# REGULATORY REFORM AND MULTIPLE CREDIT RATINGS

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**Abstract**

This paper studies the role of multiple credit ratings in the corporate bond market. By examining the change in regulatory use of multiple ratings after the Dodd-Frank Act (Dodd-Frank), we find that the elimination of ratings from regulatory requirements reduces the demand for third ratings, which are typically provided by Fitch. Specifically, firms are less likely to seek a third rating for newly issued bonds, especially for those with split ratings from Moody's and S&P. In addition, we find that third ratings become less informative following Dodd-Frank with a smaller market impact on credit spreads, especially for firms with current ratings on opposite sides of the high yield (HY) - investment grade (IG) boundary. Overall, the results challenge the existence of small CRAs, which shed light on the consequence of Dodd-Frank, and are important in that it is related to the competition in the rating industry and the cost of borrowing for issuers.

Keywords: Regulation, Dodd-Frank, Credit ratings, Bonds, Event Study

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## 1. Introduction

Credit ratings provided by credit rating agencies (CRAs) have long been used by investors, regulators, and financial institutions as an indicator to assess firms' credit risk and to determine regulatory capital requirements. However, a substantial number of unanticipated credit rating downgrades of corporations and structured securities by CRAs during the financial crisis in 2008 and 2009 has brought renewed attention to the role that CRAs play in financial markets. Specifically, CRAs downgraded a large number of mortgage-backed securities from investment to non-investment grade[1], which is arguably the largest deterioration of credit quality in history (Hanley and Nikolova, 2018). Many banks and insurance companies whose capital reserves are determined by credit ratings were severely affected by these downgrades. Ellul, Jotikasthira and Lundblad (2011) and Merrill, Nadauld, Stulz and Sherlund (2014) show that banks' and insurers' attempts to manage the depletion of regulatory capital pose a risk to the financial market stability globally. In response to the financial crisis, National Association of Insurance Commissioners (NAIC) replaced credit ratings as inputs to capital regulations in 2009, and the Congress passed the Dodd-Frank Act to reduce regulatory reliance on credit ratings (Section 939) in July 2010.

Dodd-Frank, the largest change in financial regulations since 1934, has received much attention both in the media and in the academic literature. Dimitrov, Palia and Tang (2015) provide evidence that CRAs issue lower credit ratings with weaker stock and bond market reactions, and have higher incidence of false warnings after Dodd-Frank. Becker and Opp (2014), Becker, Opp and Saidi (2018) and Hanley and Nikolova (2018) document that removing credit ratings from capital regulations by NAIC affects the insurers' behavior. Although a growing body of literature examines the impact of this regulatory reform on financial institutions, the impact on the demand for multiple credit ratings remains relatively unexplored. Are credit ratings, particularly ratings from smaller CRAs, still relevant post Dodd-Frank? This study fills this gap by examining the

[1] The investment grade (IG) is defined as ratings from BBB- to AAA while bonds with ratings lower than BBB- are classified as high yield (HY, also referred as non-investment grade) bonds.

impact of the Dodd-Frank regulatory reform on the demand for and the information content of multiple credit ratings[2].

Most large U.S. corporate bonds are rated by Moody's and S&P, and the lower rating is used for bond classification (Bongaerts, Cremers and Goetzmann, 2012). However, when bonds are rated by more than two CRAs, the second lowest rating is used to classify this bond[3]. 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). Those works evaluate three widely accepted theories about multiple ratings: information production, rating shopping and regulatory certification[4], and find that there is little empirical evidence on information production and rating shopping theories while having multiple ratings is more likely to occur primarily for regulatory purposes. For instance, Bongaerts, Cremers and Goetzmann (2012) find that when the current two ratings are on opposite sides of the high yield (HY)- investment grade (IG) boundary, a third rating provided by Fitch plays the role of a tiebreaker that differentiates between HY and IG status. We conjecture that eliminating the regulatory reliance on credit ratings reduces the demand for third ratings, particularly ratings issued by Fitch, which generally provides a 'third opinion' after Moody's and Standard & Poor's (S&P)[5]. Also, the literature documents that Fitch ratings are on average more optimistic than ratings assigned by Moody's and S&P and firms with Fitch ratings have lower yields (Cantor and Packer, 1997; Jewell and Livingston, 1999; Bongaerts, Cremers and Goetzmann, 2012; Livingston and Zhou, 2016). Since Dodd-Frank removes the regulatory reliance on ratings, we conjecture that this revision reduces the market impact of third ratings.

[2] Consistent with previous studies (e.g. Bongaerts, Cremers and Goetzmann, 2012), multiple ratings are referred to third ratings.

[3] In 2005 Lehman Brothers index included Fitch as a third rating agency when assessing the bonds' rating classifications, the rating of a bond is determined by the middle rating of the three CRAs.

[4] Under the information production hypothesis investors seek additional ratings to reduce the uncertainty about the credit quality of firms' bonds. The rating shopping hypothesis argues that issuers will shop for a better rating if they receive a disappointing one. Under the regulatory certification hypothesis, firms seek an additional rating if their existing ratings straddle the high yield (HY) and investment grade (IG) boundary.

[5] Bongaerts, Cremers and Goetzmann (2012) and Chen and Wang (2015) document that most large U.S. corporate bond issues are rated by Moody's and S&P, and Fitch is the most common third rating agency. Therefore, we follow previous studies and study the implications for having Fitch as a third rating.

Using a database of newly issued U.S. corporate bonds from 2006 to 2015, we show that firms are less likely to seek a third rating for newly issued bonds following the passage of Dodd-Frank. Specifically, firms are 17.86% less likely to seek a third rating, and the decrease is more pronounced for firms with split ratings. In addition, we show that third ratings are less informative following Dodd-Frank with a smaller market impact on credit spreads (from 2.990 basis points to 1.723 basis points while not statistically significant), and the effect is more pronounced when firms' current ratings from Moody's and S&P are at the HY-IG boundary (from 15.982 basis points to 1.515 basis points and the difference is statistically significant at 5% level). We further perform a placebo test by simulating different timing of Dodd-Frank date to mitigate the issue that the reported effects could be coincidental as they could be driven by other contemporaneous events. We find that the results strengthen with time as the uncertainty regarding the implementation of Dodd-Frank gradually resolves, which increases the confidence in attributing the reported effects to Dodd-Frank.

These results are relevant to firms and investors since acquiring a third rating from Fitch is costly (Livingston and Zhou, 2016). Also, previous literature documents that firms can improve their rating level and then decrease the cost of borrowing by seeking a third rating. Since the reduced regulatory reliance on credit ratings may remove the advantage of higher ratings, thus leads to an increased borrowing cost in the debt market. The results are also of interest to regulators as it is related to the competition in the rating industry. Specifically, if a third rating from small CRAs is not cost justified and then the demand for it is reduced, the competition is limited which affects the information efficiency of financial markets. Our results indicate that Dodd-Frank appears to be achieving its objective since it reduces the demand for ratings especially from smaller players such as Fitch.

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 presents the empirical tests. Section 5 concludes.

## 2. Related Studies and Hypotheses Development

There are three widely accepted – but not necessarily mutually exclusive – theories on why firms demand multiple ratings, namely, the information production hypothesis, the rating shopping hypothesis and the regulatory certification hypothesis (Bongaerts, Cremers and Goetzmann, 2012). Several theoretical papers (e.g. Skreta and Veldkamp, 2009; Bolton, Freixas and Shapiro, 2012; Sangiorgi and Spatt, 2017) develop models to motivate rating shopping but widespread empirical evidence on the rating shopping hypothesis is lacking. Specifically, Becker and Milbourn (2011) and Bongaerts, Cremers and Goetzmann (2012) find no robust evidence to support the rating shopping hypotheses. Bakalyar and Galil (2014) provide limited empirical evidence for rating shopping in the much smaller Israeli market. Kronlund (2017) provides evidence for rating shopping in corporate bond market but argues that firms engaging in rating shopping prefer just one rating (i.e. the highest one among big three CRAs). The author also argues that if firms need more than one rating then they would prefer to subscribe the second rating after the bond is sold. Similarly, there is limited evidence to support the information production hypothesis. Livingston and Zhou (2016) find that Fitch as the third rating brings additional information only for information-opaque bonds.

However, studies show that multiple ratings are primarily motivated by regulation. Since the Lehman index rule change in 2005 when Lehman Brothers began to include Fitch as a third rating agency when assessing the bonds' rating classifications, the rating of a bond is determined by the middle rating of the three CRAs, instead of the lower, more conservative rating issued by either Moody's or S&P (Chen et al, 2014; Chen and Wang, 2015). Similar rule can be found in NAIC guidelines that when multiple ratings are available, the second lowest rating should be used (Hanley and Nikolova, 2018). These rules present firms a free option to improve their current rating as a third rating cannot worsen the credit quality of the issuer. Opp, Opp and Harris (2013) develop a theoretical framework that regulatory reliance on credit ratings lowers ratings quality as the CRAs find it more profitable to facilitate regulatory arbitrage than to sell informative ratings. Cornaggia and Cornaggia (2013) compare the properties of ratings produced by an issuer-paid rating agency: Moody's and a subscriber-paid rater: Rapid Ratings, and conclude that the issuer-paid scheme has the conflict of interest associated with its compensation structure. Cornaggia, Cornaggia and Simin (2016), following Cornaggia and Cornaggia (2013) and Opp, Opp and Harris (2013), document evidence of regulatory arbitrage which provides a more complete view of the conflicts of interest generated by the regulatory reliance on credit ratings funded by issuers than simple rating shopping hypothesis. Empirically, financial firms investing in HY debt may need to hold additional capital 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, Cremers and Goetzmann (2012) find that issues where Fitch assigns an IG rating are associated with a 41 basis point lower spread on average than issues where Fitch allocates a HY rating. These works provide support for the regulatory certification hypothesis.

*1. Demand for Multiple Ratings*

The Dodd-Frank regulatory reform may lead to a question of whether the existence of smaller rating agencies is economically justified. Baghai, Becker and Pitschner (2018) study 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 did not examine the role of multiple ratings and the regulatory use of ratings. Specifically, since Dodd-Frank eliminates the reliance of financial institutions on credit ratings to quantify required capital, it reduces the regulatory advantage of higher ratings. Consequently we posit that the incentive to inflate ratings (by seeking a third rating) will reduce following the passage of Dodd-Frank leading to a lower demand for third ratings (Cornaggia and Cornaggia, 2013; Opp, Opp and Harris, 2013; Cornaggia, Cornaggia and Simin, 2016). We also conjecture that the effect is stronger for firms with split ratings from Moody's and S&P, as a third rating can change their current rating level[6]:

**$H_{2a}$:** Firms are less likely to seek a third rating after the passage of Dodd-Frank.

[6] The authors acknowledge that firms with Moody's and S&P ratings on opposite sides of the boundary should display the highest demand for a third rating prior to the adoption of Dodd-Frank and subsequently the largest decline. However, the sample size limitations preclude the isolation of the demand for third ratings on newly issued bonds with Moody's and S&P ratings on opposite sides of the HY-IG boundary.

**$H_{2b}$:** This effect is more pronounced for firms with split ratings from Moody's and S&P.

2. *Informational Content and Borrowing Costs*

Livingston and Zhou (2016) find that the Fitch rating, as a third rating, is not redundant but brings additional information to investors. Specifically, they find that Fitch ratings reduce the yield premiums on information-opaque bonds by about 30%, or 15 points. Bongaerts, Cremers and Goetzmann (2012) find that Fitch rating, as the tiebreaker, pushing issues into IG category has a 41 basis point lower spread on average than pushing the issues into HY category. Cornaggia, Cornaggia and Israelsen (2017) focus on the municipal bond market which is dominated by un-regulated retail investors, and find that investors continue to rely on credit ratings for information about credit risk, besides any regulatory implications. Also, Bruno, Cornaggia and Cornaggia (2016) suggest that reduced regulatory reliance on CRAs may improve the quality of issuer-paid ratings. Those works suggest that Section 939 Dodd Frank Act will not negate the role of CRAs in determining firms' creditworthiness.

On the contrary, Dimitrov, Palia and Tang (2015) provide evidence that following Dodd-Frank CRAs issue lower credit ratings with weaker stock and bond market reactions, and exhibit higher frequency of false warnings. Behr et al. (2016) examine the impact of the Securities and Exchange Commission (SEC) regulation in 1975[7] on rating inflation and find that the restriction in the competition in rating industry and the increased regulatory reliance on ratings lead to rating inflation. Dodd-Frank, which is against the SEC 1975 regulation, should have the opposite effect on rating inflation. Firms usually inflate their ratings and decrease the cost of borrowing by seeking a third rating (i.e. rating shopping hypothesis and regulatory certification hypothesis). Since the increased penalties on false ratings and the removal of reliance on credit ratings may lead to less optimistic ratings and remove the advantage of higher ratings, we posit that Dodd-Frank will lead to lower information content of the third rating and thus increased borrowing costs. The hypotheses are constructed as follows:

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

**H$_{1a}$:** The impact of a third rating on bond yields will reduce following the passage of Dodd-Frank.

**H$_{1b}$:** The effect is more pronounced for firms when existing ratings straddle the HY-IG boundary.

## 3. Data

Bond characteristics and credit ratings by Moody's, S&P and Fitch are acquired from Mergent Fixed Income Securities Database (FISD). In line with Dimitrov, Palia and Tang (2015), our sample begins in January 2006 to avoid any ongoing market adjustments to the 2002 SOX Act[8] and ends in December 2015. Following convention, ratings are converted to numerical rating codes, 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 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 as the process for assigning initial ratings is more robust than the process for monitoring ratings (Chen and Wang, 2015).

Accounting information and outstanding shares are sourced from Compustat. Equity analysts' forecasts and analyst coverage are acquired from Institutional Brokers' Estimate System (IBES). Issuing firms covered by fewer than three stock analysts are eliminated. Corporate bond prices are obtained from the Trade Reporting and Compliance Engine (TRACE) database.

[8] 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 rating industry and increases oversight of CRAs, was signed into law by the President.

# 4. Empirical Results

## 4.1 Methodology and Statistical Descriptive

### 4.1.1 Probit Model

We estimate the firms' propensity to demand a third rating using a probit model. The probit regression has the following form:

$$P(Y = 1|\, \boldsymbol{X}) = \Phi(\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{\beta}) \quad (1)$$

where $\boldsymbol{X}$ 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:

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

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

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

The vector of the coefficients $\boldsymbol{\beta}$ is estimated by the Maximum Likelihood Estimation.

### 4.1.2 Bi-variate Probit Model

To test whether two decisions are interrelated rather than independent, a bi-variate probit model can be performed:

$$Y_1{}^* = \boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{\beta} + \varepsilon_{\boldsymbol{1}}$$

$$Y_2{}^* = \boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{\beta} + \varepsilon_{\boldsymbol{2}}$$

Where the error terms $\varepsilon_{\boldsymbol{1}}$ and $\varepsilon_{\boldsymbol{2}}$ are independent if the decisions are independent.

### 4.1.3 Variable Description

For $H_1$, the dependent variable, *Fitch*, equals one if Fitch has rated the issue, and zero otherwise. The main variable, *Dodd-Frank*, represents a dummy variable equal to one if the firm's bond is issued after July 21, 2010, when Dodd-Frank was signed into federal law, and zero otherwise. *Control* encapsulates numerous bond and firm characteristics commonly quoted in literature including size and opacity. Size is a proxy for firm age and participation in the public bond market, which is positively related to the likelihood of having a Fitch rating (Cantor and Packer, 1997; Bongaerts, Cremers and Goetzmann, 2012). *Firm Size* is measured as the natural log of the market capitalization of equity. 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* ratio defined as the firm's market value of equity minus book value of equity plus total assets divided by total assets and *Intangible Assets*, calculated as the amount of intangible assets divided by total assets, as accounting proxies of opacity. Besides *Firm Size*, *Intangible Assets* and *Market-to-Book*, 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). 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). We supplement these with two opinion-based opaqueness proxies, dispersion in equity analysts' earnings forecasts, calculated as the standard deviation in earnings forecasts divided by the stock price (*Stdev of Forecasts*), and the number of analysts following a firm, *Analyst Coverage*. Brennan and Subrahmanyam (1995) show that large analyst coverage results in more information flows to investors, which reduces firms' assets opaqueness. We also employ a dispersion dummy to indicate a split rating between Moody's and S&P as an additional credit-based opacity proxy to test $H_{1b}$.

#### 4.1.4 Statistical Description

We start with 3410 newly issued domestic bonds with complete data in FISD, Compustat and IBES databases. First, we filter out 534 bonds issued by financials (GICS code starting with 40) and utilities (GICS code starting with 55) as financials and highly regulated utilities have a higher prevalence of Fitch ratings (Cantor and Packer, 1997; Becker and Milbourn, 2011)[9]. We further require bonds are rated by both Moody's and S&P within the first 30 days after issuance to avoid rating adjustment and unsolicited ratings, which excludes 1587 bond issues. As some firms issue

[9] Cantor and Packer (1997) show that financial and utilities firms are more likely to demand Fitch ratings (~40%), compared to firms in other industries (13.6%)

multiple bonds over a short period of time which are unlikely to convey additional information, 409 subsequent bond issues of the same issuing firm within the same month are also filtered out. The final sample contains 880 bond issues from 2006 to 2015[10]. Panel A in Table I provides descriptive statistics for the control variables before and after Dodd-Frank and shows that both samples are quite similar. Splitting the sample into firms rated by both Moody's and S&P that also have a Fitch rating versus firms that do not in Panel B, we can see that firms rated by Fitch are generally larger and have a lower market-to-book ratio, more intangible assets, lower leverage, higher profitability and greater coverage by analysts.

[Table 1]

The correlation matrix between all variables is reported in Table 2. As expected, *Fitch* is positively and significantly correlated with the *Firm size* and *Analyst Coverage*, and negatively and significantly correlated with *Leverage* and *PPE*. *Firm size* and *Leverage* and *Firm size* and *Analyst Coverage* along with *Intangible Assets* and *PPE* exhibit the highest correlation coefficients.

[Table 2]

### 4.2 Demand for Third Ratings

Figure 1 plots the proportion of newly issued bonds between 2006 and 2015 that are un-rated within the first 30 days after issuance. Special issues and subsequent bond issues of the same issuing firm within the same month are filtered out. Figure 2 shows 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 plots the proportion of newly issued bonds between 2006 and 2015 rated by Moody's and S&P[11] within the first 30 days after issuance that are also rated by Fitch. It can be seen that there are two clear trends in these three figures. First, there are more bonds that seek third ratings between 2006 and 2009, which is consistent with Chen and Wang (2015) that the Lehman index rule change increased the demand for third ratings. Second, after Dodd-Frank which removes

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[10] For robustness, we follow Bongaerts, Cremers and Goetzmann (2012) and extend our study to include all existing bonds which contain 8386 bonds between 2006 and 2015. The results are qualitatively similar and are reported in Appendices.

[11] The vast majority of large, liquid U.S. corporate bonds are rated by both Moody's and S&P. To rule out the possibility that the trend is driven by market condition or smaller issuers and so on, this figure only considers bonds with Moody's and S&P ratings in the denominator.

the regulatory reliance on ratings, these figures show an opposite trend. For instance, Figure 3 shows that prior to Dodd-Frank around 50% of those bonds that seek a Fitch rating. However, since the passage of Dodd-Frank the proportion has decreased to around 25%, which supports our first hypothesis.

[Figure 1, 2, 3]

Before we perform the probit regression on the demand for third ratings, we follow the methodology in Bowe and Larik (2014) and include a bi-variate probit model which tests whether the decision of having split ratings between Moody's and S&P and that of a better rating provided by Fitch are interrelated. As stated in the Section 4.1.2, the dependent variable in the first stage is a dummy that equals one if Moody's rating differs from S&P rating, and zero otherwise, while in the second-stage the dependent variable is a dummy that equals one if Fitch provides a better rating than Moody's or S&P, and zero otherwise. In Table 3, The $\rho$ indicates the error terms are highly correlated while the Wald $\chi^2(18)$, LR test statistics and $\chi^2(1)$ statistic strongly reject the hypothesis that the error terms are independent in the two models. This shows that having split ratings and a better rating provided by Fitch are interrelated, which implies that firms with split ratings are more likely to improve their ratings by seeking a Fitch rating.

[Table 3]

Table 4 provides the results of probit regressions of a Fitch rating on the Dodd-Frank dummy and firm controls. Consistent with Figure 1, firms are less likely to demand ratings from Fitch following Dodd-Frank. Specifically, in Model 1 the coefficient on the main variable, *Dodd-Frank*, is -0.526 and significant at 1% level and indicates that following the passage of Dodd-Frank, the likelihood of observing a Fitch rating decreases by 17.86 % (i.e. the average marginal effect)[12]. In Model 2 we restrict the sample to issues that are rated by both Moody's and S&P. An interaction term of the rating dispersion with the Dodd-Frank dummy is also included to examine whether split rated bonds are being influenced more by Dodd-Frank. We find that *Firm Size* is positive and statistically significant at 1% level, but none of the other control variables are significant. This

[12] $Marginal\ effect = Prob\ [Y=1|\bar{\boldsymbol{x}}_{(\boldsymbol{d})}, d=1] - Prob\ [Y=1|\bar{\boldsymbol{x}}_{(\boldsymbol{d})}, d=0]$ where $d$ denotes binary independent variable and $\bar{\boldsymbol{x}}_{(\boldsymbol{d})}$ denotes the means of all the other variables in the model (Greene 2012, p690).

suggests that large firms are more likely to demand Fitch ratings, but firm valuation uncertainty is not an important driver of the demand for Fitch ratings, consistent with Cantor and Packer (1997).[13] The coefficient on *Rating Dispersion* is positive and significant at 10% level, indicating that firms with information uncertainty are more likely to demand a Fitch rating. The coefficients on the Dodd-Frank dummy and the interaction term are -0.382 and -0.235, respectively, which are significant at 1% level and 10% level, respectively, highlighting that split rated firms are less likely to seek a Fitch rating after the passage of Dodd-Frank. These results lend support to our first hypothesis that firms are less likely to obtain a Fitch rating after the passage of Dodd-Frank, particularly firms with split ratings. For robustness, instead of using an interaction term of the rating dispersion with the Dodd-Frank dummy, the Model 2 is re-estimated for split and non-split subsamples separately. 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. -0.735 compared to -0.348) and the differences are statistically significant at 5% indicating that firms with split ratings are less likely to demand for Fitch ratings after Dodd-Frank, which is consistent with Hypothesis 1b. Our results imply that the competition in the credit rating industry is reduced following Dodd-Frank, which affects the information efficiency of financial markets[14].

[Table 4]

For robustness, in Table 5, we follow Dimitrov, Palia and Tang (2015) and re-define the post-Dodd-Frank to start in July 2009 (the first version of the legislation), December 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). Consistent with Dimitrov, Palia and Tang (2015) we find that the results strengthen as the uncertainty regarding the passage of Dodd-Frank gradually resolves. For instance, the coefficient on *Dodd-Frank* increases from -0.306 for the July 2009 date, to -0.382 for the July

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[13] For robustness we also test issue characteristics from literature such as issue-size, redeem-ability, and maturity (see, for example, Cantor and Packer, 1997; Bongaerts, Cremers and Goetzmann, 2012). Also, the probit regressions are re-examined by adding financials and utilities back into the sample (with Industry Fixed Effect). The results are qualitatively similar and available upon request.

[14] Competition in the rating industry has attracted much attention in the academic literature. Some of literature view competition as improving the quality and reliability of ratings (see Doherty et al 2012; Xia 2014; Bongaerts et al 2012 etc.) while others show that increased competition could result in impairment of the quality of ratings (see Becker and Milbourn 2011; Flynn and Ghent 2017; Baghai and Becker 2017 etc.) and does not necessarily improve rating information content (see Skreta and Veldkamp, 2009; Bolton, et al. 2012).

2010 date, and to -0.476 for the July 2012, which increases the confidence in attributing the reported effects to Dodd-Frank.

[Table 5]

### 4.2 Event Study

Next, we examine the market impact of the initiation of rating coverage by Fitch prior to and following the passage of Dodd-Frank using an event study. In line with existing literature (Jewell and Livingston, 1999; Bongaerts, Cremers and Goetzmann, 2012; Livingston and Zhou, 2016), we utilize credit spreads to control for market-wide movements in interest rates. Credit spreads are estimated by subtracting the maturity matched Treasury yield from the bond yield, calculated from the average of all trades on that day. The Fitch rating addition announcement date is defined as the event day, and the impact of the event is calculated as the difference between the pre-event and post-event credit spread closest to the announcement. As bonds are relatively illiquid, we follow Dimitrov, Palia and Tang (2015), and consider trades up to 5 days prior to and post the announcement. All rating events without at least one trade in the ±5 day window around the announcement date are eliminated. To minimize contamination, the sample is restricted to bonds rated by both Moody's and S&P where Fitch assigns the third rating (i.e. Fitch rating additions). Our final sample contains 1511 Fitch credit events.

Table 6 reports the mean and median market impacts, in basis points (bps), prior to and following the passage of Dodd-Frank. We find that bonds with Fitch rating additions exhibit lower credit spreads both before and after Dodd-Frank. Although these results support Jewell and Livingston (1999), who show that the market attaches value to Fitch ratings and firms with Fitch ratings have lower yields, in terms of the magnitude, the yield reductions with Fitch additions are less than 3 bps. This is consistent with Bongaerts, Cremers and Goetzmann (2012) that there appears to be limited information contained in Fitch ratings unless Fitch serves as the tie-breaker that will differentiate between high yield (HY) and investment grade (IG) status. In addition, results also show a reduction in the market impact of Fitch ratings following the passage of Dodd-Frank, though differences are not statistically significant. The credit quality of our sample deteriorates slightly following Dodd-Frank consistent with the higher propensity of CRAs to issue lower ratings in response to the increased legal and regulatory penalties under Dodd-Frank (Dimitrov, Palia and Tang, 2015). These results provide evidence in support of our second hypothesis that the market impact of Fitch ratings on credit spread changes diminishes following adoption of Dodd-Frank and corroborate a weaker stock and bond market reaction following its passage documented by Dimitrov, Palia and Tang (2015). Our empirical evidence confirms the theoretical predictions of the regulatory change by Opp, Opp and Harris (2013) 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.

[Table 6]

Panel B examines the market impact of Fitch additions for issues with Moody's and S&P ratings on opposite sides of the HY-IG boundary, we argue that the reduction in the market impact would be stronger for these firms. 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 and our estimates are thus conservative. According to Bongaerts, Cremers and Goetzmann (2012) a Fitch rating that raises an issue into investment grade IG rating is associated with a 41 basis point lower spread on average than issues where Fitch allocates a HY rating. As such, firms with Moody's and S&P ratings on opposite sides of the boundary should display the strongest market impact of Fitch rating additions prior to the adoption of Dodd-Frank and subsequently the largest decline. The results in Panel B are consistent with our hypothesis.

## 5. Conclusion

The Dodd-Frank Act introduced several important reforms to the credit rating industry. These include increased legal and regulatory penalties for issuing inaccurate ratings, and elimination of regulatory reliance on credit ratings by financial institutions in determining capital adequacy ratios. We present evidence that these changes materially impact the CRAs. Using newly issued U.S. bond ratings from 2006 to 2015, we find that firms are less likely to seek a third rating for newly issued bonds following Dodd-Frank, particularly for bonds with split ratings assigned by Moody's and S&P. Also, we find that third ratings become less informative with a diminished impact on credit spreads post Dodd-Frank, and the results are more pronounced when firms with current ratings on opposite sides of the HY-IG boundary. Our 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 for obtaining Fitch ratings which in turn reduces the market impact of Fitch ratings. The results are of interest to policy makers and investors for several reasons. First, Fitch ratings are proved to have effects on issuers' borrowing costs (i.e. Livingston and Zhou, 2016; Bongaerts, Cremers and Goetzmann, 2012), which leads to a question of whether this regulatory reform leads to an increased borrowing cost in the debt market. Second, the de-emphasis of ratings, mandated by Dodd-Frank, may also lead to a question of whether the existence of smaller rating agencies is economically justified, which is related to the competition in the CRAs and affects the information efficiency of financial markets.

This work is the first to examine the impact that Dodd-Frank has on the demand for Fitch ratings, which provides potential avenues for future studies. For instance, Opp, Opp and Harris (2013) argue that 'different asset classes will have different threshold levels for rating inflation, the effect of regulatory changes may be heterogeneous across asset classes'. Stanton and Wallace (2013) and Cornaggia, Cornaggia and Israelsen (2017) document that incentives for rating inflation are different in structured product markets and municipal bond markets. Therefore, follow-up studies can compare the impact of this regulatory reform on different asset classes to investigate whether the effect is more pronounced for the high risk structured products while is less pronounced for municipal bonds.

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**Figure 1 Proportion of unrated newly issued bonds**

This figure plots the proportion of newly issued bonds between 2006 and 2015 that are unrated 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.

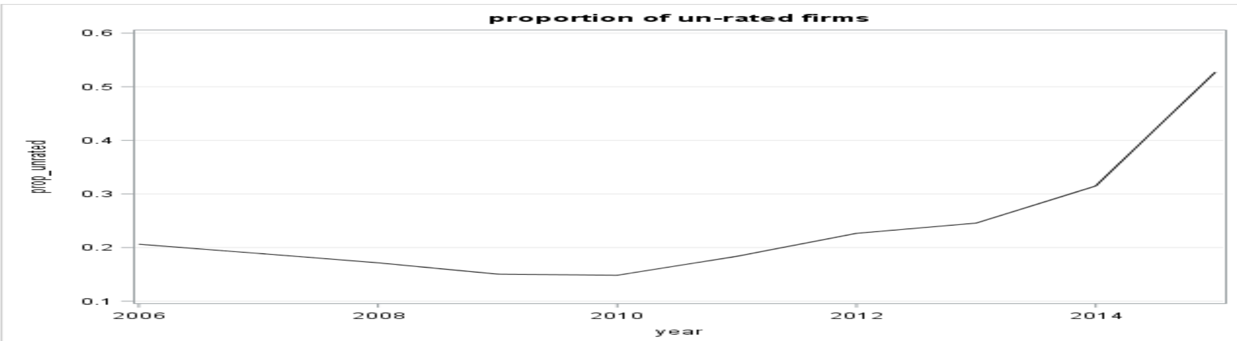



**Figure 2 Proportion of newly issued bonds with three ratings**

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.

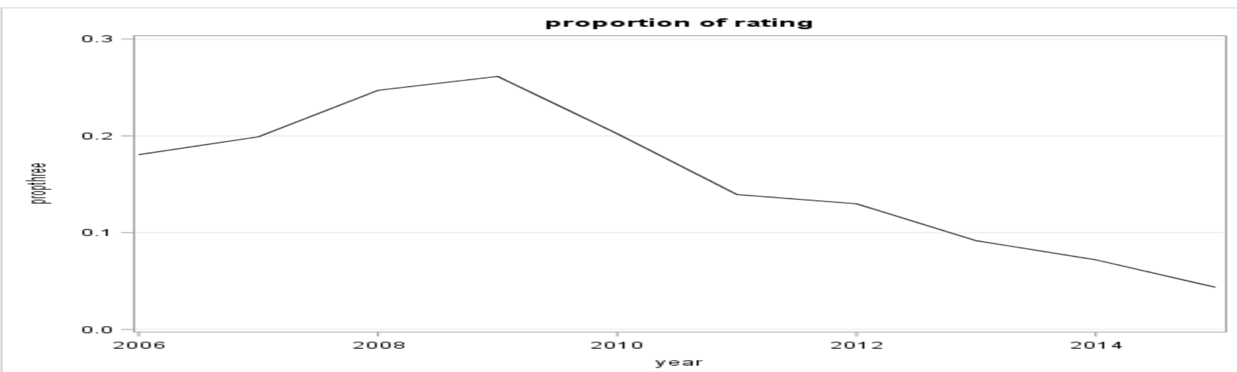



**Figure 3 Proportion of newly issued bonds rated by Fitch**

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.

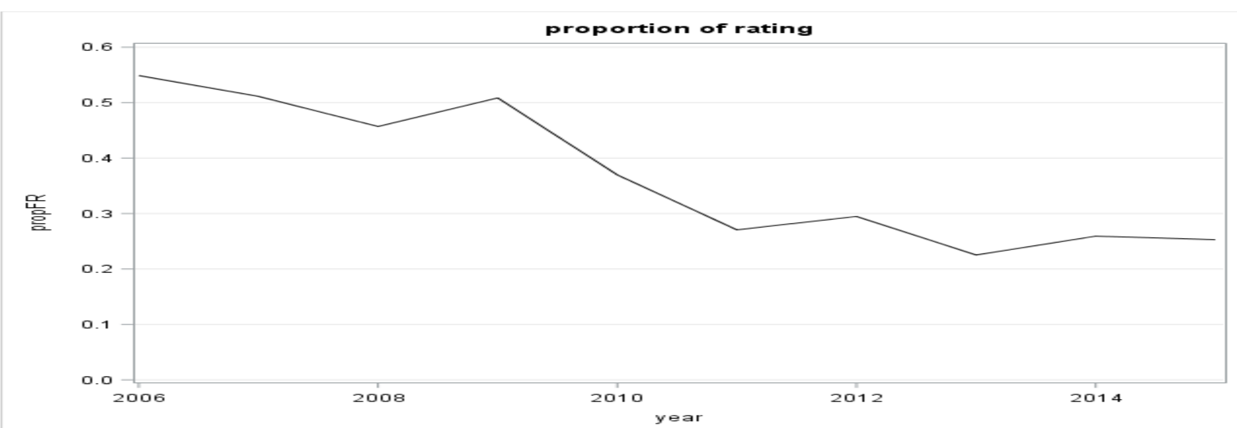


**Table 1 Descriptive Statistics for Controls Affecting Fitch Demand**

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 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 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** | 372 | 9.435 | 9.414 | 6.259 | 12.527 | 1.256 | 508 | 9.515 | 9.413 | 5.950 | 13.438 | 1.334 |
| **Market to Book** | 372 | 1.683 | 1.516 | 0.700 | 5.931 | 0.637 | 508 | 1.682 | 1.519 | 0.790 | 5.619 | 0.635 |
| **Intangible Assets** | 372 | 0.237 | 0.184 | 0 | 0.824 | 0.194 | 508 | 0.234 | 0.198 | 0 | 0.854 | 0.209 |
| **Leverage** | 372 | 0.275 | 0.242 | 0.002 | 1.372 | 0.150 | 508 | 0.309 | 0.276 | 0.050 | 1.460 | 0.169 |
| **ROA** | 372 | 0.055 | 0.058 | -0.589 | 0.220 | 0.073 | 508 | 0.042 | 0.053 | -1.219 | 0.349 | 0.104 |
| **PPE** | 372 | 0.626 | 0.609 | 0 | 2.746 | 0.415 | 508 | 0.669 | 0.585 | 0 | 4.620 | 0.539 |
| **Analyst Coverage** | 372 | 20.438 | 20 | 3 | 43 | 8.864 | 508 | 24.535 | 24 | 3 | 62 | 11.058 |
| **Stdev of Forecasts** | 372 | 0.010 | 0.004 | 0 | 0.503 | 0.036 | 508 | 0.015 | 0.003 | 0 | 0.976 | 0.066 |

| **Panel B** | **Mean** | | | **Median** | | |
|---|---|---|---|---|---|---|
| | **Whole Sample** | **Without Fitch** | **With Fitch** | **Whole Sample** | **Without Fitch** | **With Fitch** |
| **Firm Size** | 9.481 | 9.050 | 9.989 | 9.414 | 8.979 | 10.005 |
| **Market to Book** | 1.682 | 1.713 | 1.646 | 1.517 | 1.524 | 1.510 |
| **Intangible Assets** | 0.235 | 0.231 | 0.241 | 0.193 | 0.173 | 0.216 |
| **Leverage** | 0.295 | 0.310 | 0.276 | 0.259 | 0.278 | 0.246 |
| **ROA** | 0.047 | 0.043 | 0.052 | 0.056 | 0.050 | 0.060 |
| **PPE** | 0.651 | 0.681 | 0.615 | 0.592 | 0.650 | 0.541 |
| **Analyst Coverage** | 22.803 | 21.563 | 24.265 | 22 | 20 | 23 |
| **Stdev of Forecasts** | 0.013 | 0.013 | 0.013 | 0.004 | 0.004 | 0.003 |
| **Rating Dispersion** | 0.677 | 0.714 | 0.634 | 1 | 1 | 0 |
| **Rating Dispersion*Dodd-Frank** | 0.427 | 0.511 | 0.329 | 0 | 0 | 0 |
| **#Obs** | 880 | 476 | 404 | 880 | 476 | 404 |

**Table 2 Correlation Matrix– Variables Affecting Fitch Demand**

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

| | Fitch | Firm Size | Market to Book | Intangible Assets | Leverage | ROA | PPE | No. of Analysts | Stdev of Forecasts | Rating Dispersion | Rating Dispersion*Dodd-Frank |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Firm Size | 0.3599 | | | | | | | | | | |
| | *<.0001* | | | | | | | | | | |
| Market to Book | -0.0529 | 0.0230 | | | | | | | | | |
| | *0.1171* | *0.4962* | | | | | | | | | |
| Intangible Assets | 0.0249 | 0.1665 | 0.0371 | | | | | | | | |
| | *0.461* | *<.0001* | *0.2721* | | | | | | | | |
| Leverage | -0.1045 | -0.3328 | -0.0076 | -0.0437 | | | | | | | |
| | *0.0019* | *<.0001* | *0.822* | *0.1956* | | | | | | | |
| ROA | 0.0510 | 0.1740 | 0.3909 | 0.0541 | -0.2577 | | | | | | |
| | *0.1308* | *<.0001* | *<.0001* | *0.1089* | *<.0001* | | | | | | |
| PPE | -0.0668 | -0.1193 | -0.1364 | -0.5254 | 0.3873 | -0.3227 | | | | | |
| | *0.0474* | *0.0004* | *<.0001* | *<.0001* | *<.0001* | *<.0001* | | | | | |
| Analyst Coverage | 0.1298 | 0.5124 | 0.2225 | -0.0696 | -0.1798 | 0.0744 | 0.0949 | | | | |
| | *0.0001* | *<.0001* | *<.0001* | *0.0391* | *<.0001* | *0.0273* | *0.0048* | | | | |
| Stdev of Forecasts | 0.0003 | -0.0854 | -0.1424 | -0.1260 | 0.1379 | -0.2262 | 0.0956 | 0.0048 | | | |
| | *0.9924* | *0.0112* | *<.0001* | *0.0002* | *<.0001* | *<.0001* | *0.0046* | *0.887* | | | |
| Rating Dispersion | -0.0504 | -0.1402 | 0.0311 | 0.0599 | 0.0496 | -0.0084 | -0.0762 | -0.1068 | -0.0264 | | |
| | *0.1349* | *<.0001* | *0.3568* | *0.0758* | *0.1413* | *0.8025* | *0.0238* | *0.0015* | *0.4341* | | |
| Rating Dispersion*Dodd-Frank | -0.1256 | -0.0476 | 0.0054 | 0.0542 | 0.0797 | -0.0282 | -0.0377 | 0.0075 | -0.0373 | 0.7166 | |
| | *0.0002* | *0.1582* | *0.8739* | *0.108* | *0.018* | *0.4032* | *0.2643* | *0.8254* | *0.269* | *<.0001* | |
| Dodd-Frank | -0.1626 | 0.0302 | -0.0007 | -0.0074 | 0.1019 | -0.0676 | 0.0436 | 0.1951 | 0.0400 | 0.0923 | 0.5083 |
| | *<.0001* | *0.371* | *0.984* | *0.8262* | *0.0025* | *0.0449* | *0.1965* | *<.0001* | *0.2362* | *0.0062* | *<.0001* |

**Table 3. Bivariate Probit Regressions**

This table reports the results of bivariate probit regressions of Split ratings and Fitch ratings 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 Model 1 (first-stage) the dependent variable is a dummy that equals one if Moody's rating differs from S&P rating, and zero otherwise. In Model 2 (second-stage), the dependent variable is a dummy that equals one if Fitch provides a better rating than Moody's or S&P, and zero otherwise. The coefficient ρ measures the correlation between the error terms in two-stage regression equations and the null hypothesis is that this correlation is zero. The Wald $\chi^2(18)$, LR test statistics and $\chi^2(1)$ statistic relate to the null hypothesis that two equations nested in the bivariate probit specification are independent. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

| **VARIABLES** | **Model 1 (Split ratings versus no splits)** | **Model 2 (Fitch provides a better rating)** |
|---|---|---|
| Firm size | -0.152** | 0.202*** |
| | (-2.433) | (2.899) |
| Intangible Assets | 0.476 | 0.024 |
| | (1.339) | (0.058) |
| Market to Book | -0.043 | -0.281* |
| | (-0.419) | (-1.952) |
| Leverage | -0.119 | -0.257 |
| | (-0.279) | (-0.468) |
| ROA | -0.194 | 0.901 |
| | (-0.327) | (1.081) |
| PPE | -0.211 | -0.348* |
| | (-1.267) | (-1.698) |
| Analyst Coverage | -0.007 | -0.010 |
| | (-0.962) | (-1.082) |
| Stdev of Forecasts | -0.605 | 1.460 |
| | (-0.796) | (1.565) |
| **Dodd-Frank** | **0.330*** ** | **-0.205*** |
| | **(3.176)** | **(-1.658)** |
| #Obs | 880 | |
| ρ | 0.460*** | |
| Log likelihood value | -975.40 | |
| Wald $\chi^2(18)$ | 79.44*** | |
| $\chi^2(1)$ | 29.62*** | |

**Table 4. 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. Model 1 reports the results for newly issued bonds irrespective of whether the rating was issued by Moody's or S&P, While Model 2 reports the results for those rated by both Moody's and S&P within the first thirty days after issuance. 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 3) and split rated bonds (Model 4). ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

| **VARIABLES** | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
|---|---|---|---|---|
| Firm size | 0.441*** | 0.451*** | 0.419*** | 0.470*** |
| | (6.076) | (6.187) | (4.778) | (4.876) |
| Intangible Assets | -0.616 | -0.618 | -0.873 | -0.341 |
| | (-1.301) | (-1.304) | (-1.470) | (-0.564) |
| Market to Book | -0.139 | -0.145 | -0.166 | -0.123 |
| | (-1.253) | (-1.299) | (-1.099) | (-0.839) |
| Leverage | 0.631 | 0.657 | 1.106* | 0.071 |
| | (1.353) | (1.410) | (1.925) | (0.100) |
| ROA | -0.182 | -0.171 | -0.170 | -0.192 |
| | (-0.243) | (-0.227) | (-0.210) | (-0.155) |
| PPE | -0.292 | -0.291 | -0.368 | -0.188 |
| | (-1.311) | (-1.304) | (-1.335) | (-0.597) |
| Analyst Coverage | -0.001 | -0.001 | 0.001 | -0.004 |
| | (-0.100) | (-0.131) | (0.047) | (-0.306) |
| Stdev of Forecasts | 0.491 | 0.389 | 0.730 | -1.083 |
| | (0.561) | (0.443) | (0.706) | (-0.610) |
| Rating Dispersion | | 0.173* | | |
| | | (1.676) | | |
| **Rating Dispersion*Dodd-Frank** | | **-0.235*** | | |
| | | **(-1.951)** | | |
| **Dodd-Frank** | **-0.526***** | **-0.382***** | **-0.348**** | **-0.735***** |
| | **(-5.348)** | **(-3.000)** | **(-2.504)** | **(-5.272)** |
| #Obs | 880 | 880 | 432 | 448 |
| Pseudo R-squared | 0.135 | 0.139 | 0.114 | 0.166 |

**Table 5. Probit Regressions of Fitch Rating for Pseudo-events**

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, conditional on the starting date of the post-Dodd-Frank period. Financial and utilities industries are excluded, and for brevity the coefficients on the control variables omitted. 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 Dimitrov, Palia and Tang (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). ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

| | **First version 200907** | **Revised version 200912** | **Law's passage 201007** | **Section 939 effective date 201207** |
|---|---|---|---|---|
| **Rating Dispersion*Dodd-Frank** | -0.234* | -0.223* | -0.235* | -0.242* |
| | (-1.669) | (-1.695) | (-1.951) | (-1.868) |
| **Dodd- Frank** | -0.306** | -0.328** | -0.382*** | -0.476*** |
| | (-2.339) | (-2.534) | (-3.000) | (-3.223) |

**Table 6. 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. Panel B restricts the sample to bonds with Moody's and S&P at the HY-IG boundary. 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.

| Panel A | **Fitch Addition** | | |
|---|---|---|---|
| **Full sample** | | | |
| | **Obs.** | **Mean** | **Median** |
| Before Dodd-Frank | 923 | -2.990*** | -1.610*** |
| After Dodd-Frank | 588 | -1.723** | -1.202*** |
| Difference (Before - After) | | -1.267 | -0.408 |

| Panel B | **Fitch Addition** | | |
|---|---|---|---|
| **Sub-sample** | | | |
| | **Obs.** | **Mean** | **Median** |
| Before Dodd-Frank | 14 | -15.982** | -11.395** |
| After Dodd-Frank | 34 | -1.515 | 0.698 |
| Difference (Before - After) | | -14.467** | -12.093*** |

## Appendix A. Figures for Existing Bonds

**Figure 5 Proportion of bonds with three ratings**

This figure plots the proportion of existing 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.

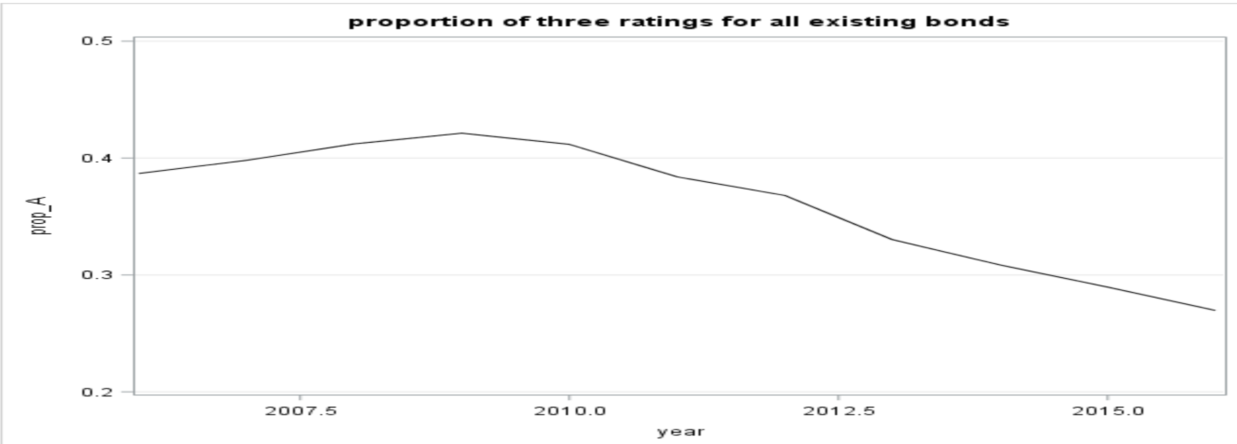
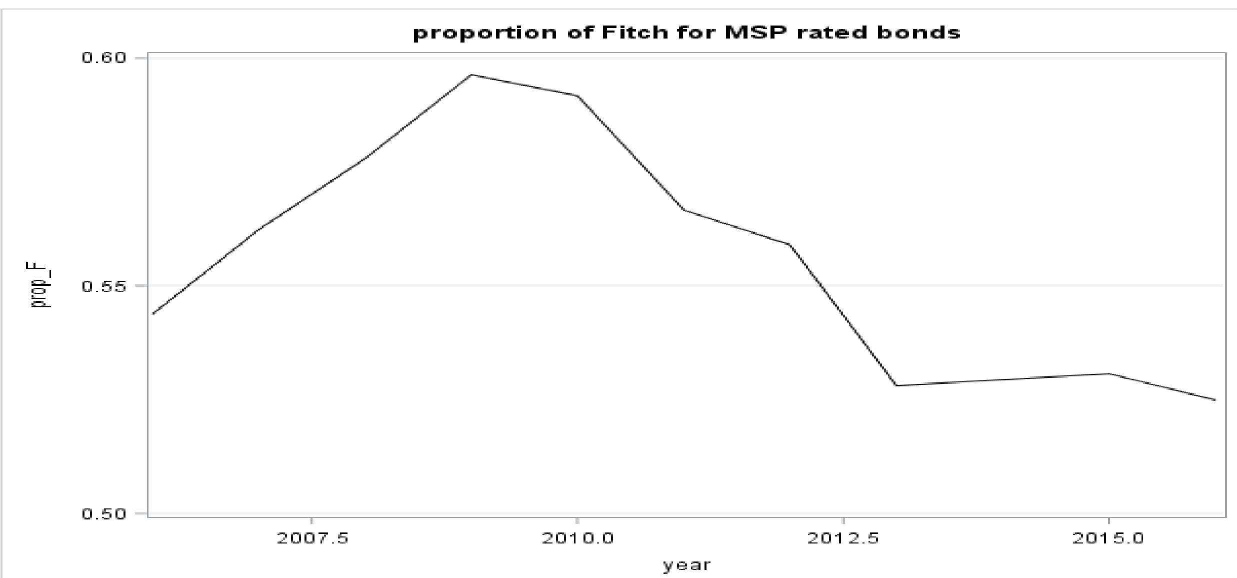



**Figure 6 Proportion of bonds rated by Fitch**

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



## Appendix B. Probit Regressions of Fitch Ratings on Existing Bonds

This tables re-examine the effect in Table 4 by running probit regressions of a Fitch rating on the Dodd-Frank dummy and firm controls on existing bonds between Jan 2006 and Dec 2015, excluding firms in the financial and utilities industries. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

| **VARIABLES** | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
|---|---|---|---|---|
| Firm size | 0.513*** | 0.518*** | 0.416*** | 0.584*** |
| | (5.285) | (5.245) | (4.082) | (5.355) |
| Intangible Assets | -0.082 | -0.078 | -0.501 | 0.202 |
| | (-0.212) | (-0.202) | (-1.046) | (0.438) |
| Market to Book | 0.000 | 0.000 | 0.000*** | -0.000 |
| | (0.187) | (0.174) | (2.618) | (-0.262) |
| Leverage | -0.050 | -0.061 | 0.062 | -0.160 |
| | (-0.124) | (-0.153) | (0.112) | (-0.359) |
| ROA | -0.275 | -0.228 | -0.960 | -0.097 |
| | (-0.597) | (-0.493) | (-0.771) | (-0.178) |
| PPE | -0.007 | -0.002 | -0.002 | -0.012 |
| | (-0.044) | (-0.015) | (-0.008) | (-0.061) |
| Analyst Coverage | -0.003 | -0.003 | 0.007 | -0.011 |
| | (-0.353) | (-0.302) | (0.611) | (-1.101) |
| Stdev of Forecasts | -0.026 | -0.038 | 1.321 | -0.032 |
| | (-0.991) | (-1.165) | (1.179) | (-1.062) |
| Rating Dispersion | | 0.077 | | |
| | | (1.164) | | |
| **Rating Dispersion*Dodd-Frank** | | **-0.027** | | |
| | | **(-0.361)** | | |
| **Dodd-Frank** | **-0.268*** ** | **-0.257*** ** | **-0.252** ** | **-0.279*** ** |
| | **(-3.843)** | **(-2.698)** | **(-2.213)** | **(-3.132)** |
| #Obs | 8,386 | 8,386 | 3,630 | 4,756 |
| Pseudo R-squared | 0.147 | 0.149 | 0.123 | 0.176 |