (HY) and investment grade (IG) status.

A number of studies examine the impact of split ratings on bond yields. Sorensen (1979) shows that a second rating reduces (increases) interest costs if the second rating is higher (lower) than the first, indicating that obtaining a second rating is not worthwhile. Billingsley et al. (1985) conclude that the market prices the divergent opinion, but only considers the more conservative opinion. Liu and Moore (1987) and Perry, Liu and Evans (1988) find that the lower rating determines bond yields consistent with Billingsley et al. (1985). The above evidence indicates that firms have no cost based incentive to seek additional ratings.

Hsueh and Kidwell (1988) argue that the power of empirical tests in the earlier studies is limited due to the sample size. The authors demonstrate that a second rating, irrespective of whether it is same or different to the first, provides incremental information to the market and reduces interest costs. Similarly, Reiter and Ziebart (1991) provide evidence that split ratings contain information and the higher rating determines the bond yields. Both studies indicate that firms have an incentive to seek additional ratings.

By contrast, Cantor, Packer and Cole (1997) find that the market places the same value on both ratings when they are split. Similarly, Jewell and Livingston (1998) re-examine the results from Billingsley et al. (1985) and show that for split rated bonds both ratings affect bond yields. Further extensions by Livingston and Zhou (2010) show that information opacity is priced by bond investors. Specifically, the yield for split rated bonds is on average 7 basis points higher than non-split rated bonds with similar risk. Livingston, Wei and Zhou (2010) follow the methodology in Livingston and Zhou (2010) to test whether investors treat ratings from Moody's and S&P as equivalent but find that split rated bonds with a superior S&P rating have higher yields than bonds with a superior Moody's rating.

With respect to the information production hypothesis, Millon and Thakor (1985) and Lizzeri (1999) argue that multiple ratings that provide more independent and reliable information may convey a positive signal to the market. However, Partnoy (1999) suggests that in most cases, ratings contain no value-relevant information because information is already incorporated into the prices of debt securities. Similarly, by using Israeli credit rating announcements, Afik, Feinstein and Galil (2014) find that ratings have no information value.

Several theoretical papers (e.g. Skreta and Veldkamp, 2009; Bolton, Freixas and Shapiro, 2012; Sangiorgi and Spatt, 2017) develop models to motivate rating shopping. Empirically, Bakalyar and Galil (2014) provide empirical evidence for rating shopping in the Israeli market. Under regulatory certification, a third agency plays the role of tiebreaker of being classified as HY or IG status. Kisgen (2006, 2009) find that credit ratings affect capital structure decisions and leverage ratios, particularly when the rating is around the HY-IG boundary. Kisgen and Strahan (2010) find that Dominion Bond Rating Service ratings affect firm's debt cost of capital, and the effect is more pronounced at the HY-IG boundary. The empirical evidence indicates the importance of regulatory certification.

Another strand of literature has examined the role that Fitch ratings play in the three existing hypotheses. Cantor and Packer (1997) show that Fitch ratings are on average more optimistic than ratings assigned by Moody's and S&P (see also Beattie and Searle, 1992; Cantor and Packer, 1995). They find that firms are more likely to obtain a third rating if they are large and experienced issuers in the capital markets. Jewell and Livingston (1999) extend Cantor and Packer (1997)'s research and find that the bond market values the ratings of all three rating agencies, and firms with Fitch ratings have lower yields. However, they fail to find evidence to support the rating shopping hypothesis.

The competition among CRAs has also attracted a lot of attention. Becker and Milbourn (2011) discover that increased competition from Fitch affects the quality of ratings from the incumbents: inflated ratings by Moody's and S&P, decreased correlation between ratings and market-implied yields, and deteriorated ability of ratings to predict default. However, Bae, Kang and Wang (2015) show that the findings in Becker and Milbourn (2011) are largely driven by the endogeneity problem due to unobservable industry effects. They conclude that competition in the rating industry does not lead to rating inflation in the corporate bond market.

Bongaerts, Cremers and Goetzmann (2012) find that the likelihood of seeking a Fitch rating is strongly related to Moody's and S&P ratings being on opposite sides of the HY-IG boundary, which supports the regulatory certification hypothesis. For instance, a Fitch rating that raises an issue into the IG category has a credit spread that is on average 41 basis points lower than if the Fitch rating lowers the issue into the HY category. Chen and Wang (2015) find that U.S. firms exhibit a sharp increase in their demand for a third rating, generally provided by Fitch, after the 2005 Lehman index rule change (i.e. Lehman Brothers started to include Fitch as a third rating agency when assessing the bonds' rating classifications in 2005), especially when firms near a rating downgrade. Livingston and Zhou (2016) examine the marginal impact of Fitch ratings on the yields of bonds rated by Moody's and S&P, and find that Fitch ratings are not redundant but bring additional information to investors. Specifically, Fitch ratings reduce the yield premiums on information-opaque bonds by about 15 basis points.

However, since Dodd-Frank eliminates the reliance of financial institutions on credit ratings to quantify required capital, it reduces the regulatory advantage of higher ratings. Opp, Opp and Harris (2013) develop a theoretical framework to examine the variation in credit rating standards and argue that this fundamental regulatory change would result in a reduction of the regulatory advantage of higher ratings. Consequently we posit that the incentive to inflate ratings (by seeking an additional Fitch rating) will diminish following the passage of Dodd-Frank leading to a lower demand for, and a smaller market impact of a Fitch rating, which usually provides a third rating. This leads to our second set of hypotheses.

H2a: Firms are less likely to seek a Fitch rating after the passage of Dodd-Frank, especially when they have been assigned a split rating from Moody's and S&P.

H2b: A Fitch rating addition will lower bond yields, but its impact will diminish following the passage of Dodd-Frank.

3. Data

Bond characteristics and ratings are acquired from Mergent Fixed Income Securities Database. In line with Dimitrov, Palia and Tang (2015), our sample begins in January 2006 to avoid any ongoing market adjustments to the 2002 SOX and ends in December 2015. Following convention, ratings are converted to numerical rating codes (AAA=1 to C=21). Consistent with Livingston, Naranjo and Zhou (2007) and Chava, Ganduri and Ornthanalai (2016) we restrict our sample to senior unsecured newly issued U.S. domestic corporate debentures rated by both Moody's and S&P. Bonds with special features such as yankee bonds, putable bonds, exchangeable bonds, preferred stocks, asset-backed bonds, convertible bonds, zero-coupon bonds, bonds with non-fixed coupon and bonds with credit enhancements are excluded. We focus on initial ratings to ensure accuracy since the process for assigning initial ratings is more robust than the process for monitoring ratings (Chen and Wang, 2015). We further require that ratings are assigned within the first 30 days after issuance to avoid rating adjustment and unsolicited ratings (Chen and Wang, 2015).

The annual accounting company data including total assets, debt, intangibles, book value of equity, PPE, net income, and outstanding shares are sourced from COMPUSTAT. The data on annual highest and lowest daily closing prices and industry (GICS) code is also downloaded. Analyst data including the number of analysts and the standard deviation of forecast annual EPS is acquired from IBES. Issuing firms with fewer than three stock analysts are eliminated. CRSP value-weighted stock market index returns are obtained from CRSP. The corporate bond pricing data is obtained from the TRACE database.

Since our three hypotheses require different variables extracted from multiple databases merged using CUSIPs, the sample size differs across samples. The filtering process and sample construction for each hypothesis is discussed separately in the next section.

4. Methodology

In this section we discuss the methodology employed by our paper. To test whether Dodd-Frank changes the likelihood of observing split ratings and the demand for Fitch ratings we use a probit regression model. To test the impact of Fitch rating additions on credit spread changes of newly issued bonds we use an event study.

4.1 The Probit Regression Model

We model the discrete outcomes of split/non-split and with-Fitch/without-Fitch proposed by the variables with a probit model. The regression has the following form:

$$P_r(Y = 1 \mid \boldsymbol{X}) = \Phi(\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{\beta}) \tag{1}$$

where P_r denotes probability, Φ denotes the cumulative distribution function of the standard normal distribution. $\boldsymbol{X}$ is a vector of variables hypothesized to affect the dependent variable Y and $\boldsymbol{\beta}$ is the vector of the coefficients. This equation can be also expressed as a latent variable model:

$$Y^* = \boldsymbol{X^T\beta} + \varepsilon \;=\; \beta_1\ \textit{Dodd-Frank} \boldsymbol{+} \textstyle\sum_{\boldsymbol{i=2}}^{\boldsymbol{k}} \beta_i\, Control_i + \varepsilon \tag{2}$$

where $\varepsilon \sim N(0,1)$ and Y^* is the latent propensity that $Y = 1$:

$$Y = \begin{cases} 1 & Y^* > 0 \\ 0 & otherwise \end{cases} = \begin{cases} 1 & -\varepsilon < \boldsymbol{X^T\beta}. \\ 0 & otherwise. \end{cases} \tag{3}$$

The vector of the coefficients $\boldsymbol{\beta}$ is estimated by the Maximum Likelihood Estimation. However, since the coefficients do not quantify the impact of $\boldsymbol{X}$ on Y, we estimate the average marginal effect which quantifies the influence of variables on the probability of having a value of Y that equals one. To test the significance of the coefficients, we cluster standard errors by firms to control for the potential problems that a single firm issues multiple bonds following Dimitrov, Palia and Tang (2015) and Bongaerts, Cremers and Goetzmann (2012).

In hypothesis 1, the dependent variable, *Split Level*, equals one if Moody's rating differs from S&P rating, and zero otherwise. P_r estimated in the probit model denotes the probability of having a split rating. Similarly, the dependent variable in hypothesis 2, *Fitch*, equals one if there is a Fitch rating, and zero otherwise, consequently the P_r estimated in the model is the probability of having a Fitch rating. The main variable, *Dodd-Frank*, represents a dummy variable equal to one if the firm's bond is issued after Dodd-Frank, and zero otherwise. *Control* represents control variables including bond and firm characteristics.

While Ederington (1986) argues that split ratings occur due to random variations in judgment, Livingston, Naranjo and Zhou (2007) find that they are more prevalent for firms with opaque assets which are harder to value. Consequently, for hypothesis 1, we control for asset opaqueness with a number of accounting, opinion, size and rating-based proxies. The accounting-based proxies include; *Market-to-Book* ratio calculated as firm's market value of equity minus book value of equity plus total assets divided by total assets (Livingston, Naranjo and Zhou, 2007). This is a common measure of firm's growth opportunities. Larger growth opportunities are associated with younger firms in newer industries, which makes them more opaque (Mclaughlin, Safieddine and Vasudevan, 1998); and *Intangible Assets*, calculated as the amount of intangible assets divided by total assets. Higher intangible assets are associated with more opaque firms as they are difficult to value (Livingston, Naranjo and Zhou, 2007). The opinion-based proxies include *Stdev of Forecasts*, the standard deviation in analysts' earnings forecasts, defined as the standard deviation of forecast annual EPS divided by the stock price, and the number of stock analysts, *No. of Analysts*. Having more dispersion in opinions among analysts indicates that firms have assets opaqueness problems (Livingston, Naranjo and Zhou, 2007). Brennan and Subrahmanyam (1995) show that large analyst coverage results in more information flows to investors, which reduces firms' assets opaqueness. The opinion-based proxies are calculated using the analysts forecast data in the fiscal year of the bond issues. Other proxies include *Firm Size* calculated as the natural log of the market capitalization of equity as larger firms are less likely to have split ratings and *S&P Rating* since split ratings are also less common for bonds with higher ratings (Livingston, Naranjo and Zhou, 2007). To control for market conditions, *Market Return*, calculated as the one-year return of the CRSP value-weighted index prior to the bond issue and *Market Vol*, calculated as the rolling standard deviation of 252-trading day returns prior to the bond issue from the CRSP value-weighted index are added to the regression.

Starting with 1653 newly issued domestic bonds with complete data in MERGENT FISD, COMPUSTAT and IBES we follow Morgan (2002) and Livingston, Naranjo and Zhou (2007), and filter out 355 issues issued by financials and utilities because financials are more likely to have split ratings given the nature of their assets while utilities are highly regulated and are less likely to have split ratings. As some firms have multiple issues over a short period of time which are unlikely to convey additional information, 417 additional bond issues of the same issuing firm within the same month are also filtered out. The final sample contains 881 bond issues from 2006 to 2015. Panel A in Appendix A provides descriptive statistics for the sample before and after Dodd-Frank. A further partitioning into non-split and split subsamples in Panel B demonstrates that firms with larger size, fewer intangible assets, greater analysts' coverage and higher credit rating are less likely to have split bond ratings.

The correlation matrix in Appendix B shows that the *Split Level* is negatively significantly correlated with *Firm Size* and *No. of Analysts*, and positively significantly correlated with *Intangible Assets, S&P Rating* and *Market Return*.

For hypothesis 2, following Cantor and Packer (1997) and Bongaerts, Cremers and Goetzmann (2012), we control for firm characteristics and proxies for information uncertainty. Besides *Firm Size* and *Intangible Assets*, other firm characteristics include *Leverage* (long-term debt divided by total assets), *ROA* (net income divided by total assets), and *PPE* (tangibility of assets measured as PPE divided by total assets). Larger firm size may indicate that firms have been active in the public bond market, which is associated with a higher probability of having a Fitch rating. Firms with higher intangibility of assets, leverage and ROA may be associated with greater firm uncertainty, which is positively related to the likelihood of having a Fitch rating (Cantor and Packer, 1997). The proxies for information uncertainty include *Stdev of Forecasts* and *Rating Dispersion* (the absolute difference of ratings from Moody's and S&P). Firms with higher information uncertainty are more likely to demand a Fitch rating (Cantor and Packer, 1997; Bongaerts, Cremers and Goetzmann, 2012).

We start with 3513 bonds with complete data in Mergent FISD, COMPUSTAT and IBES. After filtering out 555 issues issued by financials and utilities[2], and further removing 1079 additional bond issues of the same issuing firm within the same month, the final sample contains 1879 issues from 2006 to 2015.[3] Panel A in Appendix C provides descriptive statistics for the sample before and after Dodd-Frank. The data is further partitioned into samples without and with Fitch ratings in Panel B Appendix C, where the Without-Fitch and With-Fitch subsamples are defined as the bonds (rated by both Moody's and S&P) that have no Fitch ratings and bonds that have Fitch ratings, respectively. Larger firms, and firms with lower leverage, lower tangibility of assets, and higher profitability are more likely to have a Fitch rating. The proxies for information uncertainty fail to show the expected association with the likelihood of observing a Fitch rating. The correlation matrix among the regression variables is reported in the Appendix D.

[2] Financials and utilities are excluded for consistency with the previous section. Also, Cantor and Packer (1997) show that financial and utilities are more likely to demand Fitch ratings (~40%), compared to firms in other industries (13.6%).

[3] As robustness, the additional issues are added back to the sample and issue characteristics such as *Issue-size*, *Redeem-ability*, and *Maturity* are controlled for. The results do not change. All results are available upon request.

4.2 Event Study

To examine the effect of Dodd-Frank on the informativeness of Fitch ratings, we investigate bond market's response to Fitch rating additions before and after Dodd-Frank using an event study. To control for market-wide movements in interest rates we follow Jewell and Livingston (1999), Bongaerts, Cremers and Goetzmann (2012), and Livingston and Zhou (2016) and utilize credit spreads. These are estimated by subtracting the maturity matched Treasury yield from the bond yield, calculated from the average of all trades on that day. As bonds are relatively illiquid we use a 10-day event window around the Fitch rating addition announcement day and follow Dimitrov, Palia and Tang (2015), to define the pre-event (post-event) credit spread as the credit spread on the day closest and prior to (following) the announcement date. Consistent with their study, we limit our sample to bonds with at least one trade during the event window.

5. Empirical Results

5.1 Dodd-Frank and Split Ratings

The probit regression results on the influence of Dodd-Frank on split ratings are presented in Table I. The results of Model 1 show that the coefficients for *Firm Size* and *Intangible Assets* are significant at 5% level. This is consistent with Livingston, Naranjo and Zhou (2007) that issuing firms with non-split ratings are larger and have fewer intangible assets. However, in contrast to their paper the results show that the market-to-book ratio, the standard deviation in EPS forecasts and the number of analysts are no longer significantly related to the probability of split ratings. When the ordinal rating variable, *S&P Rating*[4], is added to the regression in Model 2, the coefficient for *S&P Rating* is positive, but is not statistically significant. The coefficient for *Intangible Assets* is still significant at 5% level. The significance of the *Firm Size* coefficient reduces to 10% level, as the size effect has been partially captured by the *S&P Rating*, with larger firms generally obtaining a higher rating.

[Table I]

In Model 3 and Model 4, the Dodd-Frank dummy is added to the regressions. The coefficients for the control variables *Firm Size* and *Intangible Assets* are still significant at 5% level and have the expected signs. The coefficients for *Dodd-Frank* are 0.296 and 0.297, respectively, and are significant at 1% level in both models. This implies that after the passage of Dodd-Frank, the probability of having a split rating increases 11% (i.e. average marginal effect estimation), holding all else constant.[5] This is consistent with our first hypothesis that Dodd-Frank causes more disagreement across credit rating analysts.

Since Dodd-Frank's passage takes place in 2010, which is in the early stage of the recovery from the Global Financial Crisis (GFC), market variables (i.e. *Market Return* and *Market Vol*) are added to the regression (Model 5) to examine whether the results can be explained by market conditions rather than the passage of Dodd-Frank. The coefficient for *Dodd-Frank* in Model 5 is positive and significant (at 1% level), which means the results are robust to the inclusion of these

[4] Following Livingston, Naranjo and Zhou (2007), we use S&P ratings to control for the level of credit risk. Using Moody's ratings does not impact the results. All results are available upon request.

[5] $Marginal\ effect = Prob\left[Y = 1|\overline{\boldsymbol{x}}_{(\boldsymbol{d})}, d = 1\right] - Prob\left[Y = 1|\overline{\boldsymbol{x}}_{(\boldsymbol{d})}, d = 0\right]$ where d denotes binary independent variable and $\overline{\boldsymbol{x}}_{(\boldsymbol{d})}$ denotes the means of all the other variables in the model.

additional controls.[6] The results in Model 3 to Model 5 imply that it is more difficult to reach consensus among CRAs following Dodd-Frank, which extends the Reg FD to cover CRAs. These results complement the studies by Bailey et al. (2003) that there is more disagreement among analysts after the prohibition on selective disclosure to analysts.[7]

For robustness, following Livingston, Naranjo and Zhou (2007) a different measure of the split in ratings is used where *Split Level* equals zero if non-split, one if split by one notch, and two if split by multiple notches to capture the degree of rating split between Moody's and S&P (results from ordered probit models are presented in Appendix G). The results show that there is no significant difference compared to the main results in Table I, which means that the results are also robust to different definitions of split ratings.

5.2 Dodd-Frank and the Demand for Fitch Ratings

The probit regression results on the impact of Dodd-Frank on demand for Fitch ratings are presented in Table II. Model 1 includes all newly issued bonds irrespective of whether the rating was issued by Moody's or S&P. The coefficients for *Firm Size* and *PPE* are significant at 1% level while *Leverage* is significant at 10%. This suggests that large firms and firms with greater firm uncertainty are more likely to demand Fitch ratings, which is consistent with Cantor and Packer

[6] The authors acknowledge that as is the case with majority of studies on regulation, including Bailey et al. (2003), Heflin, Subramanyam and Zhang (2003), Jorion, Liu and Shi (2005), Cheng and Neamtiu (2009) and Dimitrov, Palia and Tang (2015), the reported effects could be coincidental. 'After all, we have only one event date. Other contemporaneous events, such as the economic downturn, could have conceivably led to our time-series results' (Jorion, Liu and Shi 2005). To mitigate this issue, this study starts from 2006 to avoid any ongoing market adjustments to SOX, and controls for the market movements (i.e. market returns and volatilities) to increase the confidence in attributing the reported effects to Dodd-Frank rather than macroeconomics factors.

[7] For robustness we also test the impact of the passage of RegFD and SOX on the consensus across CRAs and find, in line with our expectations, neither of the coefficients to be significant.

(1997). The coefficient on the main variable, *Dodd-Frank*, is -0.534 and significant at 1% level indicating that following the passage of Dodd-Frank, the likelihood of observing a Fitch rating decreases by 18% (i.e. average marginal effect estimation), holding all else constant. This is consistent with hypothesis 2a that firms are less likely to obtain a Fitch rating after the passage of Dodd-Frank.

Model 2 restricts the data to bonds that are rated by both Moody's and S&P. An interaction term of rating dispersion with the Dodd-Frank dummy is also included to examine whether split rated bonds are being influenced more by Dodd-Frank. The coefficient on *Rating Dispersion* is positive and significant at 10% level, which indicates that firms with information uncertainty are more likely to demand a Fitch rating. This is consistent with the information production hypothesis and the rating shopping hypothesis. The coefficients on the Dodd-Frank dummy and the interaction term are -0.36 and -0.229, respectively, which are significant at 1% level and 10% level, respectively. This indicates that firms are less likely to seek a Fitch rating after the passage of Dodd-Frank, particularly firms with split ratings. The results are consistent with hypothesis 2(c). Model 3 further excludes bonds where Fitch ratings are assigned prior to Moody's or S&P but there is no significant difference to the main results presented in Model 2. These results suggest that the increased legal and regulatory penalties for issuing over-optimistic ratings make CRAs lower their ratings, which diminishes the advantage of Fitch, thus demotivate issuers to demand Fitch ratings. In addition, the results imply that the elimination of regulatory reliance on credit ratings by Dodd-Frank reduces the incentives to seek Fitch ratings.[8]

[8] For robustness, we re-define the post-Dodd-Frank to start in July 2009 (i.e. first draft version of the legislation), July 2010 (i.e. the law's passage date), September 2011 (i.e. SEC rules effective date) and January 2013 (OCC rules effective date). The results are consistent with Dimitrov, Palia and Tang (2015) that the effects get stronger as the

For robustness, instead of using an interaction term of the rating dispersion with the Dodd-Frank dummy, Model 2 and Model 3 in Table II are re-estimated for split and non-split subsamples separately. For instance, the sample in Model 2 of Table II is partitioned into non-split rating subsample and split rating subsample in the first two models in Table III. According to the information production hypothesis and the rating shopping hypothesis, firms with split ratings are more likely to demand a third rating. Therefore, the sample with split rated bonds is expected to have stronger effects. Comparing the coefficients on *Dodd-Frank* in each model, it can be seen that the coefficients are more negative for the split rated bonds samples (i.e. -0.704 compared to -0.306, and -0.659 compared to -0.198) and the differences are statistically significant at 5% as shown in Panel B of Table III indicating that firms with split ratings are less likely to demand for Fitch ratings after Dodd-Frank, which is consistent with our second hypothesis.

[Table II]

[Table III]

In Appendix H we re-examine the probit regressions by adding financials and utilities back to the sample. The results show that there is no significant difference, compared to the main results in Table II. The coefficients on *Dodd-Frank* are still significant and have expected negative sign, which means that the results are robust to the inclusion of financials and utilities. The coefficients on *Rating Dispersion* are still positive but no longer significant. This can be explained by the

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uncertainty regarding the passage of Dodd-Frank is reduced and the rules are implemented gradually. All results are available upon request.

increased likelihood of Fitch ratings in financials and utilities as shown in Cantor and Packer (1997) and Becker and Milbourn (2011).

5.3 Credit Spread Response to Fitch Rating Additions

This section examines the credit spread changes surrounding the Fitch rating additions announcements prior to and following the passage of Dodd-Frank. To select uncontaminated events, the sample is restricted to newly issued bonds rated by both Moody's and S&P where Fitch provides the third rating at least one day after Moody's and S&P. Consistent with Dimitrov, Palia and Tang (2015), bonds are required to have at least one trade in the 5 days prior to and 5 days following the event day, to calculate the credit spread changes. Our final sample contains 838 Fitch credit events.

Table IV reports the means, medians, and test for differences statistics for the event study analysis. It can be seen that bonds with a Fitch rating addition experience lower credit spreads both before and after Dodd-Frank. These results support Jewell and Livingston (1999) and Livingston and Zhou (2016), who show that the market attaches value to Fitch ratings and firms with Fitch ratings have lower yields. These findings further imply that firms seek Fitch ratings when they thought they are under-rated by Moody's and S&P, and on average Fitch assigns higher ratings than Moody's and S&P (Cantor and Packer, 1997; Jewell and Livingston, 1999; Bongaerts, Cremers and Goetzmann, 2012; Chen and Wang, 2015).

[Table IV]

In terms of the magnitude, this event study finds that the mean (median) impact of a Fitch rating addition on credit spread changes decreases from 6.040 (2.802) basis points to 0.684 (1.387) basis points following Dodd-Frank, even though the average credit rating changes from A to A- which is in line with Dimitrov, Palia and Tang (2015) that CRAs issue more conservative ratings following the passage of Dodd-Frank to protect their reputation in response to the increased legal and regulatory penalties for issuing inaccurate ratings. Also, the tests for differences show that after Dodd-Frank the credit spreads respond less to Fitch events, and the results are statistically significant. The results are consistent with hypothesis 2b that after Dodd-Frank the impact of Fitch rating addition on credit spread changes diminishes. These results support the reputation hypothesis and findings in Dimitrov, Palia and Tang (2015) that the stock and bond market reaction to downgrade is weaker after Dodd-Frank.

Specifically, the reduced optimism from Fitch ratings leads to a reduced demand for Fitch ratings and a diminished informativeness of Fitch ratings. These results further complement the theoretical framework in Opp, Opp and Harris (2013) by providing empirical evidence that the elimination of regulatory reliance on credit ratings by Dodd-Frank results in a reduction of the regulatory advantage of higher ratings so that the market impact of higher ratings diminishes.

6. Conclusion

We present evidence that the passage of Dodd-Frank affects split bond ratings between Moody's and S&P, the demand for Fitch ratings and credit spread response to Fitch rating additions. Specifically, using newly issued U.S. bond ratings from 2006 to 2015, we find that the passage of Dodd-Frank increases the proportion of split ratings between Moody's and S&P. The results are robust to asset opaqueness proxies, market conditions, outliers and different split measures. This work supports Dimitrov, Palia and Tang (2015) that Dodd-Frank has an adverse effect on the quality of credit ratings. Also, we shed more light on the impact of regulations on financial analysts' behavior, and complement previous studies (e.g. Bailey et al., 2003) which examine the impact of Reg FD on analysts' forecasts and conclude that there is more disagreement among analysts after the prohibition of selective disclosure to analysts. Specifically, the empirical evidence indicates that removing CRA's exemption from Reg FD, which has been documented as an informational advantage of CRAs by Jorion, Liu and Shi (2005), could lead to an impaired flow of information to CRAs, and result in difficulties in reaching consensus ratings among CRAs. Besides the academic contribution, this work is relevant to practitioners. We show that the passage of Dodd-Frank increases the propensity of CRAs to issue split ratings, which can have an impact on future rating changes, and in turn affect bond yields and prices as found by Livingston, Naranjo and Zhou (2008).

In addition, this work shows that firms are less likely to seek a Fitch rating for newly issued bonds, and the impact of Fitch rating additions on credit spread changes diminishes following Dodd-Frank, especially for bonds with split ratings. The results indicate that Fitch ratings are less informative, and are used less by issuers after Dodd-Frank, which contributes to the current literature in several aspects. First, this work contributes to current studies (see Cantor and Packer, 1997; Jewell and Livingston, 1999; Bongaerts, Cremers and Goetzmann, 2012) regarding existing hypotheses (i.e. the information production hypothesis and the rating shopping hypothesis) about multiple ratings. Specifically, the results prove that the market attaches value to Fitch ratings and firms with Fitch ratings have lower yields, which confirms the findings in Jewell and Livingston (1999). Also, this work complements the findings and theoretical framework in Dimitrov, Palia and Tang (2015) and Opp, Opp and Harris (2013) by providing additional evidence regarding the impact of Dodd-Frank on CRAs. Specifically, the results suggest that the increased legal and regulatory penalties for issuing inaccurate ratings and the elimination of regulatory reliance on credit ratings eliminate the advantage of Fitch ratings, thus undermining the rationale in obtaining a Fitch rating and reducing the market impact of Fitch ratings.

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Table I. Asset Opaqueness and Split Ratings: Probit Regressions of Split Rating

This table reports the results of probit regressions of the level of splits on proxies for asset opaqueness, bond ratings and the Dodd-Frank dummy between Jan 2006 to Dec 2015. The sample begins in 2006 to avoid any ongoing market adjustments from the 2002 Sarbanes-Oxley Act. Following previous studies issues from financial and utilities are excluded. The upper number in each cell reports the coefficients and the number in brackets reports the *z-value*. Standard errors are clustered by firms to control for potential problems with multiple bond issues by the same firm. Model 1 and Model 2 follow Livingston, Naranjo and Zhou (2007) and use the five proxies for asset opaqueness and the S&P Rating (ranging from one to twenty-one) variable in the regressions. Model 3 and Model 4 include the variable of interest, Dodd-Frank dummy, to the regression. Since Dodd-Frank's passage takes place in 2010, which is in the early stage of the recovery from the GFC, therefore in Model 5 examines whether the results can be explained by market conditions rather than the passage of Dodd-Frank. Specifically, In Model 5, *Market Return*, which is calculated as the one-year return of the CRSP value-weighted index prior to the bond issue, and *Market Vol*, which is calculated as the rolling standard deviation of 252-trading day returns from the CRSP value-weighted index are added to the regression. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Firm Size	-0.150**	-0.125*	-0.140**	-0.141**	-0.131*
	(-2.492)	(-1.784)	(-2.342)	(-2.031)	(-1.872)
Market to Book	-0.061	-0.033	-0.048	-0.048	-0.026
	(-0.625)	(-0.318)	(-0.488)	(-0.468)	(-0.243)
Intangible Assets	0.758**	0.769**	0.743**	0.742**	0.734**
	(2.441)	(2.467)	(2.392)	(2.388)	(2.367)
Stdev of Forecasts	-0.606	-0.737	-0.662	-0.659	-0.564
	(-0.802)	(-0.943)	(-0.844)	(-0.821)	(-0.691)
No. of Analysts	-0.003	-0.003	-0.007	-0.007	-0.007
	(-0.430)	(-0.442)	(-0.900)	(-0.902)	(-0.907)
S&P Rating		0.016		-0.000	0.002
		(0.672)		(-0.020)	(0.073)
Market Return					0.395
					(1.431)
Market Vol					12.618
					(1.165)
Dodd-Frank			0.296***	0.297***	0.325***
			(2.881)	(2.818)	(2.786)
#Obs	881	881	881	881	881
Pseudo R-squared	0.028	0.029	0.037	0.037	0.039

Table II. Split Ratings and Fitch Demand: Probit Regressions of Fitch Rating

This table reports the results of probit regressions of a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015, excluding firms in the financial and utilities industries. The upper number in each cell reports the coefficients and the number in brackets reports the *z-value*. Standard errors are clustered by firms to control for potential problems with multiple bond issues by the same firm. The results depict: all newly issued bonds (Model 1), newly issued bonds rated by both Moody's and S&P within the first thirty days after issuance (Model 2), and bonds with Fitch ratings assigned earlier than Moody's or S&P excluded (Model 3). ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	Model 1	Model 2	Model 3
Firm size	0.348***	0.436***	0.392***
	(7.981)	(6.467)	(5.748)
Intangible Assets	-0.525	-0.548	-0.325
	(-1.640)	(-1.200)	(-0.705)
Leverage	0.653*	0.641	0.718
	(1.915)	(1.384)	(1.537)
ROA	-0.290	-0.667	-0.389
	(-0.505)	(-0.966)	(-0.519)
PPE	-0.472***	-0.349	-0.341
	(-2.824)	(-1.587)	(-1.492)
Stdev of Forecasts	-0.083	0.529	0.659
	(-0.473)	(0.610)	(0.850)
Rating Dispersion		0.167*	0.218**
		(1.655)	(2.064)
Rating Dispersion*Dodd-Frank		-0.229*	-0.261**
		(-1.935)	(-2.121)
Dodd-Frank	-0.534***	-0.360***	-0.260*
	(-7.237)	(-2.935)	(-1.901)
#Obs	1,879	903	804
Pseudo R-squared	0.109	0.127	0.105

Table III. Split Ratings and Fitch Demand

This table reports the results of probit regressions of the Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015, excluding firms in the financial and utilities industries. The upper number in each cell reports the coefficients and the number in brackets reports the *z-value*. Standard errors are clustered by firms to control for potential problems with multiple bond issues by the same firm. In Panel A, Model 2 and Model 3 in Table II are re-estimated and instead of using the interaction term of the rating dispersion with the Dodd-Frank dummy the sample is partitioned into non-split rated bonds (Model 1 and Model 3) and split rated bonds (Model 2 and Model 4). Panel B reports the coefficient difference of the Dodd-Frank dummy and the corresponding *z-value* following Clogg, Petkova and Haritou (1995). ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

Panel A	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Firm size	0.423***	0.437***	0.359***	0.412***
	(5.559)	(4.947)	(4.609)	(4.464)
Intangible Assets	-0.835	-0.218	-0.568	-0.056
	(-1.412)	(-0.372)	(-0.942)	(-0.096)
Leverage	1.207**	-0.051	1.105*	0.241
	(2.113)	(-0.073)	(1.903)	(0.346)
ROA	-0.786	-0.524	-0.393	-0.369
	(-0.973)	(-0.493)	(-0.459)	(-0.331)
PPE	-0.469*	-0.197	-0.455	-0.197
	(-1.669)	(-0.639)	(-1.527)	(-0.633)
Stdev of Forecasts	0.799	-0.643	0.848	-0.18
	(0.784)	(-0.367)	(0.961)	(-0.106)
Dodd-Frank	-0.306**	-0.704***	-0.198	-0.659***
	(-2.373)	(-5.073)	(-1.373)	(-4.547)
#Obs	446	457	385	419
Pseudo R-squared	0.105	0.153	0.080	0.132

Panel B	**Model 1 vs Model 2**	**Model 3 vs Model 4**
Coefficient Difference	0.398**	0.461**
	(2.100)	(2.255)

Table IV. Bond Credit Spread Response to The Fitch Rating Addition before and after Dodd-Frank

This table shows credit spread changes (bond yields changes in excess of risk-free rate changes) surrounding the Fitch rating additions before and after Dodd-Frank. Before (After) Dodd-Frank is the period between January 2, 2006 and July 21, 2010 (July 22, 2010 and December 31, 2015). Mean and median are expressed as basis points. Mean and median differences are tested using the *t* and Wilcoxon two-sample tests (statistics are presented in brackets), respectively. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

		Fitch inclusion	
Full sample			
	Obs.	**Mean**	**Median**
Before Dodd-Frank	347	-6.040**	-2.802***
After Dodd-Frank	491	-0.684	-1.387***
Difference (Before - After)		-5.356*	-1.415**
		(-1.79)	(-1.91)

Appendix

Appendix A Descriptive Statistics for Controls Affecting Split Ratings

This table reports the descriptive statistics for all variables which have an influence on the likelihood of observing split ratings. The sample contains newly issued domestic bonds with complete data in MERGENT FISD, COMPUSTAT and IBES between Jan 2006 and Dec 2015, excluding financials and utilities according to GICS classification. In Panel A, the sample is partitioned into Before and After Dodd-Frank subsamples. The period prior to (following) Dodd-Frank is defined as January 2, 2006 to July 21, 2010 (July 22, 2010 to December 31, 2015). Panel B partitions data into Split and Non-Split subsamples. The Whole Sample includes all bonds being rated by Moody's and S&P. The Non-Split and Split subsamples include bonds with no split ratings and with split ratings, respectively.

Panel A	Before Dodd-Frank						After Dodd-Frank					
	#Obs	Mean	Median	Min	Max	Std	#Obs	Mean	Median	Min	Max	Std
Firm Size	375	9.450	9.467	6.259	12.527	1.259	506	9.525	9.429	5.950	13.438	1.337
Market to Book	375	1.686	1.527	0.670	5.931	0.634	506	1.676	1.516	0.790	5.619	0.633
Intangible Assets	375	0.239	0.183	0	0.824	0.197	506	0.236	0.198	0	0.854	0.212
Stdev of Forecasts	375	0.010	0.004	0	0.503	0.036	506	0.015	0.004	0	0.976	0.066
No. of Analysts	375	20.691	20	3	43	8.936	506	24.672	24	3	62	11.101
S&P Rating	375	8.408	8	1	17	2.968	506	9.544	9	1	18	3.447
Moody's Rating	375	8.660	8	1	18	2.965	506	9.857	9	1	19	3.630
Market Return	375	-0.016	-0.024	-0.472	0.781	0.285	506	0.143	0.149	-0.038	0.346	0.080
Market Vol	375	0.017	0.014	0.006	0.029	0.008	506	0.011	0.011	0.006	0.015	0.003

Panel B	Mean			Median		
	Whole Sample	Non-Split	Split	Whole Sample	Non-Split	Split
Firm Size	9.493	9.685	9.311	9.448	9.700	9.143
Market to Book	1.680	1.701	1.661	1.517	1.562	1.474
Intangible Assets	0.237	0.216	0.257	0.193	0.162	0.230
Stdev of Forecasts	0.013	0.014	0.012	0.004	0.004	0.003
No. of Analysts	22.977	24.254	21.761	22	22	22
S&P Rating	9.060	8.693	9.410	9	9	9
Moody's Rating	9.346	8.693	9.969	9	9	9
Market Return	0.076	0.061	0.090	0.128	0.127	0.130
Market Vol	0.014	0.014	0.013	0.012	0.012	0.012
#Obs	881	430	451	881	430	451

Appendix B Correlation Matrix – Controls Affecting Split Ratings

The table presents the correlations among the regression variables for hypothesis 1 along with their *p*-values in italics below coefficients.

	Split Level	Firm Size	Market to Book	Intangible Assets	Stdev of Forecasts	No. of Analysts	S&P Rating	Market Return
Firm Size	-0.141							
	0.000							
Market to Book	-0.029	0.024						
	0.386	*0.483*						
Intangible Assets	0.099	0.168	0.029					
	0.003	*0.000*	*0.388*					
Stdev of Forecasts	-0.022	-0.088	-0.143	-0.127				
	0.524	*0.009*	*0.000*	*0.000*				
No. of Analysts	-0.114	0.517	0.210	-0.068	0.002			
	0.001	*0.000*	*0.000*	*0.043*	*0.959*			
S&P Rating	0.109	-0.624	-0.367	-0.162	0.240	-0.370		
	0.001	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*		
Market Return	0.069	-0.045	0.041	0.034	0.011	0.062	0.163	
	0.040	*0.180*	*0.228*	*0.313*	*0.755*	*0.068*	*0.000*	
Market Vol	-0.036	0.008	-0.124	-0.013	-0.059	-0.078	-0.151	-0.713
	0.281	*0.806*	*0.000*	*0.697*	*0.083*	*0.021*	*0.000*	*0.000*

Appendix C Descriptive Statistics for Controls Affecting Fitch Demand

This table reports the descriptive statistics for all variables which have an influence on demand for Fitch ratings. The sample contains newly issued domestic bonds with complete data in MERGENT FISD, COMPUSTAT and IBES between Jan 2006 and Dec 2015, excluding financials and utilities according to GICS classification. In Panel A, the sample is partitioned into Before and After Dodd-Frank subsamples. The period prior to (following) Dodd-Frank is defined as January 2, 2006 to July 21, 2010 (July 22, 2010 to December 31, 2015). Panel B partitions data into Without-Fitch and With-Fitch subsamples. The Whole Sample includes all newly issued bonds irrespective of whether the rating was issued by Moody's or S&P. The Without-Fitch and With-Fitch subsamples include bonds with no Fitch ratings and Fitch ratings, respectively.

Panel A	**Before Dodd-Frank**						**After Dodd-Frank**					
	#Obs	**Mean**	**Median**	**Min**	**Max**	**Std**	**#Obs**	**Mean**	**Median**	**Min**	**Max**	**Std**
Firm Size	679	9.360	9.349	5.917	13.587	1.289	1200	9.451	9.396	5.950	13.438	1.392
Intangible Assets	679	0.225	0.182	0	0.824	0.194	1200	0.242	0.202	0	0.869	0.211
Leverage	679	0.285	0.249	0	1.548	0.161	1200	0.326	0.293	0.045	1.460	0.172
ROA	679	0.057	0.059	-0.589	0.327	0.067	1200	0.045	0.052	-1.329	0.349	0.099
PPE	679	0.651	0.611	0	2.746	0.430	1200	0.665	0.587	0	4.620	0.507
Stdev of Forecasts	679	0.019	0.003	0	5.72	0.222	1200	0.017	0.003	0	5.841	0.176

Panel B	**Mean**			**Median**		
	Whole Sample	**Without Fitch**	**With Fitch**	**Whole Sample**	**Without Fitch**	**With Fitch**
Firm Size	9.499	9.092	9.991	9.471	9.026	10.010
Intangible Assets	0.232	0.225	0.241	0.187	0.164	0.214
Leverage	0.294	0.308	0.276	0.257	0.276	0.245
ROA	0.048	0.044	0.052	0.056	0.050	0.061
PPE	0.662	0.699	0.617	0.620	0.671	0.550
Stdev of Forecasts	0.013	0.013	0.013	0.004	0.004	0.003
Rating Dispersion	0.670	0.703	0.631	1	1	0
Rating Dispersion*Dodd-Frank	0.423	0.499	0.330	0	0	0
#Obs	903	495	408	903	495	408

Appendix D Correlation Matrix– Variables Affecting Fitch Demand

The table presents the correlations among the regression variables for hypothesis 2 along with their *p*-values in italics below coefficients.

	Fitch	Firm Size	Intangible Assets	Leverage	ROA	PPE	Stdev of Forecasts	Rating Dispersion
Firm Size	0.347							
	0.000							
Intangible Assets	0.031	0.148						
	0.271	*0.000*						
Leverage	-0.098	-0.331	-0.034					
	0.003	*0.000*	*0.302*					
ROA	0.048	0.173	0.051	-0.258				
	0.147	*0.000*	*0.124*	*0.000*				
PPE	-0.082	-0.103	-0.534	0.373	-0.315			
	0.014	*0.002*	*0.000*	*0.000*	*0.000*			
Stdev of Forecasts	0.002	-0.086	-0.123	0.137	-0.226	0.092		
	0.952	*0.010*	*0.000*	*0.000*	*0.000*	*0.006*		
Rating Dispersion	-0.044	-0.142	0.066	0.054	-0.010	-0.084	-0.026	
	0.183	*0.000*	*0.047*	*0.106*	*0.758*	*0.012*	*0.427*	
Rating Dispersion*Dodd-Frank	-0.117	-0.048	0.056	0.084	-0.030	-0.043	-0.037	0.715
	0.000	*0.146*	*0.091*	*0012*	*0.366*	*0.201*	*0.263*	*0.000*

Appendix G Probit Regressions of Split Rating: Different Split Measure

This table reports the results of probit regressions of the level of splits on proxies for asset opaqueness, bond ratings and the Dodd-Frank dummy between Jan 2006 to Dec 2015. Following previous studies, financials and utilities are excluded. The upper number in each cell reports the coefficients and the number in brackets reports the *z-value*. Standard errors are clustered by firms to control for potential problems with multiple bond issues by the same firm. Following Livingston, Naranjo and Zhou (2007), a different measure of the split in ratings is used where *Split Level* equals zero if non-split, one if split by one notch, and two if split by multiple notches. See Table I for descriptions of Model 1 to Model 5. ***, **, * represent significance beyond the 1^{st}, 5^{th}, and 10^{th} percentile levels, respectively.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Firm Size	-0.125*	-0.132*	-0.116*	-0.147**	-0.139*
	(-1.902)	(-1.760)	(-1.787)	(-1.989)	(-1.846)
Market to Book	0.039	0.030	0.052	0.018	0.034
	(0.378)	(0.283)	(0.504)	(0.167)	(0.301)
Intangible Assets	0.568**	0.566**	0.553**	0.540**	0.530**
	(2.163)	(2.152)	(2.101)	(2.052)	(2.020)
Stdev of Forecasts	-0.638	-0.596	-0.667	-0.498	-0.377
	(-0.963)	(-0.892)	(-0.962)	(-0.716)	(-0.525)
No. of Analysts	-0.004	-0.004	-0.007	-0.008	-0.008
	(-0.551)	(-0.549)	(-0.930)	(-0.966)	(-0.995)
S&P Rating		-0.005		-0.021	-0.020
		(-0.208)		(-0.863)	(-0.821)
Market Return					0.487*
					(1.893)
Market Vol					13.954
					(1.415)
Dodd-Frank			0.257***	0.283***	0.312***
			(2.836)	(3.160)	(2.977)
#Obs	881	881	881	881	881
Pseudo R-squared	0.017	0.017	0.023	0.024	0.026

Appendix H Probit Regressions of Fitch Rating for All Industries

This table reports the results of probit regressions of the Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015. The upper number in each cell reports the coefficients and the number in brackets reports the *z-value*. Standard errors are clustered by firms to control for potential problems with multiple bond issues by the same firm. See Table II for descriptions of Model 1, Model 2 and Model 3. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	Model 1	Model 2	Model 3
Firm size	0.230***	0.308***	0.274***
	(7.217)	(5.776)	(5.231)
Intangible Assets	-0.159	-0.089	0.054
	(-0.675)	(-0.235)	(0.143)
Leverage	0.444	0.377	0.381
	(1.550)	(0.849)	(0.832)
ROA	0.478	0.118	0.275
	(0.865)	(0.175)	(0.368)
PPE	-0.212*	-0.087	-0.125
	(-1.692)	(-0.459)	(-0.640)
Stdev of Forecasts	-0.048	0.725	0.831
	(-1.612)	(1.358)	(1.415)
Rating Dispersion		0.109	0.161
		(1.177)	(1.641)
Rating Dispersion*Dodd-Frank		-0.197*	-0.239**
		(-1.803)	(-2.054)
Dodd-Frank	-0.478***	-0.327***	-0.210*
	(-7.561)	(-2.984)	(-1.708)
#Obs	2,302	1,080	949
Pseudo R-squared	0.076	0.092	0.076