Regulatory Reform, Multiple Credit Ratings and the Quality of the Corporate Information Environment

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Abstract

This paper examines the change in the regulatory use of multiple credit ratings after the Dodd-Frank Act (Dodd-Frank). We find that post Dodd-Frank reform firms are less likely to demand a third rating, which is typically provided by Fitch. These ratings become less informative with a much weaker market impact on credit spreads for firms on opposite sides of the high yield (HY) - investment grade (IG) boundary. Moreover, firms with reduced external monitoring from a third rating agency systematically manage their earnings more and have higher cash flow and sales volatilities post Dodd-Frank. Overall, the results shed light on the unintended consequences of Dodd-Frank on harming competition within the ratings industry and the quality of the corporate information environment.

Keywords: regulation, Dodd-Frank, credit ratings, bonds, earnings management, corporate risk-taking

JEL Classification: G01, G24, G28, G32, G34

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1. Introduction

Credit rating agencies (CRAs) have long provided credit ratings for investors, regulators, and financial institutions as an indicator to assess firms' credit risk and to determine regulatory capital requirements. However, CRAs have suffered significant reputational damage following their well-publicized failures to recognize the risks of structured securities in the lead up to the 2008-2009 global financial crisis. Their overly optimistic assessment of mortgage-related securities helped to fuel mortgage debt finance, increased risk taking by financial institutions and significantly contributed to the financial crisis.[1] In direct response to the financial crisis, in July 2010, the U.S. Congress strengthened the regulation of the financial services industry with the passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank). Dodd-Frank established greater oversight of CRAs, in particular, increased legal and regulatory penalties for issuing inaccurate ratings (Section 932 and 933) and reduced the regulatory reliance on credit ratings (Section 939). In this paper, we examine how the passage of Dodd-Frank in reforming the financial architecture has changed the demand for and the information content of multiple credit ratings.

The extant literature finds that while multiple ratings may be acquired for numerous reasons, regulatory certification is the most common (see, for example, Bongaerts, Cremers and Goetzmann, 2012; Chen and Wang, 2017). Investors generally only require one or at most two ratings, but issuers frequently obtain multiple ratings (Baker and Mansi, 2002). Most large U.S. corporate bonds are rated by Moody's and Standard and Poor's (S&P), with the lower rating

[1] Between 2000 and 2007, Moody's rated nearly 45,000 mortgage-related securities as AAA compared to six private-sector companies in the U.S. that carried AAA rating in early 2010. 83% of the mortgage securities rated AAA in 2006 were ultimately downgraded (Financial Crisis Inquiry Commission, 2011).

typically used for bond classification (Bongaerts et al., 2012). However, since the Lehman Brothers index started including Fitch as a third rating agency for assessing the rating classifications of bonds in 2005, the rating of a bond has been determined by the middle rating provided by the three CRAs (Chen, Lookman, Schürhoff and Seppi, 2014; Chen and Wang, 2017). Similarly, National Association of Insurance Commissioners (NAIC) guidelines require that the second lowest rating is used for bond classification when multiple ratings are available (Hanley and Nikolova, 2018). Consequently, issuers have an incentive to seek a third rating when there is a disagreement between Moody's and S&P, as obtaining a third rating that is better essentially presents the issuer with an opportunity to improve its average rating. In this way, Fitch acts as a tiebreaker - if it allocates a higher rating than the lowest rating assigned by either agency, the issuer's average rating increases otherwise, the issuer's rating remains unchanged. Cantor and Packer (1995) observe that this option like payoff increases the demand for a third rating as the issuer's ratings from Moody's and S&P approach investment grade (IG). Bongaerts et al. (2012) find that issuers are twice as likely to seek a Fitch rating for bond issues where Moody's and S&P ratings are on opposite sides of the high yield (HY) - IG boundary and where a third rating provided by Fitch helps to differentiate between the bond's HY and IG status. Furthermore, Mählmann (2009) shows that the increased demand for Fitch ratings is not random but stems from an anticipated favorable rating outcome, and the corresponding increase in the average rating of the issuer. The systematic issuance of more optimistic ratings by Fitch is widely documented (see, for example, Cantor and Packer, 1997; Jewell and Livingston, 1999; Livingston and Zhou, 2016) and is consistent with Fitch playing a strategic role to extract compensation for pushing bonds into the IG classification when Moody's and S&P disagree (Bongaerts et al., 2012).

Maintaining a bond's IG status is an important consideration for issuers as many banks and insurance firms are mandated by prudential regulations to hold higher reserve capital for HY bonds while pension and mutual fund investment mandates typically limit the share of HY securities in their portfolios (Baghai, Becker and Pitschner, 2018; Bongaerts et al., 2012). The reduced investor base for HY securities significantly affects firms' capital structure decisions and the cost of borrowing associated with rating changes across the HY-IG boundary (Kisgen 2006, 2009). In spite of the prior studies on multiple ratings, there is scant evidence on how the reduced rating reliance on ratings recommended by Dodd-Frank affects the demand for third ratings and ratings accuracy.

The Dodd-Frank Act presented a series of regulatory reforms to the credit rating industry. Specifically, under Section 932 of Dodd-Frank, the Securities and Exchange Commission (SEC) has the power to suspend or revoke a Nationally Recognized Statistical Rating Organization (NRSRO)'s registration regarding a particular class of securities if their ratings are inaccurate. Section 933 lessens the pleading standards for private actions against CRAs, while section 939 requires federal agencies to remove regulatory reliance on credit ratings and to make appropriate substitutions using alternative measures of creditworthiness. In particular, agencies do not need to rely exclusively on external credit ratings to determine whether a security is 'investment grade'.[2] Those sections, which are arguably the most significant provisions within Dodd-Frank regarding the regulatory use of credit ratings, have had the largest impact on CRAs. Becker and Opp (2014) and Hanley and Nikolova (2018) document that removing credit ratings from capital regulations by NAIC affects insurers' behavior. Dimitrov, Palia and Tang (2015) provide evidence that post

[2] The Office of the Comptroller of the Currency (OCC), mandated by Dodd-Frank, states that 'banks may not rely exclusively on external credit ratings, but they may continue to use such ratings as part of their determinations. A security rated in the top four rating categories by a NRSRO is not automatically deemed to satisfy the revised IG standard'.

Dodd-Frank CRAs issue lower credit ratings with weaker stock and bond market reactions and have a higher incidence of false warnings. Faced with a rating downgrade, Cohn, Rajan and Strobl (2018) show that firms are likely to become more strategic about disclosing negative information, and CRAs respond by screening more intensively. Ahmed, Wang and Xu (2017) show that CRAs have shifted their focus from qualitative to quantitative information to form their ratings post Dodd-Frank to minimize the threat of litigation.

We conjecture that eliminating the regulatory reliance on credit ratings and increasing the legal and regulatory penalties for issuing overly optimistic ratings reduce the appeal of obtaining a third rating. Since a third rating is generally provided by Fitch whose ratings are on average more optimistic than ratings assigned by Moody's and S&P[3], we anticipate a significant reduction in the demand for Fitch ratings after the passage of Dodd-Frank. Moreover, we expect that the reduced demand for Fitch ratings will translate to these ratings exerting a lower market impact when they act as a tiebreaker around the HY-IG boundary.

By providing ratings, CRAs also serve as external monitors of firms as their rating processes involve meetings with management, close examination of managerial ability and corporate governance (Jorion, Liu and Shi, 2005; Bonsall, Koharki and Neamtiu, 2016). Previous studies show that by having access to firms' management, information intermediaries such as financial analysts and rating agencies help to uncover managers' private information and detect managers' misbehavior (Healy and Palepu, 2001). Yu (2008) shows that firms with a higher level of equity analyst coverage tend to engage in less earnings management. Similarly, firms rated by fewer agencies are subject to less scrutiny and can potentially disclose less information. Hence,

[3] Most large U.S. corporate bond issues are rated by Moody's and S&P, with Fitch typically providing the third rating (Bongaerts et al., 2012; Chen and Wang, 2017). Following convention, we examine the market impact of Fitch as a third rating.

we hypothesize that firms without a third rating after Dodd-Frank are less transparent and manage their earnings more. Since Li, Griffin, Yue and Zhao (2013) show that greater earnings discretion is likely to promote corporate risk taking, we posit that firms engaging in more earnings management are more risk-seeking and thus have higher cash flow and sales volatilities.

Using a database of newly issued U.S. corporate bonds from 2006 to 2015, we show that firms are 17.3% less likely to seek a third rating for newly issued bonds following the passage of Dodd-Frank. These results strengthen with time as the uncertainty regarding the implementation of Dodd-Frank gradually resolves. We further show that post Dodd-Frank, third ratings are less informative, having a more muted impact on credit spreads at issuance when firms' existing Moody's and S&P ratings straddle the HY-IG boundary. Last, we find that the reduced demand for third ratings significantly reduces corporate monitoring and harms the financial information environment. Firms without a third rating display more earnings management after Dodd-Frank with 1.1% higher absolute discretionary accruals and approximately 1% (2.8%) higher cash flow (sales) volatility than firms with a third rating.

Our paper makes several contributes to the current literature. First, we contribute to the literature that examines the demand for and market impact of multiple ratings (see, for example, Chen and Wang, 2017; Bongaerts et al., 2012; Livingston and Zhou, 2016). The existence of multiple ratings is closely related to the competitive environment in the ratings industry, which has been linked to the quality of ratings. Some studies view competition as beneficial to improve the quality and reliability of ratings (Doherty, Kartasheva and Phillips, 2012; Xia, 2014; Bongaerts et al., 2012; Rabanal and Rud, 2017) while others show that increased competition may not necessarily improve the information content of credit ratings (Skreta and Veldkamp, 2009; Bolton, Freixas and Shapiro, 2012) or could even lead to a reduction in rating quality (see Becker and

Milbourn, 2011; Flynn and Ghent, 2017; Baghai and Becker, forthcoming). We provide new empirical evidence on the weakening of competition in the credit ratings industry post Dodd-Frank via a reduced demand for Fitch ratings.

Second, our paper contributes to the literature that explores the impact of information intermediaries on management behavior. Similar to papers that focus on equity analysts' role to uncover managers' superior information and detect managers' misbehavior (Yu, 2008; To, Navone and Wu, 2018), we show that rating agencies also provide an external monitoring role. Our results show that a reduction in external monitoring provided by multiple rating agencies leads to increased managerial misbehavior and a deterioration in the quality of the corporate information environment.

Last, we contribute to the growing body of research on the effect of Dodd-Frank on CRAs. Current studies highlight the unintended negative consequences of Dodd-Frank on the accuracy of credit ratings (Dimitrov et al., 2015); the quality of the information environment (Ederington, Goh, Lee and Yang, 2018) and the use of qualitative information in forming a rating opinion (Ahmed et al., 2017). Our findings have important policy implications. We extend this line of recent research, showing that although Dodd-Frank appears to be achieving its intended objective by reducing the demand for ratings especially from smaller players such as Fitch, it has an unintended consequence on competition within the ratings industry, and the quality of the information environment. Our research points to the need to ensure that other mechanisms be introduced to preserve the quality of the information environment as the diminished use of credit ratings becomes binding.

The remainder of the paper is organized as follows. Section 2 reviews existing literature and formulates the hypotheses. Section 3 and 4 describes the methodology and data, respectively while Section 5 presents the empirical tests. Section 6 concludes.

2. Related Studies and Hypotheses Development

Extant studies show that the demand for multiple ratings is primarily driven by financial regulation. Opp, Opp and Harris (2013) develop a theoretical framework to show that the regulatory reliance on credit ratings lowers ratings quality as CRAs find it more profitable to facilitate regulatory arbitrage than to sell informative ratings. Furthermore, Cornaggia, Cornaggia and Simin (2016) demonstrate that biased ratings are driven not only by regulatory arbitrage as predicted by Opp et al. (2013) but also the conflict of interest inherent in the issuer-pays compensation structure. They provide evidence that Moody's facilitates regulatory arbitrage by certifying riskier bonds as IG when S&P has not. Maintaining a bond issue's IG status has significant implications for issuers. For instance, financial firms investing in HY debt may need to hold additional capital under ratings contingent capital regulation and investment funds often have mandates that either restrict or entirely prohibit investments in HY debt. Kisgen (2006, 2009) and Kisgen and Strahan (2010) show that rating changes across the HY-IG boundary significantly affect firm's capital structure decisions, leverage ratios and their cost of debt. Bongaerts et al. (2012) find that issues where Fitch assigns an IG credit rating are associated with a 41 basis points (bps) lower spread on average than issues where Fitch allocates a HY rating. These studies provide support for the regulatory certification hypothesis.

Baghai et al. (2018) analyze the private use of credit ratings in investment mandates and find that the use of credit ratings in fixed income mandates has not declined. However, they do not focus on the role of multiple ratings and the regulatory use of ratings post Dodd-Frank. Specifically, since Dodd-Frank increases the legal and regulatory penalties for issuing inaccurate ratings and eliminates the reliance of financial institutions on credit ratings to quantify minimum capital requirements, it reduces the regulatory advantage of higher ratings (Opp et al., 2013; Cornaggia et al., 2016). In related literature, de Haan (2017) finds that market participants already decreased their reliance on corporate ratings after the 2008 Global Financial Crisis due to the reputational concerns with CRAs. Consequently, we posit that the incentive to inflate ratings (by seeking a third rating) should dissipate following the passage of Dodd-Frank leading to a lower demand for third ratings.

H$_1$: *The prevalence of firms seeking third ratings has declined post-Dodd Frank.*

Credit ratings have long been shown to have significant information content for market participants. Livingston and Zhou (2016) find that a third rating provided by Fitch brings additional information to investors and reduces the yield premium on information-opaque bonds by about 30%, or 15 bps. Cornaggia, Cornaggia and Israelsen (2018) focus on the municipal bond market which is dominated by unregulated retail investors and find that investors continue to rely on credit ratings for information about credit risk beyond any regulatory implications. Moreover, Bruno, Cornaggia and Cornaggia (2016) suggest that the reduced regulatory reliance on CRAs may improve the quality of issuer-paid ratings. These studies suggest that despite Section 939 of the Dodd Frank Act reducing the regulatory reliance on credit ratings, Dodd Frank remains unlikely to extinguish the role of CRAs in determining firms' creditworthiness.

Nonetheless, Dimitrov et al. (2015) provide evidence to indicate that CRAs issue lower credit ratings following Dodd-Frank and these rating announcements induce weaker stock and bond market reactions and exhibit a higher frequency of false warnings. These results suggest that Dodd-Frank reduces ratings inflation from the 1970s[4] SEC's regulatory reform documented by

[4] In June 1975, the SEC expanded the use of ratings in rules and regulations by issuing new rules that established bank and broker-dealer capital requirements based specifically on ratings (Rule 15c3-1), and they also increased the barriers to entry in the ratings industry thereby reducing competition within the credit ratings industry (Behr et al., 2016).

Behr, Kisgen and Taillard (2016) that restricted competition within the ratings industry and the increased regulatory reliance on ratings. Since the increased penalties on false ratings and the removal of the reliance on credit ratings may lead to less optimistic ratings and remove the advantage of higher ratings, we posit that Dodd-Frank has reduced the information content of third ratings. It follows that this would increase borrowing costs for firms, particularly those with existing ratings straddling the HY-IG boundary.

H_2: *The market reaction to a third rating from Fitch has significantly weakened around the HY-IG boundary.*

The muted focus on credit rating signals within financial markets arising from the Dodd Frank reform may also have implications for the financial informational environment. Healy and Palepu (2001) suggest that information intermediaries such as equity analysts and rating agencies act as external monitors to restrain managers' misbehavior. Using multiple measures of earnings management, Yu (2008) finds that firms with greater equity analyst coverage tend to have less issues with earnings management. Similarly, Irani and Oesch (2013) examine analysts' monitoring role and document that a higher number of analysts is correlated with higher financial reporting quality. To et al. (2018) find that analysts' monitoring role ensures that managers will undertake the most productive projects, therefore greater analyst coverage leads to higher total factor productivity within firms. Similar to equity analysts, credit rating agencies also serve as external monitors. The credit rating process involves regular meetings between credit analysts and the issuer's management team including on-site visits, and ongoing monitoring of the bond issuer (Bonsall et al., 2016).

Boot, Milbourn and Schmeits (2006) were among the first to theoretically ascribe a monitoring role played by CRAs, which is most apparent in their credit watch procedures.

Empirically, Bannier and Hirsch (2010) examine CRAs' economic roles by using Moody's watchlist and show that it helps CRAs to supply information to financial markets and gives rise to an active monitoring role of CRAs. Morkoetter, Stebler and Westerfeld (2017) examine the benefit of additional ratings from an investor's perspective. They show that CRAs demonstrate more effort regarding their monitoring activities in instances where there are multiple ratings as compared to single-rated tranches in the U.S. RMBS market. Cohn et al. (2018) construct a theoretical model to also show that issuers can manipulate information obtained by CRAs to induce a favorable rating. With potential access to private information from the firm's management team, credit analysts are well placed to assess corporate governance practices and can restrain managers' misbehavior (Healy and Palepu, 2001). However, with the significantly reduced incentives to obtain a third rating post-Dodd Frank, firms are likely to disclose less information. It follows that firms engaged in extensive earnings management would have greater managerial discretion, which in turn promotes corporate risk-taking (Han et al., 2010; Li et al., 2013).

H3a: *Firms without a third rating exhibit more earnings management post Dodd-Frank.*

H3b: *Firms without a third rating engage in riskier corporate operations which lead to higher cash flow and sales volatilities post Dodd-Frank.*

3. Methodology

3.1 Probit Model

To test the impact of Dodd-Frank on the propensity for firms to demand third ratings, we use a probit model. The probit regression can be expressed as a latent variable model:

$$Y^* = \boldsymbol{X^T\beta} + \varepsilon = \beta_1 \, \textit{Dodd-Frank} + \sum_{\boldsymbol{i=2}}^{\boldsymbol{k}} \beta_i \, Control_i + \delta_i + \varepsilon \qquad (2)$$

where $\varepsilon \sim N(0,1)$, δ_i denotes industry effects and Y^* is the latent propensity that a firm has a Fitch rating ($Y = 1$). The vector of the coefficients $\boldsymbol{\beta}$ is estimated by Maximum Likelihood.

Specifically, we regress the latent variable *Fitch* on a *Dodd-Frank* indicator variable and numerous bond and firm characteristics commonly quoted in the literature. Variable definitions are listed in Appendix A. We winsorize all continuous firm-level variables at the 1% level in both tails of the distribution. Consistent with prior studies, we use size to proxy firm maturity as it has been shown to be positively related to the likelihood of having a Fitch rating (Cantor and Packer, 1997; Bongaerts et al., 2012). Older firms are more inclined to participate in the public bond market, and in turn demand a Fitch rating. Opaque firms with high information asymmetry are harder to value, so Fitch ratings provide additional information that is priced by the market (Livingston, Naranjo and Zhou, 2007; Livingston and Zhou, 2016). We use the *Market to Book* and *Intangible Assets* as accounting proxies of opacity. Other firm characteristics include *Leverage*, *Profitability*, and *PPE*. Firms with higher intangible assets, leverage and profitability may be associated with greater firm uncertainty, which is positively related to the likelihood of having a Fitch rating (Cantor and Packer, 1997). We supplement these with two opinion-based proxies for firm opacity, dispersion in equity analysts' earnings forecasts, *Stdev of Forecasts*, and the number of analysts following a firm, *Analyst Coverage*. Brennan and Subrahmanyam (1995) and Yu (2008) show that large analyst coverage promotes more information flows to investors, which improves corporate transparency. We also employ a dispersion indicator variable that takes a value of one when there is a split rating between Moody's and S&P, as an additional credit-based opacity proxy. Since issues in which Fitch is the tiebreaker CRA are about twice as likely to get a Fitch rating, we also control for *Distance* which is the absolute distance from the HY-IG boundary.

3.2 Linear Regression

We estimate the impact of a Fitch rating on credit spreads, earnings management and corporate risk-taking using the following OLS regression:

$$Y = \beta_1 \textit{ Dodd-Frank} + \beta_2 \textit{ Fitch} + \beta_3 \textit{ Dodd-Frank*Fitch} + \sum_{i=2}^{k} \beta_i \, Control_i + \delta_i + \varepsilon$$

Where Y indicates alternatively, credit spreads at issuance, earnings management (i.e. absolute discretionary accruals) and corporate risk taking (i.e. cash flow volatility and sales volatility), respectively, which are explained in detail in the following sections.

In addition to the bond and firm characteristics mentioned above, to test the impact of Dodd-Frank implementation on credit spreads, we also control for CDS index values (*CDX Index*) since higher index values indicate lower overall credit quality in the aggregate credit market which typically increases credit spreads at issuance. In the OLS regression on earnings management, we follow previous studies (e.g. Yu, 2008) and use the absolute value of discretionary accruals (*ADA*) as the proxy for earnings management (estimation details are described in Appendix B). We include Altman Z-scores to account for corporate credit risk since firms close to violating their debt covenants or are under financial distress have greater incentives to increase reported earnings (DeFond and Jiambalvo, 1994). We also include *Sales Growth* and *Crash Risk* to control for the firms' strong growth and volatilities (Alissa, Bonsall, Koharki and Penn Jr, 2013). In the OLS regression on corporate risk-taking, we follow John, Litov and Yeung (2008), Dichev and Tang (2009), and Li et al. (2013) and proxy corporate risk-taking activities with firms' cash flow volatility, *Cash Flow Vol*, and sales volatility, *Sales Vol*. In addition to other firm characteristics (e.g. monitoring by institutional investors and idiosyncratic volatility), we also control for the average cash flow volatility or sales volatility of firms from the same industry to capture industry norms following Zhang (2009).

3.3 Propensity Score Matching

To address the potential selection bias when comparing firms with third ratings to those without, we use a propensity score matching approach to incorporate the probability of seeking a third rating (Rosenbaum and Rubin, 1983). The propensity score is computed using *Firm Size*, *Market to Book*, *Leverage*, *Intangible Assets*, *Profitability*, *PPE*, *Analyst Coverage*, *S&P Ratings* as well as year and industry fixed effects. We match firms with and without a third rating using one-to-one nearest neighbor with replacement based on propensity scores, calculate the average treatment effect on the treated (ATT) and test the statistical significance using the t-test.

4. Data

4.1 Sample Selection

Bond characteristics and credit ratings by Moody's, S&P and Fitch are acquired from the Mergent Fixed Income Securities Database (FISD). In line with Dimitrov et al. (2015), our sample begins in January 2006 to avoid any ongoing market adjustments following the 2002 Sarbanes-Oxley (SOX) Act[5] and ends in December 2015. Following convention, ratings are converted to numerical rating scores, from 1 to 21 (AAA to C for S&P and Aaa to C for Moody's), with lower numbers indicating a better rating. We restrict our sample to senior unsecured newly issued U.S. domestic corporate bonds 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 coupons and bonds with credit

[5] On 25 July, 2002, the Senate and the House passed the Sarbanes-Oxley Act 2002. Section 702 (b) of SOX requires SEC to study the role and function of CRAs (Cheng and Neamtiu, 2009). In response to the requirements, the SEC issued a series of reports regarding the role of CRAs and the U.S. Congress conducted a series of hearings (Cheng and Neamtiu, 2009). As a result, the Credit Rating Agency Duopoly Relief Act of 2006, which introduces competition in the ratings industry and increases oversight of CRAs, was signed into law by the President.

enhancements are excluded. We focus on initial bond ratings at issue as the process for assigning initial ratings is more robust than the process for monitoring ratings (Chen and Wang, 2017).

Accounting information and financial variables are sourced from Compustat. Equity analysts' forecasts and analyst coverage are acquired from the Institutional Brokers' Estimate System (IBES). To calculate the standard deviation in earnings forecasts, issuing firms covered by fewer than three stock analysts are eliminated. Institutional ownership data is sourced from Thomson Reuters 13F Database. Data from different databases are merged using CUSIPs. Credit Default Swap (CDS) index values from the North American Investment Grade CDS (CDX NA IG) index are obtained from Bloomberg. Firm stock returns are obtained from CRSP.

4.2 Statistical Description

We start with 3,502 newly issued domestic bonds that are rated by both Moody's and S&P within the first 30 days after issuance with complete data in Compustat and IBES databases. We exclude bond issues with missing data in Mergent FISD, and filter out subsequent bond issues of the same issuing firm within the same month. The final sample contains 1,283 bond issues from 2006 to 2015. Panel A in Table 1 provides descriptive statistics for the control variables before and after Dodd-Frank and shows that both samples are quite similar. It can be observed that the average credit quality of bonds issued after Dodd-Frank is generally lower, which is consistent with the issuance of more conservative ratings following the passage of Dodd-Frank to protect CRAs' reputation in response to the increased legal and regulatory penalties for issuing inaccurate ratings as documented by Dimitrov et al. (2015). In Table 2, the industry sample distribution (based on Mergent Industry code and GICS classification) before and after Dodd-Frank are also comparable. In Panel B, we split the sample into firms rated by both Moody's and S&P that also have a Fitch rating versus firms that do not. It can be seen that firms rated by Fitch have a tendency to be generally larger firms, with a higher market-to-book ratio, have more intangible assets, less debt, higher profitability and greater analyst coverage.

[Insert Table 1, 2 about here]

5. Empirical Results

5.1 Demand for Third Ratings

Figure 1 and Figure 2 shows the proportion of newly issued un-rated bonds between 2006 and 2015, and bonds rated by all three CRAs within the first 30 days after issuance, respectively. Figure 3 further requires that the bonds are rated by Moody's and S&P (i.e. the denominator is the number of bonds that are rated by both Moody's and S&P), and plots the proportion of those that are also rated by Fitch. There are two clear trends observable in these three figures. First, there are more bonds that seek a third rating between 2006 and 2009, which is in line with the increased demand for third ratings from the Lehman Brothers index rule change reported by Chen and Wang (2017). Second, after the removal of the regulatory reliance on ratings by Dodd Frank, the proportion of un-rated firms increases, and the proportion of firms rated by all three CRAs decreases. Figure 3 shows that prior to the introduction of Dodd-Frank around 50% of those un-rated bonds additionally seek a Fitch rating, however, since the passage of Dodd-Frank the proportion has decreased to around 25%. These results are consistent with our first hypothesis regarding the reduced demand for Fitch ratings with the weakened regulatory reliance on credit rating information.

[Insert Figures 1, 2, 3 about here]

Table 3 provides the results of probit regressions for the likelihood of getting a Fitch rating on the Dodd-Frank dummy and firm controls (equation 2). Consistent with previous figures, firms are 17.3% less likely to demand a Fitch rating following the implementation of the Dodd-Frank reform. The coefficient is significant at the 1% level. We find that *Firm Size* is positive and significant while *Distance* is negative and significant. Both coefficients are statistically significant at the 1% level. The results are in line with Bongaerts et al. (2012) who show that large firms and firms with current ratings near the HY-IG boundary are more likely to have Fitch ratings. *Leverage* is negative and statistically significant at the 5% level, which is consistent with the earlier findings of Cantor and Packer (1997). Other control variables appear to be less important. Since Fitch is more likely to rate utilities and financial firms than other industrial firms (Cantor and Packer, 1997), Model 3 re-estimates the probit regressions by excluding these sectors from the sample. The results are qualitatively similar.

[Insert Table 3 about here]

As a robustness check, in Table 4, we follow Dimitrov et al. (2015) and re-define the post-Dodd-Frank period to start in July 2009 (the first version of the legislation), December 2009 (the revised version of the legislation), July 2010 (the law's passage date), July 2012 (Section 939 effective date) and Jan 2013 (OCC rule effective date). Strikingly, we find that the results strengthen as the uncertainty regarding the passage of Dodd-Frank gradually resolves. The coefficient on *Dodd-Frank* monotonically decreases from -0.452 (July 2009) to -0.628 (Jan 2013), which increases our confidence in attributing the reported effects to the regulatory shock presented by Dodd-Frank.

In addition, we follow Bongaerts et al. (2012) and expand our study to encompass all (10,289) active bonds between 2006 and 2015. The regression results are reported in Table 5 and the figures are reported in Appendix C. These results are qualitatively similar, which lend further support to our first hypothesis that firms are less likely to obtain a Fitch rating after the passage of Dodd-Frank [6]. Since competition in the ratings industry and the existence of multiple ratings are closely related (Becker and Milbourn, 2011; Bae, Kang and Wang, 2015), our results are also indicative of reduced competition in the ratings industry following Dodd-Frank and we conjecture this in turn, affects the information efficiency of financial markets.

[Insert Table 4, 5 about here]

5.2 Market Impact of Third Ratings

Next, we examine the impact of Fitch ratings on the credit spreads at issuance for bonds rated by Moody's and S&P using OLS regressions. The dependent variable is the at-issuance credit spreads, and the main variables are *Fitch_Makes_IG* (a dummy that equals one if Moody's and S&P are at the boundary and the addition of a Fitch rating moves the bond into the IG category, and zero otherwise) and an interaction term, *Fitch_Makes_IG* with *Dodd-Frank*. We control for firm characteristics, issuer's credit quality, CDS index values and industry fixed effects. Since bonds with different issue-level characteristics issued by the same issuers have different at-issuance credit spreads, we add back the subsequent bonds made by the same issuers within the same month, and control for the issue-level characteristics discussed previously.

[6] For robustness we also test issue characteristics identified from the literature to be important determinants such as issue size, redeemability, and maturity (see, for example, Cantor and Packer, 1997; Bongaerts et al., 2012). The results are qualitatively similar and available upon request.

In Table 6, the coefficient on *Fitch_Makes_Better* (a dummy that equals one if an addition of a Fitch rating improves the overall rating of the bond, and zero otherwise) is negative but not statistically significant. However, the coefficient on *Fitch_Makes_IG* is negative and significant at the 1% level, which indicates that Fitch reduces credit spreads at issuance when it serves as the tiebreaker CRA that changes the HY-IG status. The financial payoff from obtaining a favorable rating from Fitch is higher at the HY-IG boundary as firms try to exploit the regulatory ruling. As such, firms with Moody's and S&P ratings on opposite sides of the boundary should display the strongest market impact of a new Fitch rating prior to the adoption of Dodd-Frank (Bongaerts et al., 2012). However, these effects weaken after the passage of Dodd-Frank, as indicated by the coefficient on the interaction term between *Fitch_Makes_IG* and *Dodd-Frank.* In terms of the economic magnitude, the effects on credit spreads at issuance when Fitch lifts the bonds into the IG category halves after Dodd-Frank. All controls have the expected sign and significance level. In addition, in unreported regression results, our finding remains unchanged after excluding utilities and financial firms.[7]

These results provide empirical evidence in support of our hypothesis that the market impact of Fitch ratings on credit spread changes diminishes following the adoption of Dodd-Frank and is consistent with the weakened stock and bond market reaction documented by Dimitrov et al. (2015). Our empirical evidence supports the theoretical predictions made by Opp et al. (2013). Specifically, the reduced regulatory reliance on credit ratings enforced by Dodd-Frank and the removal of the associated regulatory advantage in having higher third ratings has led to a significant reduction in the market impact of Fitch ratings at the investment grade boundary.

[7] These results are available from the authors upon request.

[Insert Table 6 about here]

5.3 Opaqueness, Earnings Management and Corporate Risk-Taking

In this section, we examine the ramifications for the quality of the financial information environment and investigate whether firms without Fitch ratings manage their earnings more. Panel A in Table 7 reports the average ADA for firms with and without Fitch ratings before and after Dodd-Frank. The unmatched results show that after Dodd-Frank, firms without Fitch ratings manage their earnings more (i.e. 0.8% higher in ADA) and the difference is statistically significant at the 5% level. Next, to resolve the selection bias when comparing firms with third ratings to those without, we match firms without a third rating (treatment group) with those with a third rating (control) using one-to-one nearest neighbor matching in terms of propensity scores ensuring that the control firm can be as similar as possible to the treated firm based on the characteristics listed in Section 3.3. As shown in Panel A, after careful matching, we continue to find that firms without Fitch ratings are associated with more earnings management post Dodd-Frank compared to those with Fitch ratings. Specifically, the difference between treated and control bond issuing firms in ADA is 1.1% (of the total assets at the beginning of the period) and is statistically significant at the 5% level. To rule out the possibility that the results are driven by other factors, we run additional regressions for ADA after controlling for variables that are associated with earnings management[8]. The results, which are reported in Table 8, do not change our conclusion - the interaction terms between *Dodd-Frank* and *Without Fitch* is positive and statistically significant at

[8] Besides the variables described in Table 1, the statistics for other variables that affect earnings management and corporate risk-taking are reported in Appendix D.

the 5% level, which indicates that the sample firms without Fitch ratings have more earnings management after Dodd-Frank[9].

Our results support prior studies showing that information intermediaries act as external monitors on managers and play an important role in effective corporate governance. Specifically, the empirical evidence complements previous studies on equity analysts' monitoring role (Yu, 2008; To et al., 2018), and shows that credit analysts can also restrain managers' misbehavior. In addition, Morkoetter et al. (2017) provide evidence that the existence of multiple ratings positively affects CRAs' efforts spent on their monitoring activities in the U.S. RMBS market. Our results are consistent with Morkoetter et al. (2017), and further show that the effect is not just confined to the RMBS market but is also present in the corporate bond market.

Since previous studies (e.g. John et al., 2008; Li et al., 2013) show earnings discretion and corporate governance are related to firms' cash flow volatility (a proxy for corporate risk-taking), we next examine whether firms without Fitch ratings also engage in riskier corporate activities that lead to more volatile earnings. Panels B and C in Table 7 show that post Dodd-Frank, firms without Fitch ratings exhibit more volatile earnings, and the difference for *Cash Flow Vol* and *Sales Vol* is statistically significant at the 1% and 5% level, respectively. Table 9 shows that after controlling for variables affecting earnings volatility, firms without Fitch ratings in the post-Dodd Frank era have 1% (2.8%) higher cash flow (sales) volatility, compared to firms still with Fitch ratings. Overall, the results are consistent with previous studies linking firms' earnings discretion activities to their corporate risk-taking activities. This indicates an unintended consequence from the Dodd Frank regulatory reform. The reduced market demand for third ratings

[9] As robustness, we also run regression using balanced (matched) data and the results are qualitatively similar. In addition, the regression is re-examined after excluding utilities and financials. The results are qualitatively similar and available upon request.

ensuing from the increased legal and regulatory penalties for issuing inaccurate ratings and the muted reliance on credit ratings, has fostered more corporate risk taking and compromised the integrity of the corporate information environment.

[Insert Tables 7, 8, 9 about here]

6. Conclusion

The Dodd-Frank reform enacted in response to the 2007-2008 Global Financial Crisis introduced several important reforms to the credit rating industry. These include increased legal and regulatory penalties for issuing inaccurate ratings, and the elimination of the regulatory reliance on credit ratings by financial institutions in determining capital adequacy ratios. We present evidence that these changes materially impacted the activities of the credit rating industry. Using newly issued U.S. bond ratings over the years from 2006 to 2015, we find that firms are less likely to seek a third rating for newly issued bonds following the implementation of Dodd-Frank. Third rating assessments typically provided by Fitch, have become less informative with a diminished impact on credit spreads post Dodd-Frank when firms with current Moody's and S&P ratings are on opposite sides of the investment grade (HY-IG) boundary. Strikingly, we find that firms without third ratings provided by Fitch in the post-Dodd-Frank era manage earnings more and have higher cash flow and sales volatilities, suggesting that they engage in greater corporate risk taking. Our results suggest that the increased legal and regulatory penalties for issuing inaccurate ratings and the reduced regulatory reliance on credit ratings has extinguished the advantage of having Fitch ratings and this has in turn significantly diminished the market impact of Fitch ratings. However, our findings suggest that a reduction in the external monitoring previously provided by multiple CRAs may inadvertently increase managerial misbehavior and incentivize corporate risk-taking. Overall, these developments may compromise the quality of the corporate information environment. Future research in this area should focus on whether this reduction in external monitoring by rating agencies may also affect corporate policies and exert real economic effects. Our research provides an important first step in linking the recent regulatory reforms concerning credit ratings to firms’ economic activities.

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Figure 1 Proportion of un-rated newly issued bonds

This figure plots the proportion of newly issued bonds between 2006 and 2015 that are un-rated within the first 30 days after issuance. 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. Subsequent bond issues of the same issuing firm within the same month are also filtered out.

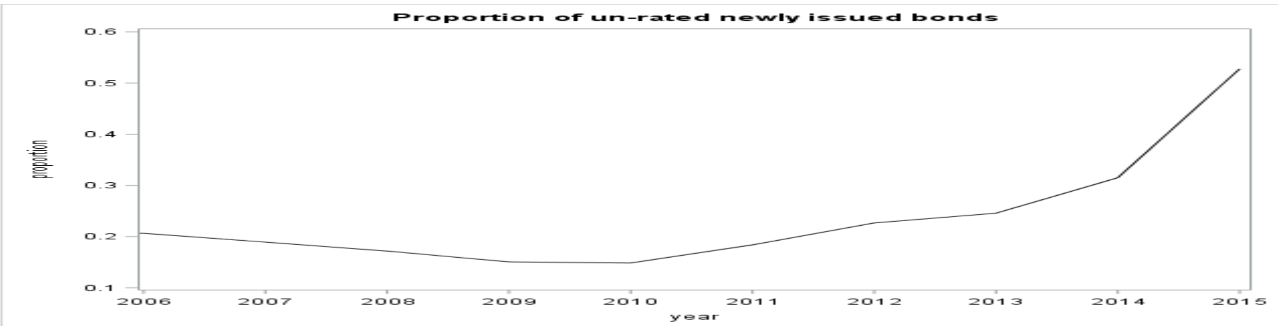


Figure 2 Proportion of newly issued bonds with three ratings

This figure plots the proportion of newly issued bonds between 2006 and 2015 that are rated by all three CRAs within the first 30 days after issuance.

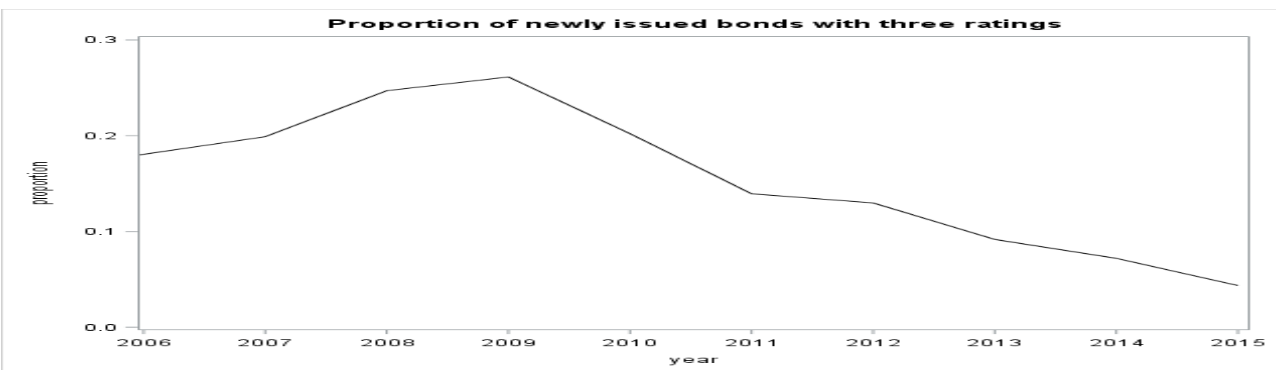


Figure 3 Proportion of newly issued bonds rated by Fitch

This figure plots the proportion of newly issued bonds between 2006 and 2015 rated by Moody's and S&P within the first 30 days after issuance that also have a Fitch rating.

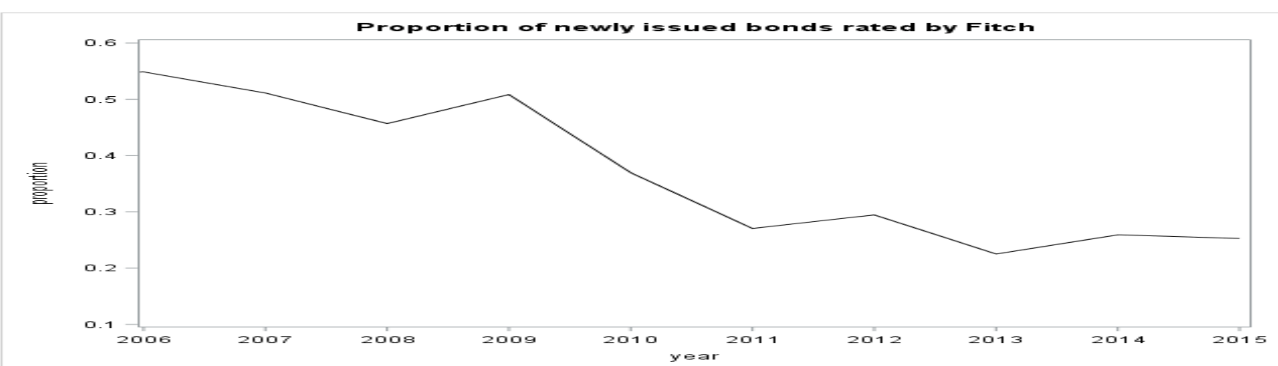


Table 1. Descriptive Statistics for Control Variables Affecting Fitch Demand

This table reports the descriptive statistics for all control variables that influence the 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. In Panel A, the sample is partitioned into Before and After Dodd-Frank subsample periods. 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 that were rated by both Moody's or S&P within the first 30 days after issuance. The Without-Fitch and With-Fitch subsamples include bonds with no Fitch ratings and with Fitch ratings, respectively.

Panel A	**Before Dodd-Frank (560 obs)**					**After Dodd-Frank (723 obs)**				
	Mean	**Median**	**Min**	**Max**	**Std**	**Mean**	**Median**	**Min**	**Max**	**Std**
Firm Size	10.320	10.136	6.538	13.752	1.966	10.185	9.871	6.538	13.752	1.871
Market to Book	1.532	1.331	0.892	4.015	0.616	1.533	1.348	0.892	4.015	0.632
Intangible Assets	0.173	0.116	0	0.720	0.187	0.182	0.115	0	0.720	0.198
Leverage	0.272	0.241	0.012	0.711	0.155	0.280	0.252	0.012	0.711	0.147
Profitability	0.042	0.032	-0.225	0.209	0.060	0.039	0.035	-0.225	0.209	0.064
PPE	0.468	0.336	0	1.761	0.428	0.529	0.414	0	1.761	0.462
Analyst Coverage	19.346	19	3	43	8.337	24.089	24	3	62	10.982
Stdev of Forecasts	0.0453	0.004	0.000	1.436	0.217	0.011	0.004	0	0.686	0.034
S&P Ratings	6.991	7	1	17	3.761	9.184	9	1	18	3.222

Panel B	**Mean**			**Median**		
	Whole Sample	**Without Fitch**	**With Fitch**	**Whole Sample**	**Without Fitch**	**With Fitch**
Firm Size	10.244	10.202	10.303	9.982	9.749	10.232
Market to Book	1.532	1.515	1.557	1.341	1.303	1.359
Intangible Assets	0.178	0.172	0.188	0.116	0.099	0.131
Leverage	0.276	0.292	0.254	0.249	0.259	0.235
Profitability	0.040	0.035	0.048	0.034	0.027	0.045
PPE	0.502	0.488	0.523	0.370	0.328	0.427
Analyst Coverage	22.019	21.584	22.636	21	20	22
Stdev of Forecasts	0.026	0.032	0.017	0.004	0.0046	0.003
Rating Dispersion	0.675	0.704	0.634	1	1	0
S&P Ratings	8.227	8.468	7.885	8	8	8
#Obs	1283	753	530	1283	753	530

Table 2. Industry Distribution

This table presents the industry distribution of the sample before and after Dodd-Frank. Panel A is based on the Mergent industry code while Panel B is based on the GICS classification.

Panel A	**Before Dodd-Frank**		**After Dodd-Frank**	
	Frequency	**Percent**	**Frequency**	**Percent**
Industrial	359	64.11%	488	67.50%
Finance	137	24.46%	166	22.96%
Utility	28	5.00%	59	8.16%
Government	36	6.43%	10	1.38%
Total	560	100%	723	100%

Panel B	**Before Dodd-Frank**		**After Dodd-Frank**	
	Frequency	**Percent**	**Frequency**	**Percent**
Energy	61	10.89%	109	15.08%
Materials	49	8.75%	56	7.75%
Industrials	99	17.68%	64	8.85%
Consumer Discretionary	52	9.29%	87	12.03%
Consumer Staples	51	9.11%	48	6.64%
Health Care	60	10.71%	75	10.37%
Financials	126	22.50%	149	20.61%
IT	23	4.11%	53	7.33%
Telecommunication	13	2.32%	29	4.01%
Utilities	24	4.29%	47	6.50%
Real Estate	2	0.36%	6	0.83%
Total	560	100%	723	100%

Table 3. Fitch Demand: Probit Regressions of Fitch Rating

This table reports the results of probit regressions with a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. Z-values are shown inside brackets. Model 1 reports the results for probit regressions after controlling for industry fixed effects, while Model 2 reports the marginal effects. Model 3 reports the results for probit regressions after excluding utilities and financial firms. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

	Model 1	Model 2	Model 3
VARIABLES	Probit	Marginal Effects	Probit
Dodd-Frank	-0.507***	-0.173***	-0.375***
	(-5.187)		(-3.551)
Firm Size	0.170***	0.057***	0.238***
	(2.740)		(2.844)
Intangible Assets	-0.524	-0.177	-0.772
	(-1.158)		(-1.539)
Market to Book	-0.118	-0.040	-0.141
	(-0.948)		(-1.107)
Leverage	-1.012**	-0.342**	-0.993
	(-2.000)		(-1.534)
Profitability	0.742	0.251	0.155
	(0.676)		(0.130)
PPE	0.437	0.148	0.235
	(1.476)		(0.734)
Analyst Coverage	-0.003	-0.001	0.010
	(-0.317)		(1.175)
Stdev of Forecasts	0.124	0.042	-0.370
	(0.308)		(-0.250)
Rating Dispersion	-0.097	-0.033	-0.042
	(-1.203)		(-0.532)
Distance	-0.133***	-0.045***	-0.155***
	(-4.037)		(-4.185)
Constant	-1.286*		-2.028**
	(-1.927)		(-2.395)
Industry FE	Yes		Yes
Observations	1,283		937
Pseudo R-squared	0.125		0.155

Table 4. Probit Regressions of Fitch Rating for Pseudo-events

This table reports the results of probit regressions for a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015, conditional on the starting date of the post-Dodd-Frank period. For brevity the coefficients on the control variables are omitted. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. Z-values are shown inside brackets. Following Dimitrov et al. (2015) we re-define the post-Dodd-Frank to start in July 2009 (the first version of the legislation), Dec 2009 (i.e. the revised version of the legislation), July 2010 (i.e. the law's passage date), July 2012 (i.e. Section 939 effective date) and Jan 2013 (i.e. OCC rule effective date). ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	First version **Jul-09**	Revised version **Dec-09**	Law's passage **Jul-10**	Section 939 effective date **Jul-12**	OCC rule effective date **Jan-13**
Dodd-Frank	-0.452***	-0.461***	-0.507***	-0.573***	-0.628***
	(-4.413)	(-4.787)	(-5.187)	(-5.169)	(-5.111)
Controls	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 5. Probit Regressions of Fitch Ratings on Active Bonds

This table re-examines the effect in Table 3 by running probit regressions of a Fitch rating on the Dodd-Frank dummy and firm controls on active bonds between Jan 2006 and Dec 2015. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. Z-values are shown inside brackets. Model 1 reports the results for probit regression, while Model 2 reports the marginal effects. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

	Model 1	**Model 2**
VARIABLES	Probit	Marginal Effects
Dodd-Frank	-0.260***	-0.083***
	(-4.016)	
Firm size	0.450***	0.142***
	(6.411)	
Intangible Assets	-0.650*	-0.206*
	(-1.852)	
Market to Book	-0.005	-0.001
	(-0.527)	
Leverage	-0.174	-0.055
	(-0.444)	
ROA	-2.088*	-0.661*
	(-1.767)	
PPE	0.135	0.043
	(0.667)	
Analyst Coverage	0.002	0.001
	(0.317)	
Stdev of Forecasts	1.576***	0.495***
	(2.773)	
Rating Dispersion	0.048	0.015
	(0.949)	
Distance	-0.105***	-0.033***
	(-3.428)	
Constant	-4.327***	
	(-6.656)	
Industry FE	Yes	
Observations	10,289	
Pseudo R-squared	0.200	

Table 6. OLS Regression of Credit Spreads

This table reports the results of an OLS regression for credit spreads at issuance on the Fitch dummies, issue characteristics and firm controls between Jan 2006 and Dec 2015. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. T-statistics are shown inside brackets. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	Model 1 Credit Spread
Fitch_Makes_IG*Dodd-Frank	75.317**
	(2.467)
Fitch_Makes_IG	-134.390***
	(-4.309)
Dodd-Frank	-52.641***
	(-6.221)
Fitch_Added_Better	-13.780
	(-1.297)
Fitch_Added_Equal	-2.725
	(-0.271)
Fitch_Added_Better*Dodd-Frank	-17.049
	(-1.206)
Fitch_Added_Equal*Dodd-Frank	-9.081
	(-0.715)
InvBoundary	83.200***
	(3.682)
Firm Size	-6.597*
	(-1.917)
Market to Book	-28.338***
	(-4.105)
Intangible Assets	-83.525***
	(-4.216)
Analyst Coverage	-1.353***
	(-3.600)
Issue Size	-0.893
	(-0.413)
Maturity	11.770***
	(4.394)
S&P Rating	27.054***
	(16.134)
CDX Index	1.388***
	(16.411)
Redeemable	18.317**
	(2.301)
Rule144a	90.510***
	(7.103)
Constant	-32.978
	(-0.619)
Industry FE	Yes
Observations	2,221
R-squared	0.780

Table 7. Earnings Management and Corporate Risk-Taking

This table reports the PSM estimations on absolute discretionary accruals (Panel A), cash flow volatility (Panel B) and sales volatility (Panel C), respectively, for firms with/without Fitch ratings before and after Dodd-Frank. The propensity scores are computed using firm size, market-to-book ratio, leverage, intangible assets, profitability, PPE, analyst coverage, credit quality as well as year and industry fixed effects. The matching is done using a one-to-one nearest neighbor matching with replacement. The average treatment effect on the treated (ATT) is reported and the statistical significance is tested using the t-test. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

Panel A- ADA	**Before DFA**				**After DFA**			
	Treated (Without Fitch)	**Controls** (With Fitch)	**ATT**	**t stat**	**Treated** (Without Fitch)	**Controls** (With Fitch)	**ATT**	**t stat**
Unmatched	0.048	0.045	0.003	0.69	0.041	0.033	0.008**	2.15
ATT	0.048	0.055	0.007	1.16	0.041	0.03	0.011**	2.09

Panel B- Cash Flow Vol	**Before DFA**				**After DFA**			
	Treated (Without Fitch)	**Controls** (With Fitch)	**ATT**	**t stat**	**Treated** (Without Fitch)	**Controls** (With Fitch)	**ATT**	**t stat**
Unmatched	0.026	0.025	0.001	0.45	0.034	0.025	0.009***	2.6
ATT	0.026	0.023	0.003	0.6	0.034	0.023	0.011***	2.89

Panel C- Sales Vol	**Before DFA**				**After DFA**			
	Treated (Without Fitch)	**Controls** (With Fitch)	**ATT**	**t stat**	**Treated** (Without Fitch)	**Controls** (With Fitch)	**ATT**	**t stat**
Unmatched	0.079	0.088	-0.009	-1.10	0.099	0.080	0.019**	2.05
ATT	0.079	0.096	-0.017	-0.83	0.099	0.072	0.026**	2.11

Table 8. OLS Regression of Fitch Ratings on Earnings Management

This table reports the results of an OLS regression for absolute discretionary accruals on the Dodd-Frank dummy, Without Fitch dummy and firm controls between Jan 2006 and Dec 2015. Without Fitch is a dummy that equals one if Fitch has not rated the issue, and zero otherwise. Consistent with Yu (2008), absolute discretionary accruals are multiplied by 100 to be presented as a percentage of lagged assets. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. T-statistics are shown inside brackets. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	**Linear Regression** Absolute Discretionary Accruals
Dodd-Frank*Without Fitch	1.110**
	(1.998)
Dodd-Frank	-1.243***
	(-2.809)
Without Fitch	-0.753
	(-1.609)
Firm Size	-0.082
	(-0.498)
Market to Book	0.426
	(0.856)
Intangible Assets	1.171
	(0.878)
Leverage	2.356*
	(1.661)
Profitability	-7.558
	(-0.912)
PPE	0.488
	(0.673)
Analyst Coverage	0.001
	(0.057)
Analyst Dispersion	8.452***
	(6.018)
Crash Risk	0.221
	(0.586)
Z-Score	-0.203
	(-1.134)
Sales Growth	2.672
	(1.206)
Constant	5.619***
	(3.023)
Industry FE	Yes
Observations	1,208
R-squared	0.163

Table 9. OLS Regressions of Fitch Ratings on Cash Flow and Sales Volatilities

This table reports the results of OLS regressions for earnings volatility on the Dodd-Frank dummy, Without Fitch dummy and firm controls between Jan 2006 and Dec 2015. Model 1 reports the results for cash flow volatility (i.e. 5-year standard deviation of ROA) while model 2 uses sales volatility (5-year standard deviation of sales (scaled by total assets)), consistent with Zhang (2009). Without Fitch is a dummy that equals one if Fitch has not rated the issue, and zero otherwise. Consistent with prior studies, the standard deviation of ROA, standard deviation of sales, idiosyncratic risk, and industry average volatility are multiplied by 100 to be presented as a percentage. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. T-statistics are shown inside brackets. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

	Model 1	**Model 2**
VARIABLES	Stdev(ROA)	Stdev(Sales)
Dodd-Frank*Without Fitch	0.987**	2.768**
	(2.461)	(2.479)
Dodd-Frank	0.217	-0.674
	(0.829)	(-0.898)
Without Fitch	-0.415	-1.153
	(-1.455)	(-1.307)
Firm Size	-0.272***	-1.261***
	(-2.874)	(-4.678)
Market to Book	0.179	-0.699
	(0.613)	(-0.556)
Leverage	0.477	-1.821
	(0.325)	(-0.548)
Profitability	6.977	-12.854
	(1.475)	(-1.244)
PPE	1.396**	-2.246
	(2.265)	(-1.293)
Z-Score	-0.012***	-0.064***
	(-4.038)	(-4.458)
Sales Growth	1.648**	14.971***
	(2.090)	(3.728)
Idiosyncratic Vol	0.254**	0.340**
	(2.414)	(2.239)
Institutional Holding	0.460	-0.758
	(1.439)	(-0.854)
Industry Average	0.002*	0.006*
	(1.775)	(1.946)
Constant	4.091***	30.665***
	(2.740)	(5.683)
Industry FE	Yes	Yes
Observations	1,152	1,174
R-squared	0.224	0.320

Appendix A Variable Definitions

Variable	Definition	Source
Fitch	A dummy variable equals one if the bond has a Fitch rating, and zero otherwise	MERGENT
Without Fitch	A dummy variable equals one if Fitch has not rated the bond, and zero otherwise	MERGENT
Dodd-Frank	A dummy variable equals one if firm's bond is issued after Dodd-Frank (i.e. 21 July 2010), and zero otherwise	MERGENT
Firm Size	Natural logarithm of the firm's total assets (in millions)	COMPUSTAT
Market to Book	The market-to-book ratio (firm's market value of equity minus book value of equity plus total assets divided by total assets)	COMPUSTAT
Intangible Assets	Firm's intangible assets scaled by total assets	COMPUSTAT
Leverage	The book value of long-term debt scaled by total assets	COMPUSTAT
Profitability	Net income scaled by total assets	COMPUSTAT
PPE	Property, plant, and equipment scaled by total assets	COMPUSTAT
Analyst Coverage	The number of analysts following a firm	IBES
Stdev of Forecasts	The standard deviation of forecast annual EPS, scaled by the firm's stock price	IBES
S&P Ratings	An ordinal number ranging from one (for AAA rated bonds) to twenty-one (for C rated bonds)	MERGENT
Moody's Rating	An ordinal number ranging from one (for Aaa rated bonds) to twenty-one (for C rated bonds)	MERGENT
Rating Dispersion	The absolute difference between ratings assigned by Moody's and S&P	MERGENT
Distance	The absolute distance from the HY-IG boundary.	MERGENT
Credit Spread	The difference between the yield of the benchmark treasury issue and the issue's offering yield expressed in basis points	MERGENT
CDX Index	CDS index values (i.e. CDX NA IG index)	BLOOMBERG
Fitch_Added_Better	A dummy that equal equals one if Fitch is added and overall rating level is improved, and zero otherwise	MERGENT
Fitch_Added_Equal	A dummy that equals one if Fitch is added and overall rating level is unchanged (i.e. Fitch cannot worsen the overall rating level), and zero otherwise	MERGENT
Fitch_Makes_IG	A dummy that equals one if Moody's and S&P are at the boundary and Fitch added and Fitch pulls IG, and zero otherwise	MERGENT
InvBoundary	A dummy that equals one if Moody's and S&P are at the HY-IG boundary, and zero otherwise	MERGENT
Issue Size	Natural logarithm of the offering amount	MERGENT
Maturity	Natural logarithm of the maturity (in month)	MERGENT
Redeemable	A dummy that equals one if the bond is redeemable, and zero otherwise	MERGENT
Rule144a	A dummy that equals one if the bond is exempt from registration under SEC Rule 144a, and zero otherwise	MERGENT

Split	A dummy variable equals one if Moody's rating differs from S&P rating, and zero otherwise	MERGENT
ADA	The absolute value of discretionary accrual, based on a modified Jones model (Dechow, Sloan and Sweeney, 1995)	COMPUSTAT
Crash Risk	A dummy that equals one if the firm experiences one or more crash weeks in the year, and zero otherwise, based on Kim, Li and Zhang (2011)	CRSP
Z-score	The Altman Z-score, based on Altman, (1968)	COMPUSTAT
Sales Growth	The changes in sales, scaled by the lagged assets	COMPUSTAT
Cash Flow Vol	The 5-year standard deviation of ROA (i.e. EBITDA/total assets)	COMPUSTAT
Sales Vol	The 5-year standard deviation of sales (i.e. sales/total assets)	COMPUSTAT
Industry Average	The average cash flow (sales) volatility of firms from the same industry	COMPUSTAT
Idiosyncratic Vol	The one-year standard deviation of firm-specific weekly returns, based on Kim et al. (2011)	CRSP
Institutional Holding	Percentage of institutional ownership	Thomson Reuters 13F

Appendix B. Variable Construction

- **Earnings Management**

We follow Yu (2008) and use a modified Jones model (Dechow et al., 1995), which estimates discretionary accruals based on the following cross-sectional model estimated for each two-digit SIC-year grouping:

$$\frac{TA_{it}}{AT_{i,t-1}} = b_0\left(\frac{1}{AT_{i,t-1}}\right) + b_1\left(\frac{\Delta SALES_{it}}{AT_{i,t-1}}\right) + b_2\left(\frac{PPE_{it}}{AT_{i,t-1}}\right) + \epsilon_{it} \tag{1}$$

Where *TA* equals net income minus cash flow from operations; *ΔSales* is the changes in sales revenues; *PPE* is the gross property, plant, and equipment. *ΔAR* is the changes in receivables; All variables are scaled by total assets at the beginning of the period (i.e. $AT_{i,t-1}$).

We use the coefficient estimates from equation (1) to calculate nondiscretionary accruals:

$$NDA_{it} = \widehat{b_0}\left(\frac{1}{AT_{i,t-1}}\right) + \widehat{b_1}\left(\frac{\Delta SALES_{it}}{AT_{i,t-1}} - \frac{\Delta AR_{it}}{AT_{i,t-1}}\right) + \widehat{b_2}\left(\frac{PPE_{it}}{AT_{i,t-1}}\right) \tag{2}$$

Our measurement of discretionary accruals (as a percentage of the assets of the firm) is the absolute value of the difference between total accruals and the nondiscretionary accruals:

$$|DA_{it}| = \left|\frac{TA_{it}}{AT_{i,t-1}} - NDA_{it}\right| \tag{3}$$

Appendix C. Active Bonds

Figure 4 Proportion of bonds with three ratings

This figure plots the proportion of active bonds with three ratings between 2006 and 2015. 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. Subsequent bond issues of the same issuing firm within the same month are also filtered out.

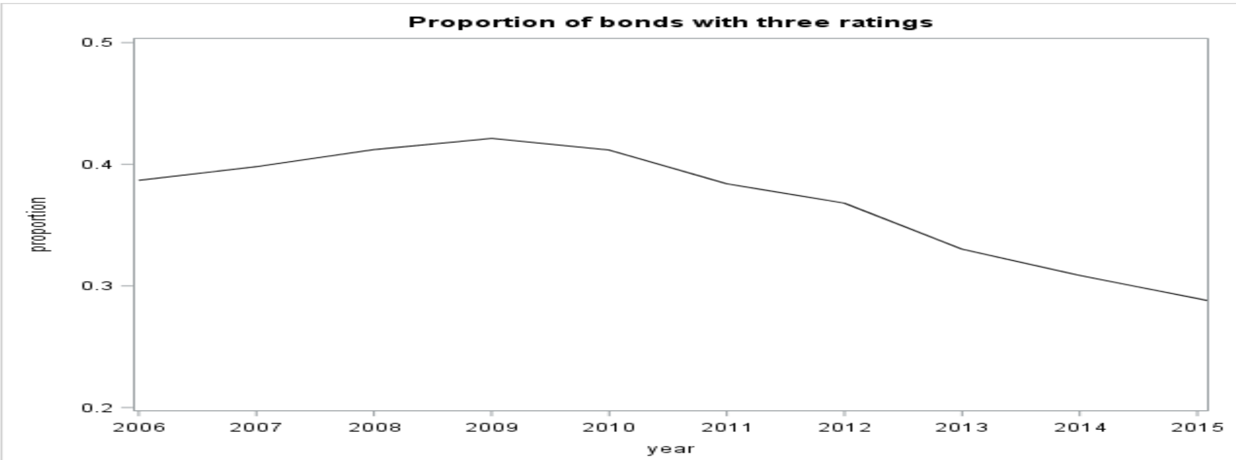
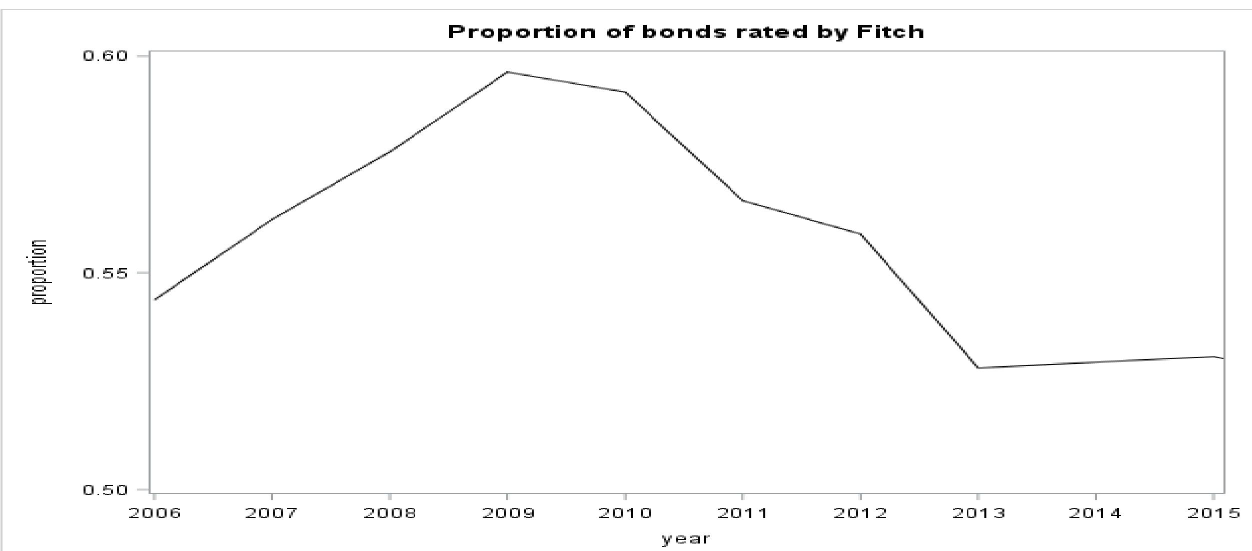


Figure 5 Proportion of bonds rated by Fitch

This figure plots the proportion of active bonds between 2006 and 2015 rated by Moody's and S&P that also have a Fitch rating.



Appendix D. Descriptive Statistics for Variables Affecting Earnings Management and Corporate Risk-Taking

This table reports the descriptive statistics for variables (i.e. additional variables besides those listed in Table 1) used in Section 4.3.3. The whole sample is partitioned into before Dodd-Frank and after Dodd-Frank subsample periods, and each subsample is further partitioned into Without-Fitch and With-Fitch groups.

	Before Dodd-Frank				After Dodd-Frank			
	Without Fitch		With Fitch		Without Fitch		With Fitch	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
ADA	0.048	0.035	0.045	0.032	0.041	0.026	0.033	0.024
Cash Flow Vol	0.026	0.014	0.025	0.017	0.034	0.021	0.025	0.019
Sales Vol	0.079	0.045	0.088	0.062	0.099	0.053	0.080	0.054
Idiosyncratic Vol	0.050	0.036	0.041	0.036	0.034	0.030	0.030	0.026
Crash Risk	0.331	0	0.193	0	0.186	0	0.140	0
Z-Score	1.512	0.927	1.749	1.355	1.528	1.025	4.735	1.512
Sales Growth	0.046	0.014	0.023	0.011	0.062	0.021	0.042	0.025
Institutional Holding	0.713	0.741	0.746	0.766	0.704	0.708	0.769	0.730
Industry Avg CF Vol	1.793	0.330	1.256	0.330	1.280	0.510	0.969	0.478
Industry Avg Sales Vol	0.416	0.218	0.386	0.240	0.244	0.220	0.200	0.191