The Game Changer:

Regulatory Reform and Multiple Credit Ratings

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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 (typically from Fitch) for ratings near the high yield (HY) - investment grade (IG) boundary to support their new corporate bond issues. Third ratings also become less informative post Dodd-Frank, with a much weaker market impact on credit spreads for firms with S&P and Moody's ratings on opposite sides of the HY-IG rating boundary. We provide new evidence on the effect of Dodd-Frank in curbing corporate borrowers' strategic use of multiple credit ratings near this boundary.

Keywords: Financial regulation, Dodd-Frank, credit ratings, corporate bonds

JEL Classification: G01, G24, G28

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1. Introduction

Credit rating agencies (CRAs) have long provided credit ratings for investors, regulators, and financial institutions as public signals of firms' creditworthiness and to determine risk-based 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 (GFC). 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 (hereafter, Dodd-Frank). Dodd-Frank established greater oversight of CRAs including 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 regulatory architecture has changed an important aspect of the credit ratings game - the demand for and the information content of multiple credit ratings. Whilst there is much attention on the important role of credit ratings in piercing through the information asymmetry faced by investors (Boot, Milbourn and Schmeits, 2005) and how competition amongst CRAs affects the credit ratings they provide (Becker and Milbourn, 2011; Bolton, Freixas and Shapiro, 2012; Bae, Kang and Wang, 2015), relatively little is known about the impact of recent

[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).

regulatory changes on the strategic use of multiple credit ratings by corporate borrowers to influence bond investors.

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, 2021). 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 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 et al., 2014; Chen and Wang, 2021). Similarly, the 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, 2020). 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 effectively presents the issuer with an opportunity to improve their 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. There is thus limited downside risk for borrowers to seek a third rating. Cantor and Packer (1997) observe that this option like payoff increases the demand for a third rating as the issuer's ratings from Moody's and S&P get closer to the investment grade (IG) boundary. Indeed, 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. Mählmann (2009) corroborates 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 critical for issuers as many banks and insurance firms are mandated by prudential regulations to hold higher reserve capital for holding risky HY bonds while pension and mutual fund investment mandates typically limit the share of HY securities in their portfolios (Bongaerts et al., 2012; Baghai, Becker and Pitschner, 2018). 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). Despite the prior studies on the use of 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 their impact on credit spreads.

Dodd-Frank presented a series of regulatory reforms to the credit ratings 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 shown to be inaccurate. Section 933 lessens the pleading standards for private actions against CRAs, while section 939 requires federal agencies to remove the 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' rating decisions. Becker and Opp (2014) and Hanley and Nikolova (2020) document that removing credit ratings from capital regulations by NAIC affects insurers' behavior. Moreover, Dimitrov, Palia and Tang (2015) provide evidence that post Dodd-Frank CRAs issue lower credit ratings that elicit 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 for firms with ratings near the HY-IG boundary. Furthermore, we expect that the reduced demand for Fitch ratings will translate to these ratings having a lower market impact when they act as a tiebreaker around the HY-IG boundary.

Using a database of newly issued U.S. corporate bonds from 2006 to 2015, we show that consistent with our hypothesis, following the passage of Dodd-Frank firms are less likely to seek

[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'.

[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, 2021). Following convention, we examine the market impact of Fitch as a third rating.

a third rating for newly issued bonds with ratings near the HY-IG boundary. Specifically, for boundary bonds rated BBB-, the probability of having a Fitch rating post Dodd-Frank reduces by 0.167. By contrast, for bonds two notches away from the boundary the probability of having a Fitch rating post Dodd-Frank decreases by 0.097. On average, a one-notch credit rating move away from the HY-IG boundary prior to Dodd-Frank reduces the probability of having a Fitch rating by 0.070. Post Dodd-Frank, the probability drops significantly to 0.029. We find the effect is significant for both HY- and IG-rated bonds. These results are consistent with Fitch ratings being used to inflate overall bond ratings as well as to provide insurance against downgrades from one of the other two incumbent agencies prior to Dodd-Frank (Bongaerts et al., 2012; Chen and Wang, 2021). However, following the diminished importance of the HY-IG boundary brought upon by Dodd-Frank, the demand for Fitch ratings falls around this boundary as they are no longer as influential in determining the overall rating of the issue. In accordance with that argument, we show that post Dodd-Frank, Fitch ratings are less informative, having a more muted impact on credit spreads of bonds at issuance when firms' existing Moody's and S&P ratings straddle the HY-IG boundary. Our findings are robust to different model specifications, a variety of controls and placebo tests.

Our paper makes several key contributions to the current literature. We extend the literature that examines the demand for and market impact of multiple ratings (see, for example, Bongaerts et al., 2012; Livingston and Zhou, 2016; Chen and Wang, 2021). Specifically, we focus on the use of multiple ratings around the HY-IG rating boundary and CRA's incentives to facilitate regulatory arbitrage. Previous studies show that ratings inflation via the use of multiple ratings is most valuable for firms near this boundary (Bongaerts et al., 2012; Opp, Opp and Harris, 2013; Behr, Kisgen and Taillard, 2016; Cornaggia, Cornaggia and Simin, 2016). Our study is complementary to this line of investigation but to the best of our knowledge we are the first study to document the diminishing strategic use of multiple credit ratings around the HY-IG boundary in light of recent regulatory reforms. In doing so, we also contribute to the nascent literature on the effect of Dodd-Frank on CRAs' ratings behavior. 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, 2019) and the use of qualitative information in forming a rating opinion (Ahmed et al., 2017). Our study extends these extant studies by showing that Dodd-Frank has been effective in curbing the strategic use of multiple credit ratings around the critical HY-IG ratings cliff. Moreover, we document that the Dodd-Frank regulatory reform has significantly weakened the market impact of Fitch ratings and ameliorated the ratings cliff effect for bond issuers.

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

2. Related Studies and Hypotheses Development

Extant studies show that the demand for multiple ratings is primarily driven by financial regulation. Opp et al. (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. Cornaggia et al. (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 where a third rating plays the role of a tiebreaker that differentiates between HY and IG status (Bongaerts et al., 2012).

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 have already decreased their reliance on corporate ratings following the 2008 GFC due to the reputational concerns with CRAs. 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. However, the reduction in demand for Fitch ratings should differ across the spectrum of ratings. Previous literature shows that ratings inflation should be most valuable for firms near the HY-IG threshold (Opp et al., 2013; Behr et al., 2016; Cornaggia et al., 2016). Behr et al. (2016)

find that after the change in SEC regulations that expanded the regulatory use of credit ratings in 1975[4], CRAs had particularly strong incentives to inflate ratings around the boundary. Similarly, Cornaggia et al. (2016) observe that Moody's certifies HY-rated bonds as IG in order to facilitate regulatory arbitrage. As motivated by those studies, we conjecture that the reduced demand for third ratings should be more pronounced for firms with ratings near the HY-IG boundary as those ratings have the greatest impact on spreads. This leads to our first hypothesis.

H$_1$: *Firms near the HY-IG boundary are less likely to seek a third rating 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 show that despite Section 939 of the Dodd Frank Act reducing the regulatory reliance on credit ratings, Dodd Frank is unlikely to completely abolish CRAs' role in providing public signals of firms' creditworthiness.

Nonetheless, Dimitrov et al. (2015) provide evidence 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

[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).

reduces the degree of ratings inflation associated with increased regulatory reliance on ratings previously documented by Behr et al. (2016). Since the increased penalties on false ratings and the removal of the reliance on credit ratings enacted by Dodd-Frank may remove the advantage of higher ratings, we posit that Dodd-Frank has reduced the information content of third ratings. This leads us to our second hypothesis.

> **H_2:** *The market reaction to a third rating for firms near the HY-IG boundary has significantly weakened post Dodd-Frank.*

3. Data

Bond characteristics and credit ratings by Moody's, S&P and Fitch are acquired from the issue and ratings history sections of 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. Consistent with existing literature, we convert all bond ratings into numerical rating scores, ranging from 1 to 21 (AAA to C for S&P and Fitch; 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 enhancements are

[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.

excluded. We focus on initial bond ratings at issuance as the process for assigning initial ratings is more precise than the process for monitoring ratings.

We start with 3,502 newly issued domestic bonds rated by Moody's and S&P within the first 30 days after issuance with available data in Compustat and IBES databases. We exclude bond issues with missing data in Mergent FISD and we 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. 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. 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.

Panel A in Table 1 provides descriptive statistics for corporate borrowers' firm-specific characteristics before and after Dodd-Frank and shows that both samples are quite similar in terms of firm size, market to book, intangible assets, leverage and profitability. However, we observe that the average credit quality of bonds issued after Dodd-Frank is generally lower. While this may be an indication of deterioration in credit quality, it is also consistent with the issuance of more conservative ratings to protect CRAs' reputation in response to the increased legal and regulatory penalties for issuing inaccurate ratings mandated by Dodd-Frank (Dimitrov et al., 2015). More importantly, we do not observe any change in the optimism embedded in Fitch ratings post Dodd-Frank, with an average Fitch rating for issues already rated by Moody's and S&P around half to a full notch higher. Our data indicates that 48.5% of new issues rated by Moody's and S&P are also rated by Fitch, which drops to 35.5%, following the implementation of Dodd-Frank. 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. Fitch-rated firms are typically larger, with a higher market-to-book ratio, have more intangible assets, less debt, higher profitability and greater analyst coverage. Full variable definitions are provided in Appendix A.

[Insert Table 1, 2 about here]

Appendix B shows the percentage of new issues where S&P, Moody's or Fitch assigned the first and third rating. Ratings where multiple agencies assigned initial ratings simultaneously are counted as the same ranking. Panel A shows that only about 40% of newly issued bonds are rated by Fitch first. By contrast, around 80% (70%) of new issues obtained S&P (Moody's) ratings first. By contrast, panel B shows that in 45% of the cases, Fitch assigned the third rating.

4. Empirical Analysis

4.1 Demand for third ratings for bonds around the HY-IG boundary

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:

$$Y^* = \beta_1 Distance_i \times Dodd\text{-}Frank + \beta_2 Distance_i + \beta_3 Dodd\text{-}Frank + \sum_{\boldsymbol{j=4}}^{\boldsymbol{k}} \beta_j \, Control_{i,j} + \delta_i + \upsilon_t + \varepsilon_i \quad (1)$$

where Y^* is the latent propensity that a firm has a Fitch rating ($Y = 1$). We regress the latent variable Fitch on a Dodd-Frank indicator variable that equals one if a firm's bond is issued after Dodd-Frank (i.e. 21 July 2010), and zero otherwise. Since bond issues in which Fitch is the tiebreaker CRA are more likely to get a Fitch rating, we include *Distance* from the HY-IG boundary and its interaction with Dodd-Frank. Distance measures the absolute difference between the effective rating (i.e. the lower rating issued by Moody's and S&P) and the HY-IG boundary (BBB-). We also control for numerous bond and firm characteristics commonly quoted in the literature. 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, standard deviation of forecasts, and the number of analysts following a firm. 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 variable that takes the absolute difference between Moody's and S&P, as an additional credit-based opacity proxy. $\varepsilon_i \sim N(0,1)$, δ_i denotes industry fixed effect, υ_t is year fixed effect. The vector of the coefficients β is estimated by Maximum Likelihood. All continuous firm-level variables are winsorized at the 1% level in both tails of the distribution.

The regression estimates of the effect of Dodd-Frank on firms' demand for third ratings are reported in Table 3. The first three columns show the regression coefficients. We report both the full sample results as well as pre- and post-Dodd-Frank sub-samples. In the remaining columns, the probit coefficients are converted into marginal effects for ease of interpretation. Focussing on the marginal effects, our results indicate that distance to the HY-IG boundary is an important determinant of the demand for Fitch ratings. The marginal effects of *Distance* are negative and significant at the 1% level, which implies that firms closer to the HY-IG boundary are more likely to demand Fitch ratings. However, this effect significantly weakens after the passage of Dodd-Frank. The marginal effects in columns 5 and 6 indicate that on average, a one-notch credit rating move from the HY-IG boundary prior to Dodd-Frank decreases the probability of having a Fitch rating by 0.070. However, post its passage, the probability only decreases by 0.029. Both marginal effects are significant at the 1% level. In untabulated results, we find that the probability of having a Fitch rating for bonds with ratings at the boundary post Dodd-Frank reduces by around 0.167, while for bonds with ratings +/- one (two) notch(es) away from the boundary the probability of having a Fitch rating reduces to 0.134 (0.097).[6] Besides distance, *Firm Size* is the only other statistically significant variable. It has a positive marginal effect which is similar across both pre- and post-Dodd-Frank periods. These results are in line with the findings of Bongaerts et al. (2012) that large firms are more likely to be rated by Fitch.

[Insert Table 3 about here]

We also test the impact of Dodd-Frank on the propensity for firms to demand third ratings by sorting firms into terciles by their distance from the HY-IG boundary to differentiate between ratings that are close to the boundary and thus more impacted by the change in legislation. We then test for differences between treated firms with greater exposure to the Dodd-Frank reforms in the bottom tercile (closest to the HY-IG boundary) relative to control firms in the top tercile

[6] The full set of marginal effects at different distances from the boundary are available from the authors upon request.

(furthest from the HY-IG boundary), excluding the middle tercile for a sharper separation. Consistent with the above analysis, the marginal effects of *Treated×Dodd-Frank* presented in Table 4 are always negative and highly significant indicating that treated firms display a significant drop in the demand for Fitch ratings post the implementation of Dodd-Frank. We find that firms closest to the HY-IG boundary have a 0.298 higher probability of having a Fitch rating prior to Dodd-Frank relative to ratings furthest from the HY-IG boundary, significant at the 1% level. By contrast, following Dodd-Frank the relative probability of those firms being rated by Fitch is significantly reduced to 0.103 and the significance level drops down to the 5% level.

[Insert Table 4 about here]

Figure 1 plots the proportion of newly issued bonds with a Fitch rating for the treated (solid line) and control groups (dashed line) between 2006 and 2015. The proportions are estimated as the number of bonds rated by all three CRAs over the number of bonds rated only by Moody's and S&P. Figure 1 shows that prior to the introduction of Dodd-Frank around 60% to 70% of firms in the treatment group sought a Fitch rating and declines to around 30% post its passage. We find that the proportion of Fitch ratings in the control group is much lower but the two groups largely trend in parallel in the years leading up to Dodd-Frank. After its passage, the proportion of Fitch ratings in both groups starts to decline and begins to converge. This indicates a slight drop in demand for Fitch ratings across all levels of creditworthiness but a more pronounced drop for firms near the HY-IG boundary as Dodd-Frank was progressively enacted.[7]

[7] Dimitrov et al. (2015) finds that the impact of Dodd-Frank on corporate bond ratings strengthens as the uncertainty regarding its passage gradually resolves (The first version of the legislation was published in July 2009, subsequently revised in December 2009 and passed in July 2010. Section 939 became effective in July 2012 and the OCC rule became effective in Jan 2013).

[Insert Figure 1 about here]

Our results are in line with prior studies documenting the importance of maintaining a bond's IG status and the value of obtaining favorable ratings near the HY-IG boundary before Dodd-Frank (Bongaerts et al., 2012; Behr et al., 2016; Cornaggia et al., 2016; Baghai, Becker and Pitschner, 2018). However, the removal of the regulatory reliance on credit ratings by Dodd-Frank greatly diminishes the incentive to acquire a third rating. Consequently, in accordance with our first hypothesis, we find that firms with ratings near the HY-IG boundary experienced the largest reduction in demand for third ratings.

To mitigate concerns that our results are attributed to other extraneous factors independent of the Dodd-Frank legislation, we carry several robustness tests. First, we replicate our analysis on a sample of non-US bonds from the remaining G7 developed countries (UK, Germany, France, Italy, Canada, Japan) using a similar empirical setup to Eq. 1 (reported in Table 3). These non-US firms were not subjected to the Dodd-Frank regulation. The placebo results, reported in Appendix C, show that none of the variables or interaction terms are significant implying that the observed effect is confined to U.S. bonds subjected to the Dodd-Frank Reform.

Second, we exclude the GFC period from our base case regression specification. Our definition of the GFC period from August 2008 to March 2009 follows that of Lins et al. (2013; 2017). The results are reported in the first three columns of Appendix D. We find that our results are not sensitive to the exclusion of this volatile period. Finally, we extend our baseline regression specification to control for overall financial market conditions and economic performance with the trailing one-year return on the S&P 500 index and its level, the trailing one-year return on the Bloomberg Barclays US Aggregate Bond Index, and the GDP growth rate. These results are presented in the remaining columns of Appendix D. We find that the results are also robust to the addition of these macro controls.

Next, we examine the potential asymmetric effect of the Dodd-Frank regulatory reform on IG- and HY-rated bonds by analysing the two classifications separately. Bongaerts et al. (2012) show that HY-rated issues should have a greater demand for third ratings compared to IG-rated issues since Fitch serves as a tiebreaker to upgrade bond issues from HY to IG classification. However, Chen and Wang (2021) find that the addition of a Fitch rating to S&P and Moody's ratings can also hedge against downgrade risk as three ratings provide a more stable rating. To increase the statistical power of our tests due to the smaller sample size in each subcategory, we aggregate the distance variable into three broader rating classes. The first group contains boundary ratings, defined by Kisgen (2006) as ratings within two notches of the boundary (BBB, BBB- for IG and BB+, BB for HY). The separation of the remaining groups follows Bongaerts et al. (2012), with IG ratings split equally into two groups (BBB+ to A+ and AA- to AAA) and HY ratings split into B- to BB- and below CCC+ categories. Similar to Table 4, we also sort both IG and HY issues into groups by their distance from the HY-IG boundary to distinguish between ratings more impacted by the change in legislation. Due to the smaller sample size, we split the sample by the median distance. The marginal effects of the main variables of interest for each specification are reported in Table 5. Columns 1 and 3 show that the marginal effects of *Distance* are always negative and highly significant for both IG and HY rating classifications. The lack of asymmetry between the rating classifications is consistent with a greater demand by IG-rated firms close to the boundary to acquire Fitch ratings to hedge against potential downgrades into junk status from Moody's and S&P (Chen and Wang, 2021), and HY-rated firms close to the boundary using Fitch ratings to upgrade their corporate bond issues to IG classification (Bongaerts et al., 2012), prior to

Dodd-Frank. However, the positive and highly significant marginal effects of *Distance×Dodd-Frank* indicate a reversal in this trend across both classifications following the passage of Dodd-Frank, in line with a lower demand for Fitch associated with the reduced prominence of the HY-IG boundary. In untabulated results, we find that the probability of boundary-rated bonds (*Distance* = 1) obtaining a Fitch rating post Dodd-Frank reduces by around 0.151 if they are in the IG category and 0.097 if they are classified as HY. A similar effect is observed by splitting the IG and HY samples into two groups by the median distance from the HY-IG boundary as shown in Columns 2 and 4. We find that the marginal effects of *Treated* are always positive and significant while the marginal effects of *Treated×Dodd-Frank* are always negative and highly significant for both IG and HY bonds. These findings are congruent with Table 4 and imply that firms acquire Fitch ratings on both sides of the HY-IG boundary but the demand moderates post Dodd-Frank.[8]

[Insert Table 5 about here]

4.2 Market Impact of Third Ratings

In this section, we examine the impact of Fitch's third ratings on the credit spreads at issuance for bonds already rated by Moody's and S&P using the following OLS regression.

$$Spread = \beta_1 Fitch\_Makes\_IG_i \times Dodd\text{-}Frank \; + \; \beta_2 Fitch\_Makes\_IG_i \; + \; \beta_3 Dodd\text{-}Frank \; + \sum_{j=4}^{k} \beta_j \, Control_{i,j} + \delta_i + \upsilon_t + \varepsilon_i \qquad (2)$$

The dependent variable is the credit spread at issuance, and the main variables of interest 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 upgrades the bond into the IG category, and zero otherwise) and an

[8] Using an above and below median distance split instead of terciles in Table 4 does not materially change our result.

interaction term, *Fitch_Makes_IG* with *Dodd-Frank*. We include two indicator variables *Fitch_Added_Better*, and *Fitch_Added_Equal* that is equal to one if the added Fitch rating is better than or equal to the overall rating of the issue, respectively, and zero otherwise.[9] These variables are also interacted with the Dodd-Frank indicator variable. *Fitch_Denies_IG* is an indicator variable that equals one if an addition of a Fitch rating does not raise the rating of the issue to the IG category, conditional on Moody's and S&P ratings straddling the HY-IG boundary, and zero otherwise. Similar to the specifications above, we interact this variable with Dodd-Frank. We also include *InvBoundary*, a dummy that equals one if Moody's and S&P are at the HY-IG boundary, and zero otherwise. Finally, we control for firm characteristics, issuer's credit quality, CDS index levels and industry and year fixed effects. Since bonds with different issue-specific characteristics issued by the same issuers have different at-issuance credit spreads, we also include the subsequent bonds made by the same issuers within the same month in the sample, and control for the issue-specific characteristics discussed previously.

The results are reported in Table 6. A full set of controls are included in all regression specifications but coefficient estimates are omitted for brevity. The first column depicts the addition of a Fitch rating to an issue already rated by Moody's and S&P. The second column shows a more detailed specification where the added Fitch rating is either better, equal or worse than the overall credit rating of the issue. None of the coefficients are statistically significant in either specification indicating that the simple addition of a Fitch rating does not impact spreads. These results are in line with Bongaerts et al. (2012) and show that our results are not driven by the additional information provided by Fitch. As none of the interactions is significant, we find that

[9] Due to the small sample size, we group Fitch ratings that are worse with *Fitch_Added_Equal* ratings as the addition of a third rating does not change the overall rating of the issue.

the impact of Fitch does not change with the passage of Dodd-Frank. In the last column, we focus on the role of Fitch around the HY-IG boundary by including two additional indicator variables *Fitch_Makes_IG* and *Fitch_Denies_IG* for bonds where Fitch either elevates bonds to the IG classification or not, respectively. The results show that the coefficient on *Fitch_Makes_IG* is negative and significant at the 5% level, while the coefficients on *Fitch_Added_Better* and *Fitch_Added_Equal* and *Fitch_Denies_IG* are not significant. This indicates that the presence of a Fitch rating reduces credit spreads at issuance only when Moody's and S&P ratings are on opposite sides of the HY-IG boundary and Fitch serves as the tiebreaker CRA and upgrades the bond's classification from an HY to an IG status. This result is consistent with the larger financial payoff from a favorable Fitch rating at the HY-IG boundary associated with the discontinuity in institutional demand (Bongaerts et al., 2012). However, as expected these effects weaken after the passage of Dodd-Frank, as indicated by the positive, and statistically significant coefficient on the interaction term between *Fitch_Makes_IG* and *Dodd-Frank.* In terms of the economic magnitude, the beneficial reduction in credit spreads at issuance when Fitch lifts the bonds into the IG category is reduced by two thirds post-Dodd-Frank (73.434/107.170 = 69%). The difference in spreads between a Fitch rating lifting an issue to IG rather than lowering it to HY drops by about 42 bps post Dodd-Frank.

These results provide empirical evidence supportive 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 also 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.

[Insert Table 6 about here]

5. Conclusion

The Dodd-Frank reform enacted in response to the mayhem of the 2008 financial crisis introduced several important reforms to the credit ratings industry. These include increased legal and regulatory penalties for CRAs 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, especially in the provision of multiple credit ratings. 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 new corporate bond issues with ratings near the HY-IG boundary 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 HY-IG boundary. Our results suggest that Dodd-Frank has diminished the advantage of having Fitch ratings either to inflate overall ratings or hedge downgrade risk near the HY-IG boundary, and this has in turn significantly weakened the market impact of Fitch ratings. Our research provides an important first step in linking the recent regulatory reforms to changes in the 'credit ratings game' and in particular, the active gaming that has historically taken place around the critical investment grade boundary due to its flow on effects for investor demand and bond pricing (Kisgen, 2006).

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Figure 1. 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, split by distance from the IG/HY boundary. The solid line depicts (treated) firms with ratings in the bottom tercile (closest to the IG/HY boundary) while the dashed line shows (control) firms in the top tercile (furthest from the IG/HY boundary). 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.

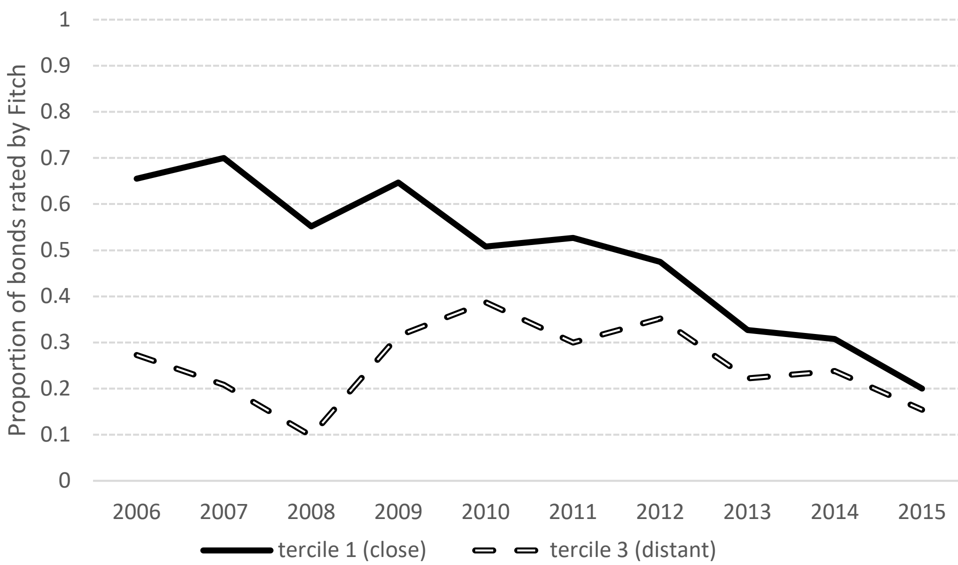


Table 1. Descriptive statistics

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 and 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	Mean				Median			
	Whole Sample	Pre-DF	Post-DF	Diff	Whole Sample	Pre-DF	Post-DF	Diff
Firm Size	10.244	10.320	10.185	0.135	9.982	10.136	9.871	0.265
Market to Book	1.532	1.532	1.533	-0.001	1.341	1.331	1.348	-0.017
Intangible Assets	0.178	0.173	0.182	-0.009	0.116	0.116	0.115	0.001
Leverage	0.276	0.272	0.280	-0.007	0.249	0.241	0.252	-0.011
Profitability	0.040	0.042	0.039	0.003	0.034	0.032	0.035	-0.003
PPE	0.502	0.468	0.529	-0.061***	0.370	0.336	0.414	-0.078***
Analyst Coverage	22.019	19.346	24.089	-4.742***	21	19	24	-5***
Stdev of Forecasts	0.026	0.045	0.011	0.034***	0.004	0.004	0.004	0
S&P Ratings	8.227	6.991	9.184	-2.193***	8	7	9	-2***
Moody's Ratings	8.495	7.186	9.509	-2.323***	8	7	9	-2***
Fitch's Ratings	7.762	7.132	8.432	-1.300***	8	7	8	-1***
Obs	1283	560	723		1283	560	723	
Obs (Fitch only)	530	273	257		530	273	257	
	41.3%	48.5%	35.5%		41.3%	48.5%	35.5%	

Panel B	Mean				Median			
	Whole Sample	Without Fitch	With Fitch	Diff	Whole Sample	Without Fitch	With Fitch	Diff
Firm Size	10.244	10.202	10.303	-0.101	9.982	9.749	10.232	-0.483***
Market to Book	1.532	1.515	1.557	-0.042	1.341	1.303	1.359	-0.056***
Intangible Assets	0.178	0.172	0.188	-0.016*	0.116	0.099	0.131	-0.032***
Leverage	0.276	0.292	0.254	0.038***	0.249	0.259	0.235	0.024***
Profitability	0.040	0.035	0.048	-0.013***	0.034	0.027	0.045	-0.018***
PPE	0.502	0.488	0.523	-0.035*	0.370	0.328	0.427	-0.099**
Analyst Coverage	22.019	21.584	22.636	-1.052**	21	20	22	-2***
Stdev of Forecasts	0.026	0.032	0.017	0.015**	0.004	0.005	0.003	0.002***
Rating Dispersion	0.675	0.704	0.634	0.070*	1	1	0	1**
S&P Ratings	8.227	8.468	7.885	0.583***	8	8	8	0
Moody's Ratings	8.495	8.773	8.1	0.673***	8	9	8	1***
Number of 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. The demand for Fitch ratings by distance to the HY-IG boundary

This table reports the coefficients (columns 1 to 3) and marginal effects (columns 4 to 6) of probit regressions with a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015. Columns 1 and 4 report the full sample results while columns 2 and 3 along with columns 5 and 6 decompose the full period into two non-overlapping sub-periods: 01/01/2006 – 07/21/2010 (pre-Dodd Frank) and 07/22/2010 – 12/31/2015 (post-Dodd-Frank). Standard errors are clustered by firms to account for multiple bond issues made by the same firm. The model includes industry and year fixed effects. Z-values are shown inside brackets. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

	Coefficients			Marginal effects		
	Full Sample	Pre-DF	Post-DF	Full Sample	Pre-DF	Post-DF
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Distance*Dodd-Frank	0.106**			0.035**		
	(2.022)			(2.050)		
Distance	-0.196***	-0.242***	-0.094***	-0.064***	-0.070***	-0.029***
	(-4.484)	(-5.112)	(-2.597)	(-4.727)	(-6.067)	(-2.680)
Dodd-Frank	-0.491**			-0.164**		
	(-2.071)			(-2.188)		
Firm Size	0.200***	0.222**	0.245***	0.066***	0.065**	0.075***
	(3.251)	(2.474)	(3.262)	(3.238)	(2.534)	(3.248)
Intangibles	-0.541	-0.802	-0.465	-0.178	-0.233	-0.143
	(-1.184)	(-1.296)	(-0.885)	(-1.180)	(-1.281)	(-0.885)
Market to Book	-0.052	-0.203	0.032	-0.017	-0.059	0.010
	(-0.403)	(-1.020)	(0.230)	(-0.404)	(-1.026)	(0.230)
Leverage	-0.772	-0.608	-0.703	-0.254	-0.177	-0.215
	(-1.517)	(-0.854)	(-1.148)	(-1.527)	(-0.852)	(-1.138)
Profitability	0.048	3.017*	-1.501	0.016	0.878*	-0.460
	(0.043)	(1.706)	(-1.197)	(0.043)	(1.741)	(-1.211)
PPE	0.388	0.120	0.490	0.128	0.035	0.150
	(1.318)	(0.302)	(1.486)	(1.334)	(0.303)	(1.486)
Analyst Coverage	-0.005	0.021	-0.018*	-0.002	0.006	-0.005*
	(-0.577)	(1.558)	(-1.943)	(-0.577)	(1.600)	(-1.928)
Analyst Forecast Dispersion	0.336	0.328	0.022	0.111	0.095	0.007
	(0.806)	(0.757)	(0.017)	(0.810)	(0.760)	(0.017)
Rating Dispersion	-0.121	-0.071	-0.147	-0.040	-0.021	-0.045
	(-1.528)	(-0.613)	(-1.594)	(-1.537)	(-0.614)	(-1.581)
Constant	-1.245*	-1.892*	-2.830***			
	(-1.851)	(-1.945)	(-3.310)			
Industry FEs	Yes	Yes	Yes			
Year FEs	Yes	Yes	Yes			
Observations	1,283	560	723			
Pseudo R-squared	0.144	0.214	0.121			

Table 4. The demand for Fitch ratings with firms split into terciles by distance to the HY-IG boundary

This table reports the marginal effects of probit regressions for a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015. The remaining columns decompose the full period into two non-overlapping sub-periods: 01/01/2006 – 07/21/2010 (pre-Dodd Frank) and 07/22/2010 – 12/31/2015 (post-Dodd-Frank). Firms are split by the "Distance" variable. Treated firms are in the bottom tercile (closest to the IG/HY boundary) while control firms in the top tercile (furthest from the IG/HY boundary). Marginal effects of controls (Eq. 1) are omitted for brevity. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. The model includes industry and year fixed effects. Z-values are shown inside brackets. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

	Full Sample	Pre-DF	Post-DF
VARIABLES	(1)	(2)	(3)
Treated*Dodd-Frank	-0.243***		
	(-6.310)		
Treated	0.357***	0.298***	0.103**
	(9.272)	(9.652)	(2.566)
Dodd-Frank	0.184***		
	(2.602)		
Controls	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	827	356	471
Pseudo R-squared	0.169	0.284	0.141

Table 5. The demand for Fitch ratings across IG and HY bonds

This table reports the marginal effects of probit regressions with a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015 for IG and HY bonds. In columns 1 and 3, firms are split by the "Distance" variable into three groups. The first group comprises boundary ratings (BBB, BBB- for IG and BB+, BB for HY). The remaining IG ratings are split into BBB+ to A+ and AA- to AAA categories while HY ratings are split into B- to BB- and below CCC+ categories. Columns 2 and 4 are split by the median distance with treated (control) firms closest (furthest) to (from) the HY-IG boundary. Marginal effects of controls (Eq. 1) are omitted for brevity. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. The model includes industry and year fixed effects. Z-values are shown inside brackets. ***, **, * represent significance at the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	IG Sample		HY Sample	
	(1)	(2)	(3)	(4)
Distance*Dodd-Frank	0.109**		0.084***	
	(2.206)		(3.473)	
Distance	-0.131***		-0.219***	
	(-2.622)		(-12.477)	
Treated_IG*Dodd-Frank		-0.129**		
		(-1.981)		
Treated_IG		0.201***		
		(3.330)		
Treated_HY*Dodd-Frank				-0.094***
				(-5.206)
Treated_HY				0.200***
				(9.041)
Dodd-Frank	-0.251***	-0.007	-0.171***	-0.001
	(-2.755)	(-0.083)	(-3.854)	(-0.034)
Control	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	975	975	308	308
Pseudo R-squared	0.138	0.142	0.350	0.321

Table 6. OLS regressions of credit spreads

This table reports the results of an OLS regression for credit spreads at issuance on the Fitch dummies, issue-specific characteristics and firm-specific controls between Jan 2006 and Dec 2015. Coefficient estimates for control variables are omitted for brevity. 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.

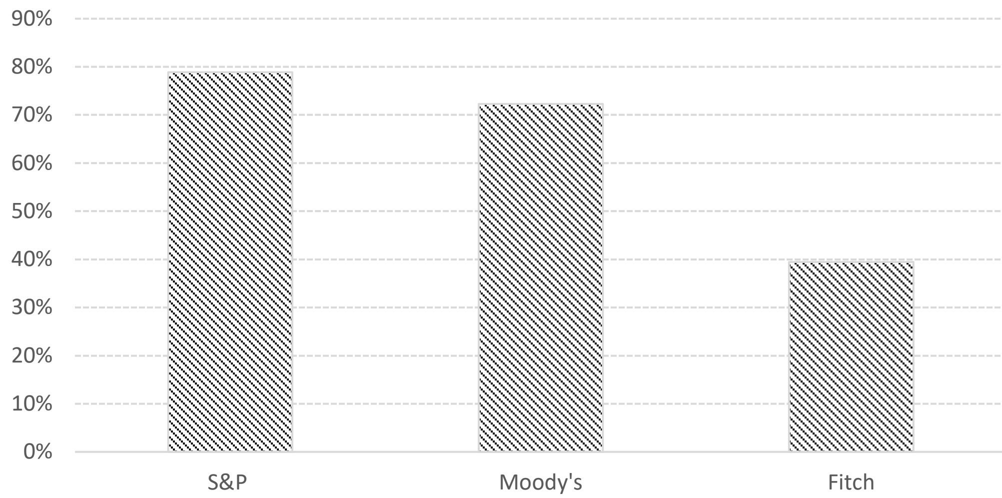
VARIABLES	(1)	(2)	(3)
Fitch_Added*Dodd Frank	-10.247		
	(-1.018)		
Fitch_Added	-5.067		
	(-0.611)		
Fitch_Added_Better*Dodd-Frank		-12.266	-18.223
		(-0.954)	(-1.392)
Fitch_Added_Equal*Dodd-Frank		-4.665	-9.011
		(-0.391)	(-0.754)
Fitch_Added_Better		-13.656	-8.954
		(-1.362)	(-0.895)
Fitch_Added_Equal		-1.001	-0.880
		(-0.109)	(-0.096)
Fitch_Makes_IG*Dodd Frank			73.434**
			(2.061)
Fitch_Makes_IG			-107.170**
			(-2.364)
Fitch_Denies_IG*Dodd Frank			31.534
			(0.943)
Fitch_Denies_IG			32.895
			(0.661)
InvBoundary			56.708
			(1.642)
Dodd-Frank	3.501	1.054	0.860
	(0.224)	(0.066)	(0.055)
Industry FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	2,221	2,221	2,221
Adjusted R-squared	0.787	0.788	0.792

Appendix A. Variable definitions

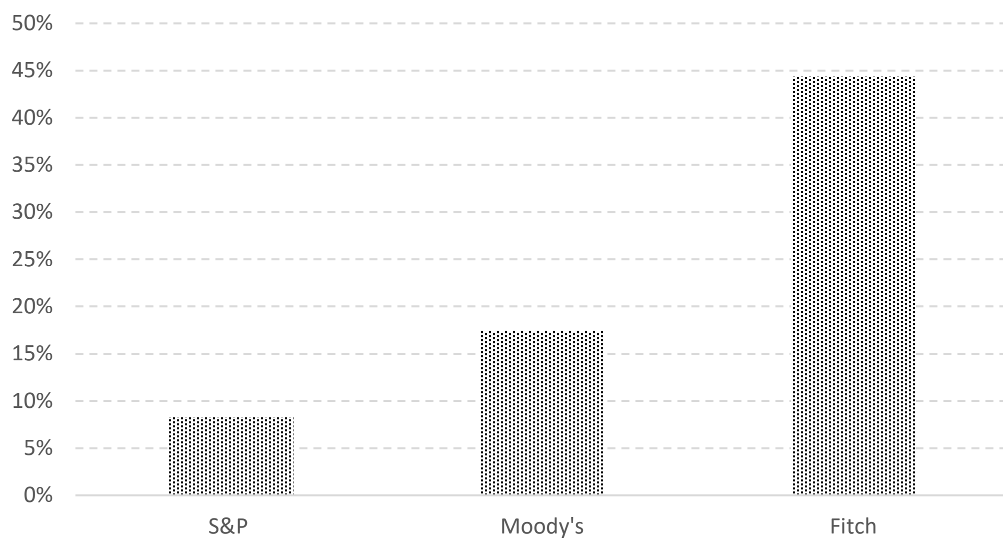
Variable	Definition	Source
Fitch	A dummy variable equals one if the bond has a Fitch rating, and zero otherwise	MERGENT
Dodd-Frank	A dummy variable equals one if firm's bond is issued after Dodd-Frank (i.e. 21 July 2010), and zero otherwise	MERGENT
Firm Size	The natural logarithm of the firm's total 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
Rating Dispersion	The absolute difference between ratings assigned by Moody's and S&P	MERGENT
Distance	The absolute distance, in notches, 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 equals one if the added Fitch rating is better than Moody's and S&P, and zero otherwise	MERGENT
Fitch_Added_Equal	A dummy that equals one if the added Fitch rating is equal to or worse than Moody's and S&P, and zero otherwise	MERGENT
Fitch_Makes_IG	A dummy that equals one if Moody's and S&P straddle the boundary and Fitch pulls the rating into the IG category, and zero otherwise	MERGENT
Fitch_Denies_IG	A dummy that equals one if Moody's and S&P straddle the boundary and the addition of a Fitch rating does not raise the rating of the issue to the IG category, and zero otherwise.	MERGENT
InvBoundary	A dummy that equals one if Moody's and S&P straddle the HY-IG boundary, and zero otherwise	MERGENT
Issue Size	The natural logarithm of the offering amount	MERGENT
Maturity	Natural logarithm of the maturity (in months)	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 that equals one if Moody's rating differs from S&P rating, and zero otherwise	MERGENT
SPIndexLevel	S&P 500 index Level	CRSP
SPIndexReturn	The trailing one-year return on the S&P 500 index	CRSP
BondIndexReturn	The trailing one-year return on the Bloomberg Barclays US Aggregate Bond Index	BLOOMBERG
GDPGrowth%	GDP growth rate	U.S. Bureau of Economic Analysis

Appendix B. Assigning first and third ratings by rating agency

Panel A. The figure shows the percentage of new issues where S&P, Moody's or Fitch assigned the first rating. If a new issue obtains initial ratings from two rating agencies simultaneously, both rating agencies are counted as providing the first rating.



Panel B. The figure shows the percentage of new issues where S&P, Moody's or Fitch assigned the third rating.



Appendix C. Placebo test

This table reports the marginal effects of placebo probit regressions with a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015 for non-US G7 bonds (UK, Germany, France, Italy, Canada, Japan) which were not subjected to the Dodd-Frank regulation. For brevity, the marginal effects of controls are omitted. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. The model includes industry, country and year fixed effects. Z-values are shown inside brackets. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

VARIABLES	(1)	(2)
Distance*Dodd-Frank	-0.013	-0.007
	(-0.971)	(-0.559)
Distance	-0.014	-0.005
	(-0.937)	(-0.324)
Dodd-Frank	-0.107	-0.114
	(-1.065)	(-1.151)
Controls	Yes	Yes
Industry FEs	Yes	Yes
Year FEs	Yes	Yes
Country FEs	No	Yes
Observations	1,427	1,427
Pseudo R-squared	0.166	0.201

Appendix D. Robustness

This table reports the marginal effects of probit regressions with a Fitch rating on the Dodd-Frank dummy and firm controls between Jan 2006 and Dec 2015. Columns 1 and 4 report the full sample results while columns 2 and 3 along with columns 5 and 6 decompose the full period into two non-overlapping sub-periods: 01/01/2006 – 07/21/2010 (pre-Dodd Frank) and 07/22/2010 – 12/31/2015 (post-Dodd-Frank). Columns 1-3 exclude the GFC period from August 2008 to March 2009 while columns 4 to 6 control for additional macro variables (S&P Index level, S&P Index return, Bond Index return and GDP Growth). See appendix A for complete variable definitions. For brevity, marginal effects of controls are omitted. Standard errors are clustered by firms to account for multiple bond issues made by the same firm. The model includes industry and year fixed effects. Z-values are shown inside brackets. ***, **, * represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

	Excluding GFC period			Including additional macro controls		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Distance*Dodd-Frank	0.034*			0.036**		
	(1.931)			(2.100)		
Distance	-0.063***	-0.069***	-0.029***	-0.065***	-0.071***	-0.030**
	(-4.408)	(-5.681)	(-2.680)	(-4.721)	(-5.942)	(-2.560)
Dodd-Frank	-0.162**			-0.069		
	(-2.152)			(-0.806)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,194	471	723	1,283	560	723
Pseudo R-squared	0.142	0.232	0.121	0.148	0.224	0.125