The Causes and Consequences of Split Credit Ratings: Evidence from the Dodd-Frank Act

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Abstract

Split credit ratings increase the cost of capital for bond issuers. The introduction of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010 reduced the importance of credit ratings and increased the penalties on credit rating agencies for inaccurate ratings. We show that Dodd-Frank increased the proportion of split-rated bonds. Investment grade and boundary bonds not preceded by earnings announcements and bonds of firms with less liquid equities experience the largest increase of 15 to 20 percentage points. These results are consistent with credit rating agencies engaging in idiosyncratic information discovery and relying public information to produce defendable quantitative information in the threat of litigation. The split rating yield premium reduces after Dodd-Frank from 23 basis points to 12 basis points, with pricing no longer based on the pessimistic credit rating.

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1. Introduction

Around half of newly issued corporate bonds receive different credit ratings from the two major credit rating agencies (CRAs). These split ratings are important to bond issuers as they lead to higher yield spreads at issue relative to non-split bonds of similar credit risk, resulting in a higher cost of capital (Livingston and Zhou 2010). In this paper, we use the introduction of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) as an experimental setting to better understand the causes and consequences of split bond ratings. The Act was introduced in 2010 to strengthen the integrity and improve the transparency of credit ratings in response to the large number of defaults of highly rated structured products that contributed to the sub-prime crisis. Dodd-Frank made a number of legislative changes that specifically targeted CRAs. We argue that these regulatory changes impacted the proportion of split ratings and the pricing of newly issued bonds.

There are a number of potential explanations for split credit ratings. Ederington (1986) argues that split ratings are random differences in judgement and simply the result of noise in the rating process. However, Livingston *et al.* (2007) and Livingston *et al.* (2008) show that split ratings are too persistent to be entirely caused by random errors and relate the divergent opinions of CRAs to uncertainty and higher issuer opacity. Split ratings can arise from information asymmetry, where CRAs have access to different information sets. However, split ratings can occur even if CRAs have access to the same information provided that they weight the information differently. This could be the result of different rating methodologies or differences in analyst beliefs for converting quantitative and qualitative information into a discrete rating. Conflicts of interest inherent in the issuer-pays business model, combined with the role of rating agencies as gatekeepers in the credit markets, can also impact the proportion of split ratings. If CRAs are incentivized to optimistically bias ratings to cater to fee-paying customers, there could be a higher proportion of ratings issued just above significant creditworthiness boundaries, resulting in fewer splits across these boundaries.

The passage of Dodd-Frank mandated several changes that allow us to examine these alternative hypotheses. First, Dodd-Frank removed all rating contingent regulation reducing the reliance on CRAs as licensing agents for the debt market. Second, Dodd-Frank required CRAs to incorporate relevant information into their ratings and not rely solely on information sourced from the issuer. Third, while CRAs were previously largely immune from civil litigation over rating failures, Dodd-Frank increased potential penalties for the issuance of biased or misleading credit ratings (White 2010). This suggests that given their commercial nature and role in certification, as well as being a benchmark in the debt market, ratings are no longer merely opinions as argued by CRAs. Therefore, post Dodd-Frank, ratings should be subjected to the same standards of liability and oversight as apply to auditors, securities analysts, and investment bankers (Partnoy 2017).[1]

Prior to Dodd-Frank, there was an over-reliance by analysts on issuers for information as there were no regulatory repercussions. This was clearly demonstrated in the structured products market where CRAs did not perform sufficient due diligence or verify the accuracy of information provided to them and was one of the factors that led to the introduction of new regulation (Harper 2011). Consequently, we expect that public criticism, regulatory scrutiny, and the threat of potential litigation motivated CRAs to improve corporate rating quality after Dodd-Frank. We argue that CRAs are more likely to invest additional resources into idiosyncratic information discovery and to verify inputs to their rating models to protect their reputation. As information is readily available after earnings announcements, we do not anticipate a change in the proportion of

[1] From recent cases it is unclear whether courts will consider credit ratings as statements of opinion that are shielded from litigation rather than commercial activity.

splits for bonds issued shortly after an earnings release. However, in the absence of an earnings announcement there is less publicly available information, requiring analysts to obtain information from company management and other sources. We hypothesize that bonds that are issued prior to earnings announcements will experience an increase in split ratings after Dodd-Frank as CRAs increasingly rely on idiosyncratic information to mitigate the threat of litigation and reputational damage from omitting other relevant information from the rating process.

The vast majority of studies on the effect of Dodd-Frank in credit markets focus on changes in the credit ratings of corporate bonds already on issue (e.g. Dimitrov *et al.* (2015); Ali *et al.* (2016); Ahmed *et al.* (2019); Toscano (2020)). In contrast, we focus our study on the credit ratings attached to newly issued bonds. For bonds that are already trading, CRAs can time their rating announcements based on the release of public information. For example, Ali *et al.* (2016) show that after Dodd-Frank, the likelihood of CRAs issuing rating downgrades following firms' earnings announcements increases. Newly issued bonds do not afford CRAs this timing. In this sense, we are able to get a clearer identification of how CRAs rate bonds in different information environments. Furthermore, using new issues alleviates concerns associated with split ratings being caused by asynchronous rating announcements by CRAs (Livingston *et al.* 2007). From a cost of capital perspective, the yield spread at issue is of greater importance to the issuer than the yield spread of an existing bond.

Our results show that the proportion of newly issued bonds that are assigned different ratings by Moody's and Standard & Poor's (S&P) increases from 52% to 58% after Dodd-Frank. After controlling for potential determinants of splits, including issuer opaqueness proxies, we find that the increase is concentrated in bonds receiving an investment grade (IG) – high yield (HY) boundary rating, consistent with ratings catering. However, once we control for the information environment, we find that the increase in splits is confined to IG and IG-HY boundary bonds without an earnings announcement and bonds where the underlying firms have less liquid equity markets. The proportion of splits rises by 15 to 20 percentage points after Dodd-Frank for these bond issues. Interestingly, we do not detect a meaningful change in the proportion of splits for HY bonds. Given HY bonds are closer to default, CRAs are more likely to scrutinize them irrespective of the legislative impact of Dodd-Frank. These ratings are also less likely to be subject to litigation as the underlying default rate in these rating categories is non-trivial. Our results are consistent with CRAs' preference for verifiable and defendable quantitative information in the event of litigation with splits increasing under higher information asymmetry or when public information is limited. CRAs need to rely more on private information and additional analysis leading to divergent opinions on creditworthiness. Our results do not support the random error hypothesis of Ederington (1986) as we would not expect any change in the proportion of splits after Dodd-Frank, or across the different rating categories (IG, boundary or HY) based on random differences of opinion. Our results are also inconsistent with widespread rating catering, as we observe splits in all IG bonds and not just in boundary-rated bonds after partitioning by proximity to earning announcements or information asymmetry.

We next turn our attention to the pricing implications of this regulatory-induced increase in split rated bonds. Analysis on bond yields at issue show that split rated bonds were priced in line with the more pessimistic (i.e. lower) credit rating prior to Dodd-Frank, with regression coefficients revealing a split premium of 23 basis points (bps), when compared to non-split bonds of a similar credit rating. However, after Dodd-Frank, bonds are priced closer to the average of the split rating, with the split premium reducing to 12 bps. This indicates that although the proportion of split rated bonds has increased, the adverse impact of these split ratings on the cost of capital has substantially reduced after Dodd-Frank. The reduction in the split premium could be the result of a change in the relative information content of ratings, or it could be due to Dodd-Frank removing the regulatory classification of bonds that was typically determined by the more conservative rating between Moody's or S&P.

Overall, our findings suggest that the passage of Dodd-Frank has changed the rating process of CRAs for high information asymmetry issues and issues not preceded by public disclosure. This has led to an increased proportion of newly issued bonds receiving different ratings from the two major CRAs. These split-rated bonds continue to trade at a higher yield to non-split rated bonds despite a reduction in the premium after Dodd-Frank. This indicates that Dodd-Frank has imposed higher borrowing costs on firms with less publicly available information.

The remainder of the paper is organized as follows. Section 2 reviews the Dodd-Frank Act and discusses the impact of rating contingent regulation on credit ratings. Section 3 describes the data. Section 4 provides empirical results and section 5 concludes.

2. Literature review and hypothesis development

In order to develop our hypotheses, we first review the literature on the causes of split credit ratings. We then present details on the relevant changes to CRAs that were induced by the introduction of Dodd-Frank. A number of papers have examined the impact that Dodd-Frank had on CRAs. We link these two strands of literature to develop our hypotheses.

2.1. The determinants of split credit ratings

Split ratings can arise from information asymmetry, where different CRAs have access to different information sets. Bonsall *et al.* (2017) show that issuer-pay CRAs, such as Moody's and

S&P, have access to private information not available to investor-pay CRAs, such as Egan-Jones. CRAs receive private information from issuers and their advisors, as well as from other sources, including commercial vendors and public disclosures by firms. Ahn *et al.* (2019) show that firms provide less optimistic information to CRAs in their private communications and this information is reflected in ratings. Bonsall *et al.* (2017) reveal that private information increases the precision of ratings for borrowers with higher information uncertainty while Huang *et al.* (2019) find that it also helps to detect fraud.

However, split ratings occur even when CRAs have access to the same information. The rating process for corporate issuers typically involves a quantitative analysis of financial information as well as an assessment of qualitative factors, such as the governance framework, the financial strategy or the experience and credibility of management. Kraft (2015) provides evidence that ratings are more than just mechanical mappings of these firm characteristics, with financial data frequently adjusted to better reflect reality and capture the underlying economic fundamentals. CRAs have considerable discretion over these quantitative and qualitative adjustments and Kraft (2015) shows that these adjustments can be large and are priced by the credit markets. These differences in interpretation across CRAs can cause split ratings. Bowe and Larik (2014) find that Moody's places more emphasis on firm governance and specific financial characteristics with smaller, less profitable companies with low interest coverage, limited board independence and lower institutional ownership, more likely to be split.

An extensive literature examines the link between firm opacity and disagreement between CRAs using numerous proxies for information uncertainty. Morgan (2002) finds that more opaque industries such as banking are more likely to receive split ratings from Moody's and S&P. Using several accounting and opinion based proxies, Livingston *et al.* (2007) extend the analysis to nonbanking firms and corroborate that asset opaqueness leads to a higher probability of split bond ratings. Similar conclusions between increased information opacity and divergence of opinion between CRAs can be drawn using the readability of financial disclosures and reporting quality, as proxies of opacity (Bonsall and Miller (2017); Akins (2018)).

One of the early hypotheses put forward to explain split credit rating was the random errors hypothesis of Ederington (1986). He argues that the differences in judgement by CRAs are random and this leads to split ratings when the issuer is near the boundary between two rating notches. Livingston *et al.* (2008) show that splits are unlikely to be caused by random error, with the majority of split rated bonds remaining split rated, and the rating agencies generally maintaining their initial relative ratings. Moreover, split ratings between Moody's and S&P are not symmetric, with Moody's typically issuing the more conservative rating.

Split credit ratings assigned to issuers can be also influenced by ratings' role in regulation. Opp *et al.* (2013) argue that the rating process is affected by the regulatory use of ratings and provided that the advantage of highly rated securities is sufficiently large, it may be optimal for rating agencies to facilitate regulatory arbitrage by inflating ratings rather than providing informative ratings. Using a theoretical model, they show that due to their regulatory advantage, ratings around the IG-HY and the AAA-AA boundaries are most susceptible to manipulation. Their empirical predictions are supported by Cornaggia *et al.* (2015). They compare Moody's ratings with Financial Health Ratings produced by Rapid Ratings, which have no regulatory implications, and show that Moody's assigns a disproportionate number of Baa ratings, which are the lowest within the IG category. These bonds also exhibit a higher default frequency. Similar evidence is provided by Behr *et al.* (2016), who document the presence of rating inflation since a regulatory change by the SEC in 1975 increased the dependence on ratings for regulation. They find the inflation is also most pronounced at the IG-HY boundary, with Baa rated firms in the post-regulation period 19% more likely to be negatively downgraded to HY than Baa rated firms in the pre-regulation period.[2]

Regulations explicitly mandate limits to investments in specific credit ratings and force financial firms to either hold higher capital reserves for lower rated securities or sell downgraded bonds (Ellul *et al.* 2011). These are generally letter boundaries rather than ''notch'' ratings due to the regulatory focus on broader ratings (Kisgen 2006). Kisgen (2006) shows that managements' concerns about the large impact of credit rating downgrades across letter ratings impact firms' capital structure decisions. The importance of maintaining a within-letter rating to avoid triggering rating-based covenants is clearly evident from the weaker market response to one-notch rating revisions within the same broad rating category than revisions spanning two adjacent broad ratings (Jung *et al.* 2013). Institutional investment guidelines also frequently contain self-imposed restrictions on the minimum credit quality thresholds for holdings (Chen *et al.* 2014). Cantor *et al.* (2007) survey U.S. investment managers and find that while the IG boundary is the most frequently used threshold (88%), around 80% of U.S. managers also use the AAA, AA and A letter-grade cut-off. Consequently, under rating contingent regulation companies issuing bonds with expected ratings near either the IG-HY boundary, or the letter boundaries, may have their rating increased to avoid the resulting higher yield that investors will demand for bonds that are deemed to be a riskier credit. This would lead to fewer split ratings at these letter boundaries.

[2] In June 1975, the SEC expanded the use of ratings in 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).

2.2. *The impact of Dodd-Frank on CRAs*

Credit ratings have been widely used by investors and financial institutions in assessing firms' creditworthiness, compliance with investment mandates, and determining regulatory capital requirements. However, a large number of unanticipated credit rating downgrades of structured securities by CRAs during the financial crisis has raised concerns about their objectivity and quality (deHaan (2017); Jankowitsch *et al.* (2020)). CRAs have been widely criticized for the significant role their inflated ratings of structured products played in the crisis and the serious weaknesses affecting the quality and integrity of the rating process have been the subject of numerous government reports (Financial Crisis Inquiry Commission, 2011).[3] In response to the increased pressure on policy makers to enhance regulation of the credit rating industry, the U.S. Congress passed the Dodd-Frank Act on July 21, 2010. Dodd-Frank outlined several reforms to the industry to strengthen the integrity and improve the transparency of credit ratings, which previously mostly relied on self-regulation (White 2010). Sections 931 to 939H of the legislation specifically target CRAs.

Dodd-Frank substantially enhances oversight of CRAs by the Securities and Exchange Commission (SEC). It increases CRAs exposure to litigation related to their rating opinions by lowering liability protection and grants SEC greater power to impose penalties for providing inaccurate ratings. Most notably, Section 932 enhances regulation, accountability, and transparency of CRAs. Under the increased disclosure mandated by Dodd-Frank, CRAs must file annual reports on internal controls with the SEC, disclose their rating methodologies, make third-party due-diligence reports public, and disclose the accuracy of their past credit ratings. Section 935 of the legislation increases CRAs accountability, and transparency of rating methodologies

[3] https://www.govinfo.gov/app/details/GPO-FCIC

and mandates agencies to consider all credible information when determining ratings, not just information provided by the issuer. Section 939A removes all credit rating references for financial institutions in determining capital adequacy ratios and increases penalties for issuing inaccurate ratings. Specifically, the Office of the Comptroller of the Currency (OCC) requires that banks do not have to rely exclusively on external credit ratings. Consequently, a security rated in the top four letter rating categories by CRAs does not automatically satisfy the revised investment grade standard. Huang et al. (2021) show that lower regulatory reliance on credit ratings post Dodd-Frank reduces the demand for a favourable third rating for bonds near the IG-HY boundary. Section 939B extends the Regulation Fair Disclosure (Reg FD) Act to encompass CRAs by eliminating the exemption in Rule 100(b)(2)(iii) specifically granted to CRAs under Reg FD.[4] Although the removal of this exemption theoretically eliminates CRAs access to non-public information, firms are still able to selectively disclose non-public information to anyone who expressly agrees to keep the information confidential. Bonsall and Miller (2017) confirm that the access to private information is unaffected by Dodd-Frank.

Opp *et al.* (2013) predict that removing rating-contingent regulation and increasing CRAs legal liability for issuing inaccurate ratings systematically shifts the distribution of credit ratings downward. They argue that without rating contingent regulation it is optimal for CRAs to acquire costly information and publish informative ratings as truthful disclosure maximizes the rents that can be extracted from the private information they possess. Dimitrov *et al.* (2015) present evidence that issuer-paid ratings have indeed become more conservative post Dodd-Frank while Toscano (2020) finds that they are also lower than investor-paid ratings. Alp (2013) documents a similar

[4] On 23 October 2000, Reg FD banned firms from selectively disclosing material non-public information to analysts and investors who would be reasonably expected to trade securities based on the information or provide others with advice about securities trading (SEC 2000). Reg FD permitted the disclosure of non-public information to CRAs for the purpose of determining or monitoring credit ratings, provided the ratings were publicized.

increase in rating conservatism following passage of the Sarbanes-Oxley Act (SOX) in 2002.[5] These findings suggest that increased regulatory scrutiny forces CRAs to become less optimistic to protect their reputation, particularly given the asymmetric nature of litigation risk, with CRAs more likely to be penalized for issuing overly optimistic ratings than assigning overly pessimistic ratings.

The passage of Dodd-Frank significantly increases CRAs' liability for issuing misleading or biased ratings, and makes it easier for the SEC to impose sanctions and penalties. Ahmed *et al.* (2019) and Bozanic and Kraft (2018) argue that this incentivizes issuers to shift their focus from qualitative information to quantitative information in the rating process. While soft information involves judgement and might prove difficult to defend in court, quantitative information is more verifiable and enables CRAs to prove that they acted without negligence. This mitigates the threat of regulatory penalties, sanctions and the threat of private litigation. Bozanic and Kraft (2018) show empirically that the explanatory power of regressions of ratings on firm fundamentals increases post Dodd-Frank and the association between credit ratings and accounting variables as well as market fundamentals is significantly stronger. Ahmed *et al.* (2019) find that increased weight on fundamental information in credit ratings after Dodd-Frank leads to better prediction of future default.

In a separate strand of literature, Cohn *et al.* (2018) emphasize CRAs reliance on issuers for much of the information on which they base their ratings and argue that strategic disclosure by issuers is also an important and often overlooked aspect of the ratings process. They construct a theoretical model to investigate the implications of issuers' ability to distort information used to

[5] On 25 July, 2002, the Senate and the House passed the SOX Act. Section 702 (b) of SOX requires SEC to study the role and function of CRAs. 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 CRA Duopoly Relief Act of 2006, which introduces competition in the rating industry and increases oversight of CRAs, was passed.

rate securities. Their model predicts that when the manipulation cost is low, it is optimal for lower creditworthiness firms to manipulate CRAs information to obtain a better rating. They further show that CRAs respond to such strategic disclosure by issuers with increased monitoring, particularly under increased penalties such as those mandated by Dodd-Frank. Ali *et al.* (2016) provide empirical evidence that is consistent with issuers becoming more strategic about disclosing negative information to CRAs post Dodd-Frank. A weaker stock price reaction to rating downgrades following Dodd-Frank documented by Bedendo *et al.* (2018) and Ederington *et al.* (2019), suggests a higher reliance on public information by CRAs after its passage.

2.3. Hypotheses

The threat of litigation faced by CRAs from regulators for inaccurate ratings and the additional mandated disclosure is the channel via which we expect Dodd-Frank to impact ratings. As CRAs seek to reduce reliance on private information from issuers and engage in idiosyncratic information discovery that is verifiable, we expect to see an increased divergence in ratings. This could be the result of the use of different information or from the use of different models. However, we anticipate the divergence in credit ratings to be mitigated for issues with low information asymmetry. We consider two information settings. Given the abundance of information around earnings announcements, we do not expect a change in the proportion of splits for bonds issued shortly after earnings are released. The level of information asymmetry can also be proxied by equity market liquidity (Welker, 1995), and thus we also do not expect a change in the proportion of splits for bonds of firms with liquid equity markets.

Our second hypothesis concerns the market's view of split ratings after Dodd-Frank. With the reduced regulatory reliance on credit ratings we anticipate that the yield spread will no longer be based on the lowest credit rating out of Moody's and S&P. Furthermore, if investors know that CRAs are now investing more time and resources in attempting to provide more informative ratings then we expect investors to weigh these ratings more equally, leading to a reduction in the yield premium attached to split rated bonds.

3. Data

Bond characteristics and credit ratings issued by Moody's, S&P and Fitch are obtained from the issue and ratings history within the Mergent Fixed Income Securities Database (FISD). Our sample begins in January 2006 to avoid contamination from the 2002 SOX Act and ends in December 2015 to ensure a similar time frame before and after the regulatory change. 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 bonds. Yankee bonds and bonds issued through private placements are excluded. Following existing literature, we focus on Moody's and S&P ratings as they capture most of the corporate bond issuance market (Akins (2018); White (2010)). We only focus on initial ratings as the process for assigning initial ratings is timelier and more accurate than the process for monitoring ratings (Chen and Wang 2021).

Accounting information and financial market data are sourced from Compustat. Bid-ask spreads, our empirical measure of market liquidity, are obtained from the TAQ daily database. Equity analysts' forecasts and analyst coverage are acquired from Institutional Brokers' Estimate System (IBES). Stock market index returns are downloaded from Center for Research in Security Prices (CRSP). Bloomberg Barclays U.S. Aggregate Bond Index levels and bond yields at issue are sourced from Bloomberg. Moody's Aaa corporate bond yields and 10-year U.S. Treasury yields are sourced from the St. Louis Federal Reserve Economic Database. Credit default swap (CDS) data is obtained from Markit.

To construct our dataset we require that the stock of each bond issuer is covered by at least three equity analysts in IBES to enable the calculation of our dispersion measure. We also require each firm to have complete data in Compustat and ratings in Mergent FISD. Our initial dataset comprises 2,615 newly issued domestic bonds. Following Morgan (2002) and Livingston *et al.* (2007), we filter out 567 bonds issued by financials and utilities (GICS codes starting with 40 and 55). Financials are more likely to have split ratings given the nature of their assets while ratings of highly regulated utilities are less likely to be split. We remove 580 subsequent bond issues of the same issuing firm that occur within the same month as multiple issues over a short period are unlikely to convey additional information. Our final sample contains 1,468 bond issues from January 2006 to December 2015.

We draw upon prior literature to identify key bond and firm characteristics of split ratings as controls in the regression models. We include the natural log of the firm's total book assets as a proxy for firm size, as smaller firms are more likely to receive split ratings (Livingston *et al.* (2007); Bowe and Larik (2014)). Livingston *et al.* (2007) show that opaque firms are associated with an increased probability of a split rating due to higher information asymmetry and valuation difficulty so we incorporate multiple controls for opacity. We use two accounting proxies of opacity: the market-to-book ratio defined as (Total assets – book equity + market equity)/total assets, and intangible assets scaled by total assets. We supplement these with two equity analyst-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 indicating analyst coverage. Brennan and Subrahmanyam

(1995) show that greater analyst coverage results in more information flows to investors, which reduces the opaqueness of firm assets. Following Dimitrov *et al.* (2015), we also control for market conditions using the trailing one-year return on the S&P 500 index and its level at bond issue. To control for credit market conditions, we include the trailing one-year return on the Bloomberg Barclays US Aggregate Bond Index. We include an indicator variable to identify if Fitch also rated the bond issue. Finally, we include an indicator variable to indicate the presence of CDS contracts traded on the firm's debt. CDS contracts may provide an additional information channel to investors (Acharya and Johnson 2007) and their presence has been shown to mute the stock price reaction of ratings (Chava *et al.* 2019). A complete description of all variables is tabulated in Appendix A.

Panel A in Table 1 provides descriptive statistics for all variables before and after the passage of Dodd-Frank. Consistent with Livingston *et al.* (2007), we find that S&P ratings are generally more optimistic but both rating agencies issue lower ratings post Dodd-Frank on average, in line with Dimitrov *et al.* (2015). Partitioning the data into non-split and split subsamples, Panel B shows that firms with larger size, lower standard deviation of analysts' forecasts, greater analysts' coverage, higher credit rating, and CDS contracts on their debt are less likely to have split bond ratings.

[Insert Table 1]

4. Results

We begin our analysis by examining the proportion of split-rated bonds before and after Dodd-Frank across the different rating classifications. Table 2 presents the results. From panel A, we can see that prior to Dodd-Frank, 52.0% (312/600) of all newly issued bonds were assigned a split rating by Moody's and S&P. This proportion has been relatively stable with around half of all bonds split at the notch level each year on average between 1983 and 2009 (Morgan (2002); Livingston *et al.* (2007); Bowe and Larik (2014); Akins (2018)). However, we find that post Dodd-Frank the proportion of split ratings rose to 57.9% (503/868). While this overall increase in the proportion of split ratings is significant at the 5% level, it obscures the divergence in splits across different rating categories. In subsequent columns, we use two definitions of boundary bonds to partition the sample into three categories based on S&P ratings: IG, boundary and HY. The letter-based boundary bonds are defined as AAA, AA-, A- and BBB-, IG bonds as AA+, AA, A+, A, BBB+ and BBB, with all bonds rated BB+ and below classified as HY. Given the IG-HY boundary is also of importance, we consider a boundary consisting of S&P ratings assigned within two notches of the IG-HY threshold (rating classification of BBB, BBB-, BB+ or BB).[6]

[Insert Table 2]

The results based on the letter boundary in panel A reveals that prior to Dodd-Frank, 41.5% of non-boundary IG bonds were split compared to 46.7% of boundary IG bonds and 66.5% of HY bonds. This pattern is similar to the IG-HY boundary definition, where the proportion of split rated bonds ranges from 46.1% for IG rated bonds to 66.3% for HY rated bonds, with the proportion of boundary split rated bonds in line with the IG category at 46.8%. The higher proportion of splits for lower rated bonds is consistent with Livingston *et al.* (2007). Turning our attention to the proportion of splits post Dodd-Frank, we find that the increase in split ratings is largely confined to the letter boundary rating category and is most prominent in letter boundary and IG-HY boundary rated bonds, which were most susceptible to manipulation pre-Dodd-Frank. Using the letter-grade boundaries, we find that the proportion of split rated bonds in the IG boundary category

[6] Using ratings assigned by Moody's rather than S&P does not affect the significance of our results using slightly different boundary thresholds to adjust for Moody's lower ratings, on average.

rises from 46.7% (49/105) to 55.9% (99/177), a difference of 9.3%, significant at the 10% level of significance. The effect is more pronounced around the IG-HY boundary, with the proportion of split rated bonds in that category rising from 46.8% (94/201) to 58.7% (155/264), a difference of 12.0%, significant at the 5% level of significance. In untabulated results, we find that this difference increases to 15.9% when only boundary bonds rated BBB- are considered. The results in Table 2 show that post Dodd-Frank, the proportion of split rated bonds increases monotonically between IG and HY rated bonds for both boundary definitions.

Panels B and C show the Moody's rating relative to S&P, before and after Dodd-Frank. An inspection of these relative ratings reveals that the increase in the percentage of split ratings in the IG and boundary categories following Dodd-Frank is largely attributed to a higher proportion of superior Moody's ratings relative to S&P ratings. While only 12.4% (13/105) of Moody's ratings were higher pre-Dodd-Frank, this proportion rose to 26.0% (46/177) post-Dodd-Frank. The percentage of split ratings in the HY category is largely unchanged as the lower proportion of superior ratings issued by Moody's is offset by a higher proportion of inferior ratings. The distribution of Moody's ratings relative to S&P ratings across the three rating categories for both boundary classifications is illustrated in Figure 1.

[Insert Figure 1]

4.1. The increase in split ratings around the introduction of Dodd-Frank

The above univariate results show that splits have increased after Dodd-Frank. To test our hypotheses, we estimate a series of probit models with the dependent variable, *Split*, being equal to one if the bond had a different rating assigned by Moody's and S&P when issued, and zero otherwise. We control for a number of firm-specific financial variables, asset opaqueness proxies and market wide equity and bond conditions that could potentially influence bond credit ratings. The probit regression results are contained in Table 3 and Table 4. In our first set of tests we primarily focus on a series of independent indicator variables. All specifications include an indicator variable, *DF*, equal to one for bonds issued after the passage of the Dodd-Frank legislation on July 21, 2010. Table 3 uses the letter boundary (AAA, AA-, A- and BBB-) to identify boundary bonds. Model 1 contains the full sample of bonds and includes an indicator variable for bonds rated at the letter boundary as well as an indicator variable for those classified as HY. The baseline is IG, non-boundary bonds. These two rating-related indicator variables are interacted with the *DF* indicator variable to allow for differential effects from Dodd-Frank across each rating category. We expect Dodd-Frank to lead to an increase in splits, with potentially differing impacts across rating categories if ratings catering is present. Models 2-4 report results from separate regressions for the non-overlapping groups of investment grade, letter boundary and high yield bonds. Table 4 defines the boundary as those bonds two notches either side of the IG-HY boundary. Model 1 contains the full sample results with rating category interactions with the *DF* variable. Models 2-4 contain the separate regression results for the non-overlapping groups of IG, IG-HY boundary and HY bonds. Models 5 and 6 of Table 4 include an indicator variable for those bonds with a credit rating below the IG-HY boundary based on S&P and Moody's, respectively. As these regression results are difficult to interpret, we present the predictive margins in Table 5. Since our variables of interest are indicator variables, we can provide an intuitive interpretation as these margins are the predicted probabilities for each of the different rating groups before and after the introduction of Dodd-Frank. The predicted probabilities also take into account the influence of the control variables.

The first model of Table 3 presents the full sample results and shows that the probability of being split for bonds around the boundary is significantly higher after Dodd-Frank. The sum of the coefficients on *DF* and *DF* × *Bound* is positive and statistically significant at 1%. HY bonds are more split before Dodd-Frank and this is not affected by the regulatory change. We do not observe any increase in splits for IG bonds under this specification. The separate regressions for boundary, IG and HY in column 2-4 reveal an increase in splits for letter boundary bonds at the 10% significance level. The majority of the control variables are consistently insignificant, with the exception of the standard-deviation of equity analysts' earnings forecasts, indicating that asset opaqueness does influence split ratings.

[Insert Table 3]

The results in Table 4 with the IG-HY boundary are, in general, similar to those using the letter boundary. The full sample results in model 1 show that only boundary firms have more split ratings after Dodd-Frank, with a coefficient being signficant at 1%. The separate regressions in models 2-4 show that IG bonds have slightly more splits after Dodd-Frank once the AAA, AA- and A- bonds are shifted from the boundary classification to the IG group. That said, boundary bonds retain their significant increase, with no change for HY bonds.[7] The results in column 5 and 6 are similar and show that when bonds are separated into only IG and HY that the introduction of Dodd-Frank only impacts the proportion of splits for IG bonds.

[Insert Table 4]

[7] To mitigate concerns that our results are attributed to other extraneous factors independent of the Dodd-Frank legislation, we extend our analysis to a sample of non-US bonds from the remaining G7 countries (UK, Germany, France, Italy, Canada, Japan) using similar empirical setup reported in Tables 3 and 4. These non-US firms were not subjected to the Dodd-Frank regulation. This table can be found in Appendix B. The insignificant results imply that the observed effect is confined to U.S. bonds subjected to the Dodd-Frank Act.

To better understand the changes in split ratings we now turn our attention to the predicted probabilities in Table 5. We present the results in six panels with the predicted probabilities corresponding to the probit regression results in Table 3 and Table 4. Panel A contains the results from model 1 of Table 3 and panel B reports those from columns 2-4. We can see from panel A for the full sample regression using the letter boundary that the probability of being split before Dodd-Frank is 40.3% for IG bonds, 43.4% for boundary bonds and 62.2% for HY bonds. Under this specification boundary bonds are the only group that experience a significant change in the probability of being split, increasing by 15.9 percentage points to 59.3%. We observe similar results in the separate regressions for each credit rating group in panel B. We can see from panel C for the full sample regression using the IG-HY boundary that there is no significant change for IG and HY bonds, while the proportion of splits bonds increases from 46.2% to 62.1% for boundary bonds. In the separate regression for each credit rating group in panel D, we observe an 11.3 percentage point increase in splits for IG bonds that is significant at 10%. The increase in splits for boundary firms is a significant 11.6 percentage points. Again, there is no change in the split probability for HY bonds. Panels E and F contain the results where a HY indicator variable and its interaction with the Dodd-Frank indicator variable are included. For both S&P and Moody's the same conclusion is reached – splits increase by around 11 percentage points for IG bonds, whereas HY bonds maintain the same proportion of splits. These results show that Dodd-Frank led to an increase in split ratings primarily for both letter boundary bonds and IG-HY boundary bonds. The concentration of splits in boundary bonds suggests the potential presence of ratings catering prior to Dodd-Frank.

[Insert Table 5]

4.2. Information Asymmetry and split probabilities

We now incorporate two measures of information asymmetry, earnings announcements and market liquidity into our analysis to determine if an information-based explanation is more appropriate than a manipulation-based explanation. The results of the probit regression controlling for earnings announcements are presented in Table 6 for the letter boundary specification and in Table 7 using the IG-HY boundary definition. We now include an additional indicator variable that is equal to one if a bond issued within 30 days of an earnings announcement.[8] We anticipate that bonds not preceded by an earnings announcement will have a higher probability of being split because of the threat of litigation stemming from inaccurate ratings and CRAs exerting increased idiosyncratic information collection and analysis. The earnings indicator variable is interacted with the Dodd-Frank, the boundary and the HY indicator variables. The results in both tables show that the probability of splits generally increase after Dodd-Frank and that the presence of an earnings announcement reduces this probability. The coefficient attached to the *DF* indicator variable shows that issues that are not preceded by an earnings announcement have a significantly higher probability of being split after Dodd-Frank. The sum of the *DF* and the *DF* × *Earnings* coefficient are all insignificantly different from zero across all specifications.

[Insert Table 6]

[Insert Table 7]

To simplify interpretation the predicted probabilities are reported in Table 8 and provide clear evidence that earnings announcements play a crucial role in explaining the increase in splits. In general all IG and boundary bonds issued without recent earnings announcements exhibit substantially higher split probabilities. Bonds issued after earnings announcements do not

[8] The results are robust to different lengths between the issue date and the earnings announcement date.

experience a signficant increase in splits. HY bonds also do not experience any change in split probabilities after Dodd-Frank. The panels in Table 8 again link to the models in Table 6 and Table 7, displaying the predicted probabilities for the various combinations of pre- and post-Dodd-Frank, IG, boundary and HY, as well as bonds issues with and without an earnings announcement in the preceding 30 days.

Turning our attention first to the full sample results in panel A, it is clear that splits are more likely for newly issued bonds that are not preceded by an earnings announcement. The proportion of splits for IG bonds without earnings news increases from 36.2% to 48.7% after Dodd-Frank, whereas those IG bonds that are issued after earnings are disclosed do not experience a change in the proportion of splits. The boundary bonds are more likely to be split after Dodd-Frank, increasing from 40.1% to 60.3%. Boundary bonds without earnings also increase, but the change is smaller and insignificant. As with the previous results, the proportion of splits for HY bonds remains relatively constant. Running the probit regression separately for each rating group yields broadly similar results. IG bonds have an 11.8 percentage point increase in splits and letter boundary bonds experience an 18.7 percentage point increase. Altering the definition of boundary to the IG-HY slightly alters the proportion level, but the increases are still between 15.8 and 20 percentage points. The results are similar if the probit specification only uses a HY indicator variable to control for ratings differences (panels E and F). Here, the IG bonds issued without earnings announcements increase by 16 percentage points and all other issues are insignificant.

[Insert Table 8]

The results of probit regressions controlling for market liquidity are presented in Table 9 for the letter boundary specification and in Table 10 using the IG-HY boundary definition. In line with Welker (1995), we estimate market liquidity with bid-ask spreads. Specifically, we use the high-frequency TAQ database to calculate the daily average effective bid-ask spreads and then split the sample into high and low liquidity stocks at the median value based on the measure from the prior fiscal year.[9] We include this market liquidity measure as additional information asymmetry indicator variable that is equal to one if the equity of the underlying firm issuing the bond is in the high liquidity group. We expect that bonds in the low market liquidity group to have a higher probability of being split because of the reliance on additional idiosyncratic information that CRAs need gather to form an accurate opinion about their creditworthiness. The market liquidity variable is then interacted with the Dodd-Frank, the boundary and the HY indicator variables as previously. We find that the results in Table 9 & 10 are broadly similar to the earnings announcements reported in Table 7 & 8 with high market liquidity bonds exhibiting a significantly higher probability of being split after Dodd-Frank. However, given the easier and more informative interpretation of predictive probabilities, we focus our discussion on Table 11.

[Insert Table 9]

[Insert Table 10]

The results in Table 11 show that bonds of firms with less liquid equity exhibit significantly higher split probabilities across all panels while bonds in the more liquid group do not. In line with results presented in Table 8, the increase in more pronounced at the boundary bonds but also present to a lesser extent in investment grade bonds. The proportion of splits at the letter boundary increase by between 23.5 and 28.1 percentage points while the proportion of splits at the IG-HY boundary increase by between 18.7 and 21.7 percentage points, depending on the definition of the boundary. All results are statistically significant at either 1% or 5% level of significance.

[9] The relative effective spread is considered a good proxy for stock liquidity (see, for example, Fang *at al.*, 2009; Goyenko et al., 2009; Hasbrouck, 2009).

[Insert Table 11]

These results provide strong support for Dodd-Frank changing how information is used in the rating process. The threat of litigation combined with additional idiosyncratic information gathering leads to an increase in disagreement between the two CRAs for bond issues with higher information asymmetry. Although CRAs can still access private information from firm management they need to demonstrate additional analysis and consideration of all credible information, which we argue leads to differences of opinion regarding bond creditworthiness. Our results are consistent with this hypothesis. The differential impact of Dodd-Frank across the different rating categories allows us to rule out alternative explanations. Once we incorporate our two information asymmetry settings, earnings announcements and market liquidity, we do not find support for ratings catering prior to Dodd-Frank as non-boundary bonds in the IG category also experience an increase in splits. The absence of any effect on HY issuers is not surprising when one considers the higher split probability before Dodd-Frank. These bonds require additional analysis by CRAs to ensure that they provide more accurate ratings on bonds that are known to be closer to default when they are issued.

4.3. The implications of increased splits for bond yields

An important consideration is whether the increase in split bond ratings induced by Dodd-Frank has implications for the cost of capital. Given the prevailing view that split rated bonds attract a yield penalty, we ascertain whether the introduction of Dodd-Frank impacts the yields spreads by regressing the bond yield at issue against the credit rating and a number of other control variables. We include an indicator variable equal to one for split rated bonds (*Split*), an indicator variable equal to one for bonds issued after Dodd-Frank (*DF*), as well as their interaction. The regression specification includes indicator variables for each rating notch. The sample used in the yield analysis contains 991 bonds as we were unable to obtain the yield at issue for some bonds from either Bloomberg, Mergent FISD or Thomson Reuters SDC. Table 12 contains six different specifications based on the credit rating that we assign each bond with a split rating. Model 1 uses the more optimistic credit rating out of S&P and Moody's, and model 2 uses the more pessimistic rating. Model 3 presents the optimistic rating results where S&P is more optimistic and model 4 contains the results where Moody's is more optimistic. Models 5 and 6 contain the regressions where S&P and Moody's are more pessimistic, respectively.

[Insert Table 12]

Our primary focus in these results is the coefficient attached to *Split* before and after the introduction of Dodd-Frank to determine whether the regulatory change has altered the market's pricing of split rate bonds vis-à-vis non-split bonds. We can see from model 1 that bonds with split ratings require a significantly higher yield when the optimistic rating is used. Before Dodd-Frank this is 53 bps and it declines slightly to 46 bps after the change in the regulatory environment. There is no significant difference in the yield on split bonds before Dodd-Frank when the pessimistic rating is used. This implies that bonds are priced in line with the pessimistic rating prior to the introduction of Dodd-Frank. After Dodd-Frank the coefficient on split bonds is -23 bps and is significant at 5%. This suggests that investors no longer solely use the pessimistic rating to price split bonds. However, as noted above, the bond is not priced off the optimistic rating either.

To ensure that these findings are not driven by a particular rating agency, we separately analyse the optimistic and pessimistic samples based on a single agency being more optimistic. 459 out of 991 bonds have the same rating from both agencies. S&P has a more optimistic rating on 371 bonds and Moody's is more optimistic for 161 bonds. Where S&P provides the optimistic rating, the yield is 60 bps higher before Dodd-Frank and 41 bps higher after Dodd-Frank (model 3). The yield spread attributable to splits for bonds where Moody's is more optimistic is 41 bps before Dodd-Frank, but is not statistically significant. After Dodd-Frank the split coefficient is 61 bps and is significant at 1%. The coefficients on the split indicator variables using the pessimistic rating are all negative before and after Dodd-Frank for both S&P and Moody's. However, the only significant coefficient is for Moody's after Dodd-Frank. The coefficient is -26 bps, which is similar in magnitude to the corresponding full sample results.

In summary, the results show that split rated bonds have higher yield spreads before Dodd-Frank and appear to be priced in line with the inferior rating. After Dodd-Frank, split rated bonds are priced about one-third of the distance between rating notches based on a -23 bp coefficient on splits in the pessimistic model and +46 bp coefficient in the optimistic model (23/(23+46)). These results indicate that there is a cost to bond issuers that receive a split rating as the bond is not priced half-way between the yield from the pessimistic rating and the yield from the optimistic rating. Livingston and Zhou (2010) show that split-rated bonds trade at a 5 to 20 bp premium to non-split rated bonds of similar credit risk depending on the magnitude of the split. We find that the split bond premium is equal to 23 bps before Dodd-Frank and almost halves to 12 bps after the regulation is introduced.[10] Although Dodd-Frank led to an increase in the proportion of split-rated bonds, it did not lead to a higher cost of capital as the yield premium required on split rated bonds has reduced following the change in regulation. The decline in the split premium could be driven by the reduced reliance on the most pessimistic rating in regulation or it could be driven by an unobservable change in the market's view of the credit ratings issued by the two CRAs.

[10] The 23 bp premium is calculated as -6.55 + [53.25-(-6.55)]/2 and the 12 bp premium is calculated as -22.74 + [46.15-(-22.74)]/2. If we treat the insignificant coefficient of -6.55 as zero then the premium before Dodd-Frank is 26.6 bp.

5. Conclusion

The introduction of the Dodd-Frank Act allows us to distinguish between the different explanations for split credit ratings. Our results do not support the random errors hypothesis or rating inflation in the corporate bond market before Dodd-Frank. We observe that the increase in split ratings occurs in bonds that are investment grade or those that are rated near either the letter boundary or IG-HY boundary. The proportion of splits for high yield bonds are not impacted by Dodd-Frank. These results indicate that the threat of litigation for inaccurate ratings and increased regulatory scrutiny of CRAs has led to the increased use of verifiable and defendable information in the rating process. This reduced reliance on the issuing company for information and increased idiosyncratic collection of information has resulted in more divergent opinions on the creditworthiness of newly issued corporate bonds. The reduced regulatory importance of credit ratings introduced by Dodd-Frank impacts the pricing of corporate bonds. Prior to Dodd-Frank, the yield on newly issued corporate bonds was in line with the more pessimistic of the split ratings. This is not the case after the change in regulation. The split premium has reduced from 23 to 12 basis points as the pricing moves more towards the value expected if both CRAs provide information on creditworthiness. Collectively, these results show that Dodd-Frank has impacted the credit ratings of CRAs and it has also impacted market participants pricing of bonds, leading to a reduced cost of capital for bonds issued with a split rating. However, those bonds that are not issued after earnings announcements now incur a higher costs of capital than they did before Dodd-Frank.

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Figure 1
Distribution of Moody's Ratings Relative to S&P Ratings

This figure shows the proportion of Moody's ratings that are higher, the same, or lower than S&P ratings. The results are partitioned into bonds issued before and after Dodd-Frank (DF). The proportions are presented for two different boundary definitions. The letter boundary includes bonds rated AAA, AA-, A- or BBB-, and high yield (HY) includes bonds rated below BBB-. IG non-boundary includes all investment grade bonds that are not at the letter boundary. The second boundary definition is the investment grade-high yield boundary (IG-HY) that includes bonds rated BBB, BBB-, BB+ and BB). Bonds above these ratings are investment grade and bonds below are high yield.

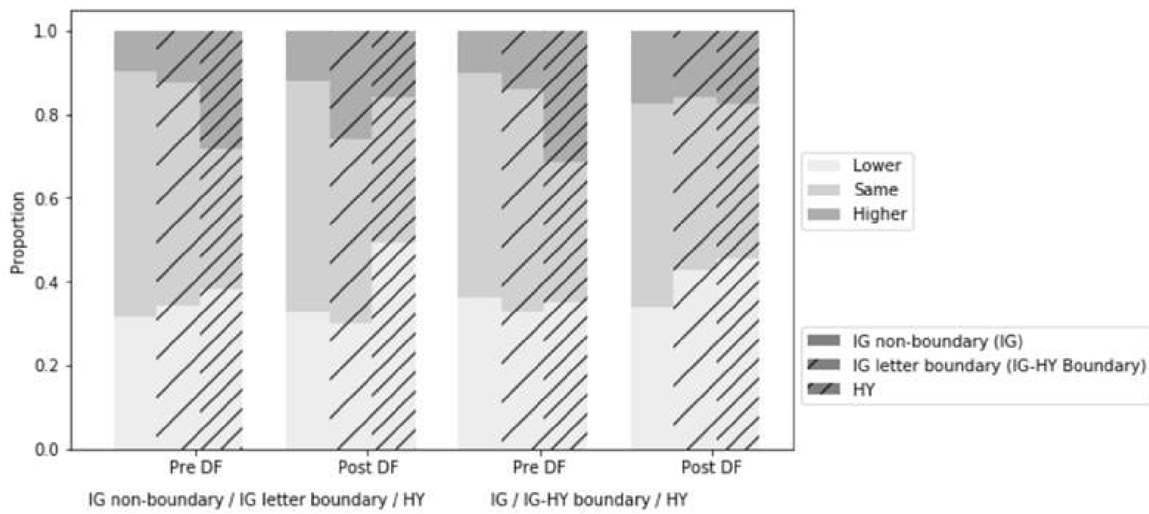

Table 1
Descriptive Statistics

The sample contains newly issued domestic bonds between Jan 2006 and Dec 2015, excluding financials and utilities as defined by their GICS classification. Panel A partitions the bonds based on whether the issue date is before Dodd-Frank (January 1, 2006 to July 21, 2010) or after Dodd-Frank (July 22, 2010 to December 31, 2015). Panel B partitions all bonds into non-split and split bonds. All variables are defined in Appendix A.

Panel A	Before Dodd-Frank (600 observations)					After Dodd-Frank (868 observations)				
	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std
S&P Rating	9.852	9	1	18	3.581	10.972	11	1	19	3.683
Moody's Rating	10.105	9.5	1	19	3.593	11.342	12	1	19	3.862
Ln(Firm Size) $m	9.162	9.070	5.832	12.537	1.390	9.082	9.025	5.602	13.438	1.416
Market to Book	1.589	1.422	0.700	5.931	0.604	1.607	1.436	0.790	6.339	0.632
Intangible Assets	0.242	0.185	0	0.873	0.210	0.228	0.176	0	0.856	0.223
Stdev of Forecasts	0.020	0.004	0	2.106	0.106	0.038	0.004	0	5.949	0.251
Analyst Coverage	19.017	19	3	43	9.181	22.377	22	3	62	11.094
Stock Market Return	-0.021	0.036	-0.477	0.686	0.268	0.131	0.128	-0.027	0.329	0.075
S&P 500 Index Level	1149.4	1116.0	696.3	1562.5	221.7	1471.3	1379.3	1051.9	2126.6	276.6
Bond Market Return	0.062	0.064	-0.011	0.134	0.028	0.047	0.051	-0.033	0.102	0.031

Panel B	Mean			Median		
	Full Sample	Non-Split	Split	Full Sample	Non-Split	Split
S&P Rating	10.514	9.933	10.980	10	9	12
Moody's Rating	10.837	9.933	11.561	10	9	12
Ln(Firm Size) $m	9.115	9.374	8.907	9.049	9.320	8.836
Market to Book	1.599	1.625	1.578	1.429	1.467	1.408
Intangible Assets	0.234	0.225	0.241	0.180	0.170	0.193
Stdev of Forecasts	0.031	0.019	0.040	0.004	0.004	0.004
Analyst Coverage	21.003	22.400	19.885	20	21	19
CDS contracts	0.687	0.757	0.632	1	1	1
Observations	1468	653	815	1468	653	815

Table 2
Proportion of Bonds with Split Ratings around Dodd-Frank

This table reports the proportion of newly issued US corporate bonds with split ratings before Dodd-Frank (January 1, 2006 to July 21, 2010) and after Dodd-Frank (July 22, 2010 to December 31, 2015). For the Letter Boundary columns, Investment Grade bonds comprise ratings AA+, AA, A+, A, BBB+ and BBB, Boundary bonds are rated AAA, AA-, A- and BBB-, while High Yield bonds are those rated BB+ and below. For the IG-HY columns, Investment Grade includes bonds rated AAA- to BBB+ while boundary contains bonds rated BBB to BB and High Yield bonds are those rated BB- and below. Moody's ratings are relative to S&P ratings. p-values are for the z-test difference in proportion test. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

			Letter Boundary						IG-HY Boundary					
	Full Sample		Investment Grade		Boundary		High Yield		Investment Grade		Boundary		High Yield	
Panel A: Split Ratings														
Before Dodd-Frank	312	(52.0%)	110	(41.5%)	49	(46.7%)	153	(66.5%)	106	(46.1%)	94	(46.8%)	112	(66.3%)
After Dodd-Frank	503	(57.9%)	102	(44.7%)	99	(55.9%)	302	(65.2%)	130	(51.0%)	155	(58.7%)	218	(62.5%)
% Diff	5.95%**		3.23%		9.27%*		-1.29%		4.89%		11.95%**		-3.81%	
p-value	0.0241		0.2352		0.0660		0.6323		0.2816		0.0105		0.3981	
Total	1468		493		282		693		485		465		518	
Panel B: Moody's Rating before DF														
Higher	104	(17.3%)	26	(9.8%)	13	(12.4%)	65	(28.3%)	23	(10.0%)	28	(13.9%)	53	(31.4%)
Same	288	(48.0%)	155	(58.5%)	56	(53.3%)	77	(33.5%)	124	(53.9%)	107	(53.2%)	57	(33.7%)
Lower	208	(34.7%)	84	(31.7%)	36	(34.3%)	88	(38.3%)	83	(36.1%)	66	(32.8%)	59	(34.9%)
Total	600		265		105		230		230		201		169	
Panel C: Moody's Rating after DF														
Higher	146	(16.8%)	27	(11.8%)	46	(26.0%)	73	(15.8%)	44	(17.3%)	42	(15.9%)	60	(17.2%)
Same	365	(42.1%)	126	(55.3%)	78	(44.1%)	161	(34.8%)	125	(49.0%)	109	(41.3%)	131	(37.5%)
Lower	357	(41.1%)	75	(32.9%)	53	(29.9%)	229	(49.5%)	86	(33.7%)	113	(42.8%)	158	(45.3%)
Total	868		228		177		463		255		264		349	

Table 3
Probit Regressions of Split Ratings around Dodd-Frank using Letter Boundary

This table contains probit regressions of the level of splits between Jan 2006 and Dec 2015. *Split* is an indicator variable equal to one for bonds issued with split ratings, *DF* is an indicator variable equal to one if the firm's bond was issued after 21 July 2010, *Bound* is an indicator variable equal to 1 if the bond is rated AAA, AA-, A- or BBB-, and *HY* is an indicator variable equal to one for bonds with a rating below BBB-. All other variables are defined in Appendix A. Model 1 covers the full sample, Models 2-4 cover the investment grade, boundary and high yield sub-samples, respectively. Each regression includes industry fixed effects. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	(1) **Full Sample**	(2) **IG**	(3) **Letter Boundary**	(4) **HY**
Constant	0.3136	-0.7464	2.1044	0.4085
	(0.58)	(-0.73)	(1.60)	(0.62)
DF	0.1844	0.2238	0.4204*	0.1133
	(1.23)	(1.15)	(1.86)	(0.82)
Bound	0.0846			
	(0.43)			
DF × Bound	0.2373			
	(0.98)			
HY	0.5832***			
	(3.32)			
DF × HY	-0.0832			
	(-0.45)			
Firm Size	-0.0452	0.0794	-0.4728***	0.0117
	(-0.84)	(0.77)	(-3.34)	(0.16)
Market to Book	0.0469	0.0750	-0.0541	0.1148
	(0.54)	(0.49)	(-0.28)	(0.70)
Intangible Assets	0.0314	-0.2478	1.0234	0.1500
	(0.12)	(-0.46)	(1.48)	(0.39)
Stdev of Forecasts	0.4796*	16.2819*	5.0102	0.5092**
	(1.86)	(1.72)	(0.61)	(1.97)
Analyst Coverage	-0.0019	-0.0259**	0.0344**	0.0030
	(-0.31)	(-2.11)	(2.20)	(0.34)
S&P500 Index Return	-0.0077	-0.1825	-0.1598	0.0918
	(-0.04)	(-0.48)	(-0.27)	(0.29)
S&P500 Index Level	-0.0003*	-0.0001	-0.0002	-0.0004
	(-1.75)	(-0.21)	(-0.57)	(-1.64)
Bond Index Return	2.3550*	1.1461	0.6589	4.3141**
	(1.79)	(0.55)	(0.20)	(2.22)
Fitch	-0.0483	-0.0009	0.1304	-0.3916**
	(-0.47)	(-0.01)	(0.59)	(-2.23)
CDS	-0.1556	-0.8498***	0.9887***	-0.0899
	(-1.27)	(-2.67)	(2.91)	(-0.62)
Obs	1,468	493	282	693
Pseudo R-Sqd	0.0741	0.2170	0.1170	0.0379

Table 4
Probit Regressions of Split Ratings around Dodd-Frank using IG-HY Boundary

This table contains probit regressions of the level of splits between Jan 2006 and Dec 2015. *Split* is an indicator variable equal to one for bonds issued with split ratings, *DF* is an indicator variable equal to one if the firm's bond was issued after 21 July 2010, *Bound* is an indicator variable equal to 1 if the bond is rated within the two notches of the IG-HY boundary (i.e. BBB, BBB-, BB+, BB). For model 1 *HY* is an indicator variable equal to one for bonds rated below BB. For models 5 and 6 the *HY* indicator variable equals one if the rating is below BBB-. All other variables are defined in Appendix A. Model 1 covers the full sample, Model 2-4 cover the investment grade, boundary and high yield sub-samples, respectively. Models 5 and 6 exclude the boundary indicator variable and include the high yield indicator variable (*HY*). Each regression includes industry fixed effects. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	(1) **Full Sample**	(2) **IG**	(3) **IG-HY Boundary**	(4) **HY**	(5) **S&P HY indicator variable**	(6) **Moody's HY indicator variable**
Constant	1.2923**	1.5538	1.6741	0.9785	0.3213	0.1048
	(2.17)	(1.35)	(1.48)	(1.33)	(0.60)	(0.20)
DF	0.2042	0.3593*	0.3168**	0.0889	0.2999**	0.2936**
	(1.31)	(1.81)	(2.02)	(0.55)	(2.49)	(2.40)
Bound	-0.1204					
	(-0.63)					
DF ×Bound	0.2262					
	(1.19)					
HY	0.1491				0.5519***	0.6161***
	(0.67)				(3.38)	(3.88)
DF × HY	-0.1996				-0.1986	-0.1878
	(-0.98)				(-1.24)	(-1.16)
Firm Size	-0.1105*	-0.1634	-0.2603**	-0.0129	-0.0469	-0.0270
	(-1.91)	(-1.42)	(-2.16)	(-0.15)	(-0.87)	(-0.50)
Market to Book	-0.0516	-0.2207	0.1501	-0.1466	0.0375	0.0630
	(-0.58)	(-1.31)	(1.02)	(-0.76)	(0.44)	(0.72)
Intangible Assets	-0.0773	-0.2572	-0.0523	0.3706	0.0407	0.0483
	(-0.29)	(-0.46)	(-0.11)	(0.82)	(0.15)	(0.17)
Stdev of Forecasts	0.6127**	24.4421*	3.1502*	0.4536	0.4837*	0.4865*
	(2.07)	(1.67)	(1.69)	(1.57)	(1.87)	(1.86)
Analyst Coverage	-0.0018	0.0011	-0.0003	-0.0012	-0.0011	-0.0017
	(-0.28)	(0.08)	(-0.02)	(-0.12)	(-0.18)	(-0.26)
S&P500 Index Return	0.0642	0.0825	-0.3032	0.4167	-0.0230	-0.0322
	(0.32)	(0.22)	(-0.84)	(1.17)	(-0.11)	(-0.16)
S&P500 Index Level	-0.0003	-0.0006*	0.0003	-0.0005*	-0.0003*	-0.0003*
	(-1.35)	(-1.80)	(0.83)	(-1.68)	(-1.65)	(-1.71)
Bond Index Return	2.4285*	0.3828	2.7320	3.2160	2.4247*	2.3632*
	(1.85)	(0.16)	(1.21)	(1.41)	(1.84)	(1.79)
Fitch	-0.1087	-0.0771	-0.0605	-0.2044	-0.0625	-0.0636
	(-1.06)	(-0.45)	(-0.34)	(-0.95)	(-0.61)	(-0.63)
CDS	-0.2093*	-0.1214	-0.1984	-0.0915	-0.1598	-0.1669
	(-1.70)	(-0.31)	(-1.01)	(-0.52)	(-1.31)	(-1.38)
Obs	1,468	485	465	518	1,468	1,468
Pseudo R-Sqd	0.0631	0.1920	0.0821	0.0453	0.0709	0.0742

Table 5
Predicted Probabilities of Split Rated Bonds around Dodd-Frank

This table presents the predicted probabilities from the probit regression specifications in Table 3 and Table 4. Bonds are separated into investment grade, boundary and high yield groups before and after Dodd-Frank. Panels A and B represent the results for the letter boundary specification in Table 3. Panel A contains the predicted probabilities for the full sample results (model 1, Table 3) and panel B presents the separate regression for investment grade, boundary and high yield partitions (models 2-4, Table 3). Panels C-F contain the results using the investment grade-high yield boundary from Table 4. Panel C contains the predicted probabilities for the full sample results (model 1, Table 4) and panel D presents the separate regression for investment grade, boundary and high yield partitions (models 2-4, Table 4). Panels E and F use a high yield indicator variable and correspond to models 5 and 6 of Table 4. p-values from a test for differences in proportions are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Investment Grade	**Boundary**	**High Yield**
Panel A: Letter Boundary Combined			
Before DF	0.403	0.434	0.622
After DF	0.472	0.593	0.658
Difference	0.069	0.159**	0.036
p-value	(0.217)	(0.027)	(0.434)
Panel B: Letter Boundary Separate			
Before DF	0.398	0.435	0.629
After DF	0.465	0.581	0.670
Difference	0.068	0.146*	0.040
p-value	(0.246)	(0.057)	(0.410)
Panel C: IG-HY Boundary Combined			
Before DF	0.507	0.462	0.562
After DF	0.582	0.621	0.564
Difference	0.076	0.159***	0.002
p-value	(0.188)	(0.001)	(0.976)
Panel D: IG-HY Boundary Separate			
Before DF	0.429	0.470	0.615
After DF	0.542	0.586	0.647
Difference	0.113*	0.116**	0.032
p-value	(0.067)	(0.046)	(0.584)
Panel E: IG-HY (S&P)			
Before DF	0.415		0.622
After DF	0.526		0.656
Difference	0.110**		0.034
p-value	(0.014)		(0.465)
Panel F: IG-HY (Moody's)			
Before DF	0.403		0.634
After DF	0.510		0.668
Difference	0.107**		0.034
p-value	(0.019)		(0.450)

Table 6
Letter Boundary Splits and Earnings Disclosure

This table contains probit regressions of the level of splits between Jan 2006 and Dec 2015. *Earnings* is an indicator variable equal to one if there is an earnings announcement within 30 days prior to the bond issue. *Bound* is an indicator variable that equals one if the bond is rated AAA, AA-, A- or BBB-. *HY* is an indicator variable equal to one for bonds rated below BBB-. All other variables are as previously defined. Each regression includes industry fixed effects. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	(1) **Full sample**	(2) **IG**	(3) **Letter Boundary**	(4) **HY**
Constant	0.1539	-0.8493	1.9899	0.2814
	(0.28)	(-0.82)	(1.50)	(0.43)
DF	0.3379**	0.3949*	0.5390**	0.2499*
	(2.02)	(1.86)	(2.04)	(1.65)
Bound	0.1092			
	(0.45)			
DF × Bound	0.2001			
	(0.67)			
Earnings	0.2786*	0.3035*	0.2555	0.1174
	(1.70)	(1.73)	(0.96)	(0.64)
DF × Earnings	-0.3621*	-0.4106*	-0.3382	-0.3815*
	(-1.70)	(-1.74)	(-1.01)	(-1.81)
Bound × Earnings	-0.0587			
	(-0.19)			
DF × Bound × Earnings	0.0854			
	(0.22)			
HY	0.6946***			
	(3.47)			
DF × HY	-0.1528			
	(-0.70)			
Earnings × HY	-0.2564			
	(-1.06)			
DF × Earnings × HY	0.1245			
	(0.41)			
Firm Size	-0.0466	0.0707	-0.4738***	0.0173
	(-0.87)	(0.69)	(-3.34)	(0.24)
Market to Book	0.0576	0.0828	-0.0511	0.1285
	(0.66)	(0.54)	(-0.26)	(0.77)
Intangible Assets	0.0535	-0.2413	0.9928	0.2165
	(0.19)	(-0.45)	(1.43)	(0.56)
Stdev of Forecasts	0.4899*	15.2494	4.8352	0.5269*
	(1.83)	(1.64)	(0.58)	(1.93)
Analyst Coverage	-0.0016	-0.0249**	0.0351**	0.0030
	(-0.26)	(-2.01)	(2.25)	(0.35)
S&P500 Index Return	-0.0195	-0.2286	-0.0792	0.1055
	(-0.10)	(-0.60)	(-0.13)	(0.33)
S&P500 Index Level	-0.0003*	-0.0001	-0.0002	-0.0004*
	(-1.67)	(-0.13)	(-0.56)	(-1.66)
Bond Index Return	2.4730*	1.1763	0.6605	4.5019**
	(1.87)	(0.56)	(0.20)	(2.31)
Fitch	-0.0532	-0.0085	0.1175	-0.4017**
	(-0.52)	(-0.05)	(0.53)	(-2.32)
CDS Indicator Variable	-0.1459	-0.8508***	1.0137***	-0.0856
	(-1.19)	(-2.65)	(2.96)	(-0.59)
Obs	1,468	493	282	693
Pseudo R-Sqd	0.0775	0.2220	0.1200	0.0431

Table 7
Investment Grade-High Yield Boundary Splits and Earnings Disclosure

This table contains probit regressions of the level of splits between Jan 2006 and Dec 2015. *Earnings* is an indicator variable equal to one if there is an earnings announcement within 30 days prior to the bond issue. *Bound* is an indicator variable equal to one if the rating is within the two notches of the boundary (i.e. BBB, BBB-, BB+, BB). *HY* is an indicator variable equal to one for bonds rated below BB (model 1) and *HY* equals one if the ratings is below BBB- (model 5 and 6). All other variables are as previously defined. Each regression includes industry fixed effects. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	(1) **Full sample**	(2) **IG**	(3) **Boundary**	(4) **HY**	(5) **S&P HY**	(6) **Moody's HY**
Constant	1.2012**	1.5131	1.5772	0.9063	0.1671	-0.0243
	(2.00)	(1.31)	(1.40)	(1.24)	(0.31)	(-0.04)
DF	0.4287**	0.5371**	0.4382**	0.1914	0.4324***	0.4379***
	(2.34)	(2.44)	(2.33)	(1.05)	(3.01)	(3.03)
Bound	-0.1632					
	(-0.75)					
DF × Bound	0.1111					
	(0.46)					
Earnings	0.2184	0.2158	0.3020	-0.0094	0.2610*	0.2254
	(1.23)	(1.15)	(1.61)	(-0.04)	(1.88)	(1.60)
DF × Earnings	-0.4957**	-0.4301*	-0.2909	-0.2814	-0.3313*	-0.3606**
	(-2.22)	(-1.72)	(-1.22)	(-1.14)	(-1.90)	(-2.03)
Bound × Earnings	0.0952					
	(0.38)					
DF × Bound × Earnings	0.2139					
	(0.67)					
HY	0.2592				0.6544***	0.6856***
	(1.05)				(3.51)	(3.75)
DF × HY	-0.3718				-0.2531	-0.2576
	(-1.52)				(-1.29)	(-1.31)
Earnings × HY	-0.3049				-0.2341	-0.1509
	(-1.12)				(-1.03)	(-0.68)
DF × Earnings × HY	0.3352				0.1013	0.1221
	(1.01)				(0.37)	(0.45)
Firm Size	-0.1132**	-0.1739	-0.2583**	-0.0092	-0.0480	-0.0283
	(-1.96)	(-1.52)	(-2.13)	(-0.11)	(-0.89)	(-0.52)
Market to Book	-0.0444	-0.2230	0.1586	-0.1304	0.0483	0.0721
	(-0.49)	(-1.32)	(1.06)	(-0.67)	(0.56)	(0.82)
Intangible Assets	-0.0616	-0.2460	-0.0289	0.4082	0.0619	0.0666
	(-0.23)	(-0.45)	(-0.06)	(0.90)	(0.22)	(0.24)
Stdev of Forecasts	0.6292**	22.6944	2.8652	0.4914	0.4937*	0.4858*
	(2.03)	(1.60)	(1.51)	(1.58)	(1.84)	(1.83)
Analyst Coverage	-0.0017	0.0024	-0.0008	-0.0017	-0.0008	-0.0014
	(-0.27)	(0.18)	(-0.07)	(-0.18)	(-0.13)	(-0.22)
S&P500 Index Return	0.0536	0.0365	-0.2832	0.3931	-0.0325	-0.0377
	(0.27)	(0.10)	(-0.78)	(1.10)	(-0.16)	(-0.19)
S&P500 Index Level	-0.0002	-0.0006	0.0003	-0.0005*	-0.0003	-0.0003
	(-1.28)	(-1.59)	(0.75)	(-1.68)	(-1.56)	(-1.63)
Bond Index Return	2.4777*	0.3662	2.7039	3.3955	2.5442*	2.4464*
	(1.88)	(0.15)	(1.20)	(1.49)	(1.92)	(1.85)
Fitch	-0.1209	-0.0903	-0.0859	-0.1932	-0.0679	-0.0691
	(-1.19)	(-0.53)	(-0.48)	(-0.91)	(-0.67)	(-0.68)
CDS Indicator Variable	-0.1999	-0.1290	-0.1894	-0.0917	-0.1499	-0.1580
	(-1.62)	(-0.33)	(-0.96)	(-0.52)	(-1.23)	(-1.31)
Obs	1,468	485	465	518	1,468	1,468
Pseudo R-Sqd	0.0682	0.1960	0.0835	0.0504	0.0743	0.0770

Table 8
Predicted Probabilities of Split Rated Bonds and Earnings Disclosure

This table presents the predicted probabilities from the probit regression specifications in Table 6 and Table 7. Bonds are separated into investment grade, boundary and high yield groups before and after Dodd-Frank. They are further separated by whether or not the firm issuing the bond had an earnings announcement in the preceding 30 days. Panels A and B represent the results for the letter boundary specification in Table 6. Panel A contains the predicted probabilities for the full sample results (model 1, Table 6) and panel B presents the separate regression for investment grade, boundary and high yield partitions (models 2-4, Table 6). Panels C-F contain the results using the investment grade-high yield boundary from Table 7. Panel C contains the predicted probabilities for the full sample results (model 1, Table 7) and panel D presents the separate regression for investment grade, boundary and high yield partitions (models 2-4, Table 7). Panels E and F use a high yield indicator variable and correspond to models 5 and 6 of Table 7. p-values from a test for differences in proportions is reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Investment Grade		**Boundary**		**High Yield**	
	Without Earnings	**With Earnings**	**Without Earnings**	**With Earnings**	**Without Earnings**	**With Earnings**
Panel A: Letter Boundary Combined						
Before DF	0.362	0.464	0.401	0.483	0.620	0.628
After DF	0.487	0.455	0.603	0.582	0.686	0.609
Difference	0.125**	-0.009	0.202**	0.099	0.065	-0.019
p-value	(0.042)	(0.905)	(0.028)	(0.297)	(0.217)	(0.781)
Panel B: Letter Boundary Separate						
Before DF	0.363	0.452	0.405	0.494	0.615	0.657
After DF	0.480	0.447	0.592	0.564	0.703	0.610
Difference	0.118*	-0.033	0.187**	0.070	0.087	-0.047
p-value	(0.060)	(0.547)	(0.036)	(0.512)	(0.101)	(0.508)
Panel C: IG-HY Boundary Combined						
Before DF	0.476	0.558	0.416	0.532	0.573	0.541
After DF	0.634	0.533	0.616	0.627	0.594	0.502
Difference	0.158**	-0.025	0.200***	0.095	0.021	-0.039
p-value	(0.018)	(0.745)	(0.001)	(0.165)	(0.748)	(0.640)
Panel D: IG-HY Boundary Separate						
Before DF	0.405	0.472	0.425	0.536	0.615	0.611
After DF	0.574	0.506	0.585	0.589	0.682	0.578
Difference	0.169**	0.034	0.160**	0.053	0.067	-0.033
p-value	(0.012)	(0.677)	(0.018)	(0.478)	(0.295)	(0.695)
Panel E: IG-HY (S&P)						
Before DF	0.376	0.473			0.620	0.630
After DF	0.538	0.511			0.684	0.607
Difference	0.162***	0.038			0.063	-0.023
p-value	(0.002)	(0.517)			(0.231)	(0.741)
Panel F: IG-HY (Moody's)						
Before DF	0.370	0.453			0.626	0.653
After DF	0.534	0.482			0.689	0.632
Difference	0.164***	0.029			0.063	-0.021
p-value	(0.002)	(0.630)			(0.223)	(0.752)

Table 9
Letter Boundary Splits and Market Liquidity

This table contains probit regressions of the level of splits between Jan 2006 and Dec 2015. *Liquidity* is an indicator variable equal to one if liquidity of the underlying stock is above the median value. *Bound* is an indicator variable that equals one if the bond is rated AAA, AA-, A- or BBB-. *HY* is an indicator variable equal to one for bonds rated below BBB-. All other variables are as previously defined. Each regression includes industry fixed effects. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	(1) **Full sample**	(2) **IG**	(3) **Letter Boundary**	(4) **HY**
Constant	0.401	-1.061	1.767	0.725
	[0.685]	[-0.995]	[1.263]	[0.954]
DF	0.309	0.461*	0.685**	0.182
	[1.462]	[1.803]	[2.309]	[1.006]
Bound	-0.073			
	[-0.269]			
DF × Bound	0.455			
	[1.242]			
Liquidity	0.120	0.132	0.174	0.275
	[0.609]	[0.599]	[0.607]	[1.404]
DF × Liquidity	-0.323	-0.442	-0.543	-0.241
	[-1.214]	[-1.536]	[-1.452]	[-1.051]
Bound × Liquidity	0.256			
	[0.719]			
DF × Bound × Liquidity	-0.265			
	[-0.583]			
HY	0.610***			
	[2.629]			
DF × HY	-0.146			
	[-0.534]			
Liquidity × HY	0.086			
	[0.300]			
DF × Liquidity × HY	0.131			
	[0.370]			
Firm Size	-0.062	0.093	-0.479***	-0.023
	[-1.075]	[0.857]	[-3.284]	[-0.293]
Market to Book	0.055	0.096	-0.124	0.116
	[0.603]	[0.634]	[-0.645]	[0.657]
Intangible Assets	-0.112	-0.206	0.473	0.109
	[-0.407]	[-0.365]	[0.684]	[0.267]
Stdev of Forecasts	0.207	16.840	11.600	0.229
	[0.707]	[1.439]	[0.771]	[0.821]
Analyst Coverage	0.000	-0.024*	0.036**	0.005
	[0.058]	[-1.928]	[2.148]	[0.582]
S&P500 Index Return	0.062	-0.076	-0.430	0.156
	[0.280]	[-0.195]	[-0.613]	[0.456]
S&P500 Index Level	-0.000*	-0.000	0.000	-0.001
	[-1.788]	[-0.516]	[0.075]	[-1.611]
Bond Index Return	2.085	1.008	2.254	3.761*
	[1.541]	[0.476]	[0.632]	[1.845]
Fitch	-0.070	-0.020	0.105	-0.419**
	[-0.668]	[-0.120]	[0.466]	[-2.287]
CDS Indicator Variable	-0.135	-0.853**	0.896***	-0.061
	[-1.037]	[-2.410]	[2.599]	[-0.393]
Obs	1,358	470	259	629
Pseudo R-Sqd	0.0865	0.232	0.129	0.0412

Table 10
Investment Grade-High Yield Boundary Splits and Market Liquidity

This table contains probit regressions of the level of splits between Jan 2006 and Dec 2015. *Liquidity* is an indicator variable equal to one if liquidity of the underlying stock is above the median value. *Bound* is an indicator variable equal to one if the rating is within the two notches of the boundary (i.e. BBB, BBB-, BB+, BB). *HY* is an indicator variable equal to one for bonds rated below BB (model 1) and *HY* equals one if the ratings is below BBB- (model 5 and 6). All other variables are as previously defined. Each regression includes industry fixed effects. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	(1) **Full sample**	(2) **IG**	(3) **Boundary**	(4) **HY**	(5) **S&P HY**	(6) **Moody's HY**
Constant	1.409**	1.505	1.640	1.385	0.355	0.151
	[2.173]	[1.302]	[1.375]	[1.626]	[0.621]	[0.263]
DF	0.350*	0.518**	0.518**	0.202	0.483***	0.441***
	[1.676]	[2.205]	[2.459]	[0.945]	[3.015]	[2.712]
Bound	-0.102					
	[-0.418]					
DF × Bound	0.244					
	[0.874]					
Liquidity	0.097	-0.033	0.249	0.471*	0.186	0.176
	[0.453]	[-0.142]	[1.198]	[1.943]	[1.123]	[1.053]
DF × Liquidity	-0.271	-0.313	-0.381	-0.392	-0.379*	-0.306
	[-0.975]	[-0.996]	[-1.367]	[-1.415]	[-1.751]	[-1.398]
Bound × Liquidity	0.010					
	[0.035]					
DF × Bound × Liquidity	-0.078					
	[-0.201]					
HY	0.043				0.628***	0.679***
	[0.154]				[2.972]	[3.283]
DF × HY	-0.243				-0.323	-0.259
	[-0.838]				[-1.389]	[-1.097]
Liquidity × HY	0.424				0.019	0.029
	[1.281]				[0.072]	[0.108]
DF × Liquidity × HY	-0.085				0.187	0.072
	[-0.216]				[0.588]	[0.227]
Firm Size	-0.131**	-0.158	-0.303**	-0.057	-0.061	-0.041
	[-2.092]	[-1.341]	[-2.348]	[-0.592]	[-1.050]	[-0.699]
Market to Book	-0.048	-0.215	0.115	-0.117	0.046	0.073
	[-0.515]	[-1.258]	[0.743]	[-0.562]	[0.513]	[0.799]
Intangible Assets	-0.194	-0.690	0.063	0.410	-0.106	-0.107
	[-0.711]	[-1.224]	[0.127]	[0.859]	[-0.382]	[-0.387]
Stdev of Forecasts	0.291	27.034*	5.607	0.168	0.218	0.246
	[0.887]	[1.824]	[1.607]	[0.547]	[0.740]	[0.814]
Analyst Coverage	0.001	0.002	0.006	-0.000	0.001	0.000
	[0.119]	[0.118]	[0.522]	[-0.034]	[0.158]	[0.022]
S&P500 Index Return	0.096	0.074	-0.354	0.451	0.042	0.033
	[0.432]	[0.179]	[-0.913]	[1.176]	[0.190]	[0.150]
S&P500 Index Level	-0.000	-0.001	0.000	-0.001*	-0.000*	-0.000*
	[-1.304]	[-1.497]	[0.967]	[-1.705]	[-1.750]	[-1.773]
Bond Index Return	2.071	0.656	2.904	2.010	2.110	2.060
	[1.555]	[0.269]	[1.269]	[0.825]	[1.564]	[1.518]
Fitch	-0.129	-0.088	-0.034	-0.213	-0.087	-0.088
	[-1.233]	[-0.504]	[-0.187]	[-0.967]	[-0.828]	[-0.842]
CDS Indicator Variable	-0.209	-0.197	-0.203	-0.081	-0.140	-0.144
	[-1.609]	[-0.474]	[-1.000]	[-0.427]	[-1.084]	[-1.119]
Obs	1,358	461	430	467	1,358	1,358
Pseudo R-Sqd	0.0746	0.193	0.0927	0.0550	0.0821	0.0847

Table 11
Predicted Probabilities of Split Rated Bonds and Market Liquidity

This table presents the predicted probabilities from the probit regression specifications in Table 9 and Table 10. Bonds are separated into investment grade, boundary and high yield groups before and after Dodd-Frank. They are further separated by high/low liquidity. Panels A and B represent the results for the letter boundary specification in Table 9. Panel A contains the predicted probabilities for the full sample results (model 1, Table 9) and panel B presents the separate regression for investment grade, boundary and high yield partitions (models 2-4, Table 9). Panels C-F contain the results using the investment grade-high yield boundary from Table 10. Panel C contains the predicted probabilities for the full sample results (model 1, Table 10) and panel D presents the separate regression for investment grade, boundary and high yield partitions (models 2-4, Table 10). Panels E and F use a high yield indicator variable and correspond to models 5 and 6 of Table 10. p-values from a test for differences in proportions is reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Investment Grade		Boundary		High Yield	
	Low Liquidity	High Liquidity	Low Liquidity	High Liquidity	Low Liquidity	High Liquidity
Panel A: Letter Boundary Combined						
Before DF	0.372	0.416	0.347	0.484	0.599	0.672
After DF	0.486	0.411	0.628	0.550	0.657	0.662
Difference	0.114	-0.005	0.281***	0.066	0.058	-0.010
p-value	(0.142)	(0.942)	(0.004)	(0.488)	(0.369)	(0.869)
Panel B: Letter Boundary Separate						
Before DF	0.369	0.407	0.408	0.468	0.591	0.689
After DF	0.506	0.413	0.643	0.517	0.657	0.669
Difference	0.137*	0.005	0.235**	0.049	0.066	-0.020
p-value	(0.064)	(0.936)	(0.017)	(0.626)	(0.315)	(0.746)
Panel C: IG-HY Boundary Combined						
Before DF	0.473	0.509	0.435	0.475	0.489	0.677
After DF	0.602	0.538	0.653	0.566	0.529	0.589
Difference	0.129*	0.029	0.217***	0.091	0.04	-0.088
p-value	(0.090)	(0.718)	(0.002)	(0.199)	(0.615)	(0.238)
Panel D: IG-HY Boundary Separate						
Before DF	0.430	0.420	0.415	0.505	0.549	0.716
After DF	0.593	0.484	0.602	0.555	0.624	0.651
Difference	0.163**	0.064	0.187**	0.050	0.074	-0.064
p-value	(0.026)	(0.446)	(0.012)	(0.524)	(0.344)	(0.376)
Panel E: IG-HY (S&P)						
Before DF	0.367	0.434			0.600	0.673
After DF	0.546	0.473			0.657	0.661
Difference	0.179***	0.039			0.057	-0.011
p-value	(0.002)	(0.541)			(0.380)	(0.853)
Panel F: IG-HY (Moody's)						
Before DF	0.358	0.421			0.610	0.682
After DF	0.521	0.472			0.674	0.664
Difference	0.163***	0.051			0.064	-0.018
p-value	(0.006)	(0.430)			(0.316)	(0.765)

Table 12
Yields at Issue and Split Ratings

This table examines whether split rated bonds required a higher yield between Jan 2006 and Dec 2015. The dependent variable is the yield spread at issue. All variables are defined in Appendix A. The different specifications differ by the credit rating assigned to each bond. Model 1 uses the optimistic (i.e. higher) rating out of S&P and Moody's, model 2 uses the pessimistic (i.e. lower) rating out of S&P and Moody's. Model 3 (4) includes non-splits bonds and bonds where S&P (Moody's) was optimistic. Model 5 (6) includes non-splits bonds and bonds where S&P (Moody's) was pessimistic. Each regression includes industry and year fixed effects. Standard errors are clustered by firm and ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	(1) **Optimistic**	(2) **Pessimistic**	(3) **Optimistic: S&P**	(4) **Optimistic: Moody's**	(5) **Pessimistic: S&P**	(6) **Pessimistic: Moody's**
Constant	-14.76	-133.38	-9.84	-272.95	-324.41*	-100.27
Split	53.25***	-6.55	59.57***	41.18	-10.68	-6.23
Split × DF	-7.10	-16.19	-18.93	19.91	-1.76	-19.72
DF	-117.77***	-110.07***	-115.89***	-119.90***	-115.54***	-108.41***
AA+	-21.39		13.46			
AA	-46.82	-21.76	-26.74	-41.62	-25.17	-14.29
AA-	-81.27	-58.00	-66.97	-102.22**	-95.04**	-45.64
A+	-16.07	-4.86	16.01	-38.15	-30.76	24.29
A	-15.22	-2.46	19.87	-35.15	-25.59	20.37
A-	21.66	51.10	55.94	22.53	22.95	86.28
BBB+	75.01	67.87	103.09	58.25	50.04	97.89
BBB	105.57*	129.67**	139.76**	92.04*	105.01**	151.62**
BBB-	173.83***	152.47***	203.99***	134.25***	121.53***	185.83***
BB+	299.55***	270.13***	323.78***	299.45***	267.36***	301.47***
BB	314.42***	337.53***	342.03***	329.43***	327.19***	365.59***
BB-	348.72***	358.80***	376.98***	333.72***	331.39***	382.42***
B+	458.12***	413.82***	486.83***	419.07***	401.65***	440.41***
B	472.77***	489.21***	512.11***	455.55***	480.59***	507.67***
B-	500.42***	534.60***	530.06***	499.49***	507.88***	562.83***
CCC+	661.05***	586.84***	646.14***	621.23***	559.02***	615.41***
CCC	749.77***	801.86***	766.38***	905.70***	805.75***	830.14***
CCC-		752.44***				760.05***
Maturity	-14.90	-10.96	-9.82	-9.36	-5.14	-7.06
Proceeds	-7.14	-2.72	-8.28	1.87	3.81	-4.88
R144A	24.49	6.88	25.19	32.16	17.73	7.61
Floating	-9.77	-5.17		-7.89	-41.21	
Callable	14.22	15.00	-18.83	44.65	47.93*	-15.45
Shelf	-25.62	-34.33	-24.08	-6.27	-18.11	-31.89
Risk Prem	2.63***	2.69***	2.69***	2.67***	2.70***	2.72***
Obs	991	991	830	620	620	830
Adj R-Sqd	0.746	0.765	0.743	0.766	0.779	0.759

Appendix A: Variable Definitions

Variable	Definition	Source
S&P Ratings	An ordinal number ranging from one (for AAA rated bonds) to twenty-one (for C rated bonds).	Mergent
Moody's Rating	An ordinal number ranging from one (for Aaa rated bonds) to twenty-one (for C rated bonds).	Mergent
Split	An indicator variable equals one if Moody's rating differs from S&P rating, and zero otherwise.	Mergent
DF	An indicator variable equals one if firm's bond is issued after Dodd-Frank (i.e. 21 July 2010), and zero otherwise.	Mergent
Firm Size	Natural logarithm of the firm's total assets (in millions).	Compustat
Market to Book	The market-to-book ratio (firm's market value of equity minus book value of equity plus total assets divided by total assets).	Compustat
Intangible Assets	Firm's intangible assets scaled by total assets.	Compustat
Analyst Coverage	The number of analysts following a firm.	IBES
Stdev of Forecasts	The standard deviation of forecast annual EPS, scaled by the firm's stock price.	IBES
S&P 500 Index Level	S&P 500 index Level.	CRSP
S&P 500 Index Return	The trailing one-year return on the S&P 500 index.	CRSP
Bond Index Return	The trailing one-year return on the Bloomberg Barclays US Aggregate Bond Index.	Bloomberg
Fitch	An indicator variable equals one if the bond has a Fitch rating, and zero otherwise.	Mergent
CDS Indicator Variable	An indicator variable that equals one if the bond had a CDS contract on its debt, and zero otherwise.	Markit
Earnings	An indicator variable that equals one if there is an earnings announcement within 30 days prior to the bond issue, and zero otherwise.	IBES
Yield Spread	The difference between the yield of the benchmark treasury issue and the issue's offering yield expressed in basis points.	Bloomberg
Proceeds	Natural logarithm of the offering amount.	Mergent
Maturity	Natural logarithm of the maturity (in month).	Mergent
R144A	An indicator variable that equals one if the bond is exempt from registration under SEC Rule 144a, and zero otherwise.	Mergent
Floating	An indicator variable that equals one if the bond had a variable coupon, and zero otherwise.	Mergent
Callable	An indicator variable that equals one if the bond is callable, and zero otherwise.	Mergent
Shelf	An indicator variable that equals one if the bond is a SEC Rule 415 shelf registration, and zero otherwise.	Mergent
Risk Prem	The difference between the yield on the Moody's Aaa Corporate Bond yield and 10-year U.S. Treasury yield	St. Louis Federal Reserve Economic Database

Appendix B: Placebo test

This table contains probit regressions of the level of splits 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. *Split* is an indicator variable equal to one for bonds issued with split ratings, *DF* is an indicator variable equal to one if the firm's bond was issued after 21 July 2010. *Bound* and *HY* are indicator variables defined using IG-HY boundary (Letter boundary). All other variables are defined in Appendix A. Model 1 (4) covers the full sample using IG-HY boundary (Letter boundary), models 2-3 (5-7) cover the investment grade, boundary and high yield sub-samples, respectively using IG-HY boundary (Letter boundary). The high yield sub-sample based on IG-HY boundary does not have enough observations, so it is omitted. Each regression includes industry fixed effects. Coefficient estimates of controls are omitted for brevity. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	IG-HY Boundary **Full Sample**	**IG**	**Boundary**	Letter Boundary **Full Sample**	**IG**	**Letter Boundary**	**HY**
Constant	3.2837	5.4763	0.3010	2.9846	4.9388	-2.7615	9.9462*
	(1.24)	(0.98)	(0.09)	(1.19)	(1.15)	(-0.60)	(1.88)
DF	-0.2937	-0.2042	-0.2847	-0.1225	-0.0441	-0.0474	-1.7953**
	(-1.01)	(-0.70)	(-0.67)	(-0.45)	(-0.16)	(-0.16)	(-2.25)
Bound	-0.1543			0.0853			
	(-0.42)			(0.25)			
DF × Bound	0.1675			-0.1127			
	(0.37)			(-0.31)			
HY	0.4035			0.8445*			
	(0.66)			(1.78)			
DF × HY	0.2044			-0.7221			
	(0.32)			(-1.11)			
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	491	308	159	491	216	195	66
Pseudo R-squared	0.147	0.227	0.231	0.151	0.251	0.282	0.313