# Regulation, Asset Complexity, and the Informativeness of Credit Ratings

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**Abstract**

We show that the effect of regulation on credit rating informativeness depends on asset complexity. Using the Dodd-Frank Act as a shock to the rating industry, we analyze the impact of rating changes on market prices, conditioning on various measures of complexity. Rating informativeness improves after Dodd-Frank, but not for assets with high complexity. Our results are robust to alternative measures of informativeness and provide strong empirical evidence that the impact of regulation varies in the cross-section of securities. Our findings are consistent with models combining rating shopping with rating agencies strategically deciding on information acquisition and rating inflation.

**JEL-Classification:** G01, G12, G24
**Keywords:** ratings, regulation, asset complexity, corporate bonds, information costs

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# 1 Introduction

Credit rating agencies (CRAs) are meant to provide information for market participants about the creditworthiness of various securities. Their relevance is accentuated by rating-contingent regulation, which forces certain investors to take ratings into account in their investment strategies. However, the amount of information they provide to investors, as well as how it varies over time and cross-sectionally is still the object of debate.[1]

In this paper, we aim to provide novel insights on this discussion. In particular, we explore how changes in the regulatory conditions after the introduction of the Dodd-Frank Act alter the informativeness of credit ratings in the US corporate bond market, taking into account cross-sectional differences in complexity among securities. Credit ratings play a major role in the valuation of assets in the US corporate bond market, making it an ideal laboratory for our study. First, it is an institutional market where many investors are exposed to rating-contingent regulation. Second, its over-the-counter (OTC) structure makes relevant information more difficult to access, thus increasing the importance of ratings.

To understand how regulatory conditions and asset complexity are linked, consider that CRAs strategically decide on the degree of information acquisition before awarding their ratings. Within this decision process, rating-contingent regulation provides incentives to inflate ratings without acquiring private information. Therefore, as discussed in recent theoretical papers, CRAs face the trade-off between costly information acquisition and inflating ratings when the regulatory advantage is sufficiently high.[2] Asset complexity affects the cost of information acquisition and, thus, changes in regulation lead to different optimal levels of information production across securities.

We use the passage of the Dodd-Frank Act as a clear structural change in the regulatory

[1]See, for example Chava, Ganduri, and Ornthanalai (2019) and Badoer and Demiroglu (2019).

[2]This trade-off has been formalized in models of strategic CRAs behavior, such as Opp, Opp, and Harris (2013).

environment that affects the regulatory advantage of credit ratings. Dodd-Frank followed the 2008-09 financial crisis, which was characterized by massive and sudden downgrades of highly rated securities, undermining the reputation of CRAs, and bringing their business model into question. Dodd-Frank was introduced on July 21, 2010 and, among other objectives, aims to improve rating informativeness by making rating agencies legally liable when they provide biased or misleading information to the market. After July 21, 2010, the Securities and Exchange Commission (SEC) was empowered to sanction rating agencies more easily, while courts were enabled to entertain private actions against CRAs. Moreover, as a subsidiary objective, rating-contingent regulation had to be gradually dismantled.[3]

Overall, Dodd-Frank represents a negative shock to the regulatory advantage of credit ratings. Recent theoretical papers (e.g., Opp, Opp, and Harris (2013)) guide our intuition on how CRAs could respond to this change. In general, CRAs have greater incentives to issue more informative ratings because of the increased litigation risk and gradual removal of rating-contingent regulation. In particular, these theories argue that reducing the regulatory advantage raises the threshold level, beyond which information acquisition is no longer optimal as its costs are outweighed by the benefits of rating inflation. Therefore, the precise impact depends on the size of the regulatory shock and the costs of information acquisition, which are heterogenous across securities due to differences in asset complexity. Following this argument, the impact of Dodd-Frank on the regulatory advantage could be large enough, such that CRAs will find it optimal to acquire more information for all securities, or so low that CRAs do not adjust their behavior at all. However, as important alternative outcome, rating informativeness could only improve for securities with

[3] According to Section 933 of the Act, the statements of CRAs should be considered as *statements made by a registered public accounting firm or a securities analyst under the securities laws* and not *forward-looking statements*. Additionally, in private actions, it is sufficient to prove that the agency *knowingly or recklessly failed to conduct a reasonable investigation of the rated security* or *to obtain reasonable verification of the information provided with the rating*. Section 939A instead called for a removal of references to credit ratings for regulatory purposes. See for details https://www.congress.gov/111/plaws/publ203/PLAW-111publ203.pdf

low complexity, but not for those with high complexity, as for such securities the costs of information acquisition could still be too high compared to the reduction in the regulatory advantage. As outlined by this discussion, the interaction between regulatory changes and asset complexity in shaping the informativeness of credit ratings is ultimately an empirical question that we aim to answer through our analysis.

We measure informativeness by the impact that rating downgrades have on the market prices of bonds affected by these events. Our sample covers the period January 2003 to May 2014, including 1,180 relevant rating events. Mindful of the impact that the business cycle can have on informativeness, we analyze three distinct time periods: before the financial crisis, during the crisis, and after the passage of Dodd-Frank. We split the sample according to asset complexity into simple and complex securities using three different firm-specific measures: financial vs. non-financial firms, the number of business segments, and number of geographical locations. Following Morgan (2002), we consider the securities from financial firms harder to rate, given their exposure to multiple risk factors and their more complex financial structures. More business segments and geographical locations are known to add to the complexity of business activity (see, e.g., Bushman, Piostrosku, and Smith (2004) and Cohen and Lou (2012)) and, thus, the analysis and information acquisition is more challenging and costly. Also, our analysis is focused on rating downgrades, which have been found in past studies to be more relevant for investors than upgrades.[4]

We start by providing a descriptive analysis of average announcement bond returns for downgrades among the three time periods and across security complexity levels. Three main patterns stand out. First, informativeness is rather low before the crisis (when the economy is booming and rating-contingent regulation is in place) for both complex and simple bonds, with price effects being of the same order of magnitude as average transaction

[4]The previous literature shows that rating downgrades provide relevant information to market participants, whereas upgrades often show no significant price effects (see, e.g., Chava, Ganduri, and Ornthanalai (2019) or Badoer and Demiroglu (2019)). Results for upgrades, not presented in detail, confirm this conjecture for our sample, as well.

costs. Second, during the financial crisis, both simple and complex bonds show the highest price reactions in line with theoretical models arguing that the business cycle shifts the informativeness of credit ratings. Third, informativeness increases post Dodd-Frank relative to the pre-crisis period, but only for simple bonds, hinting at a heterogeneous impact of regulatory shocks in the cross-section of securities depending on levels of complexity.

Armed with this preliminary evidence, we provide a more formal test of our mechanism by regressing excess bond returns around downgrades on time period dummies interacted with the particular complexity measures, as well as a wide set of controls. The results strongly confirm that the impact of regulation varies in the cross-section of securities: for each of our complexity measures, simple bonds experience after Dodd-Frank an increase in informativeness relative to the pre-crisis period, while more complex bonds do not show any significant change. The larger price reactions for simple bonds are well beyond average transaction costs, ranging from -0.71% up to -1.11%, depending on the measure of complexity applied. In the spirit of Dimitrov, Palia, and Tang (2015), we repeat our analysis using the reaction of stock prices to these rating downgrades as a dependent variable. In this case, the magnitudes of the effect are even larger, with the stocks of firms with low complexity showing larger price reactions of about -1.82% to -2.46% depending on the complexity measure. Overall, our findings provide empirical support to the idea that the differences in the complexity across assets influences rating informativeness, which was suggested in theoretical models by Opp, Opp, and Harris (2013), for example.

While the bond/stock price reaction to rating changes is a direct measure of the information provided by CRAs to market participants, it relies on relatively infrequent events. In the second part of the paper, we employ a different approach to measuring rating informativeness based on the consistency between credit ratings and corporate bond yield spreads. First, we test the ability of traded yield spreads to predict future downgrades. If, ceteris paribus, bonds with higher yield spreads are more likely to be downgraded, it means that market prices already contain a relatively larger fraction of the increased credit risk and downgrades provide less information. Second, in the spirit of Becker and Milbourn (2011), we explore the conditional correlation of yield spreads at the time of the bond offering and credit ratings. A higher conditional correlation between yields and credit ratings corresponds to higher rating informativeness, as primary market investors consider ratings more important when pricing bonds. The first approach has the advantage of relying on a larger cross-section of bonds, while the latter is based on issuance yields, which capture the benefits of ratings that accrue to the issuers, corresponding more directly to the quantities described in most theoretical models of CRAs. The results of both tests are perfectly in line with our documented price reactions. Following Dodd-Frank for simple bonds downgrades are less predictable and prices in the primary market are more dependent on credit ratings, whereas for complex bonds we do not find any significant changes.

In an additional analysis, we explore a further layer of heterogeneity in the shock to the regulatory advantage, based on the fact that Dodd-Frank does not affect all investors in the same manner. While the increased liability for CRAs came into force immediately, the objective of removing rating-based regulation was announced but its implementation has been assigned to individual federal agencies. As a consequence, the removal of rating-based regulation concerning corporate bonds applied less to insurance companies and mutual funds, which still use credit ratings to compute their capital charges or determine their investment mandates (Baghai, Becker, and Pitschner (2020), Becker, Opp, and Saidi (2021), and NAIC (2021)). Thus, insurance companies/mutual funds both still have an incentive to hold highly rated securities. If our results are indeed driven by a shock to the regulatory advantage induced by Dodd-Frank, we should observe that our effects are weaker (or even not present) in bonds that are mostly held by such investors. To that end, we repeat our main analysis of bond and stock price reactions to rating changes by splitting our sample into bonds with high and low ownership by insurance companies/mutual funds. Consistent with the heterogeneous change in the regulatory advantage of ratings, we find that the documented increases in informativeness for simple assets come mainly from bonds that have a low ownership representation from mutual funds and insurance companies.

We present an extensive battery of robustness tests that rule out other factors that could affect our findings. First, we explore various sample selections, to test how consistent our results are. Specifically, we repeat our analysis excluding confounding events such as announcements of earnings as well as mergers and acquisitions that overlap with the rating event. Second, we also control for regulation-induced trading by excluding events crossing the investment-speculative grade rating threshold. Third, we consider systematic shifts in the rating distribution across periods. Fourth, we check whether our results could have been driven by time-varying risk premia in corporate bonds. We do not find any indication that these factors significantly impact our findings.

Our paper is the first to empirically document that cross-sectional differences in asset complexity among securities can explain the heterogeneous impact of regulatory changes. In particular, we show that Dodd-Frank only improves the quality of ratings for securities with low complexity in the US corporate bond market. Although recent theoretical papers present the economic mechanism behind this possibility, these models often have the higher costs of information acquisition for structured products compared with other assets in mind, when discussing heterogeneous effects. Therefore, it is particularly interesting to find these differences even *within* the corporate bond market. Our results indicate that stricter changes in regulation would have been necessary to improve the rating informativeness of all bonds. One possibility to achieve this is highlighted in our results based on holding data. If rating-contingent regulation is not removed by the same degree for all investors, then the risk of having heterogeneous outcomes increases. Thus, our results suggest that future regulatory policies targeting the rating industry should take such factors into account.

Overall, our results provide an empirical validation for recent theoretical studies concerning the strategic behavior of CRAs and contribute to various strands of the literature. First, we relate to the recent empirical literature that explores variations in credit ratings informativeness over time (Behr, Kisgen, and Taillard (2018), Badoer and Demiroglu (2019), and Chava, Ganduri, and Ornthanalai (2019)). The papers that are most closely related to ours are Dimitrov, Palia, and Tang (2015) and Toscano (2020), both of which analyze the impact of Dodd-Frank on credit ratings, but with conflicting results. Both argue that CRAs became more protective of their reputation: Dimitrov, Palia, and Tang (2015) show they do so by issuing less informative ratings, while Toscano (2020) provides evidence supporting the opposite. Our paper differs significantly from those studies, as we consider the *interaction* of regulation with asset complexity, a distinction that is crucial in explaining the mixed evidence. Second and more broadly, our paper adds to the extensive empirical literature studying the general announcement effects of credit ratings and credit outlook changes by assessing these interactions.[5] Third, we provide empirical support for the recent and growing literature tackling the strategic behavior of rating agencies and changes in rating informativeness (e.g., Skreta and Veldkamp (2009), Bolton, Freixas, and Shapiro (2012), Bar-Isaac and Shapiro (2013), and Opp, Opp, and Harris (2013)). We discuss in detail how we link our work to these theoretical papers when presenting the economic mechanisms relevant for our empirical analysis.

The remainder of this paper is organized as follows. Section 2 presents the theortical foundations that guide our empirical analysis. We describe the data and our empirical methodology in Section 3. In Section 4, we present our empirical results. Section 5 concludes. The Appendix contains all the technical details relating to our variable definitions, while the Internet Appendix reports results not included in the paper for brevity.

[5]See, for example, Katz (1974), Weinstein (1977), Wakeman (1978), Griffin and Sanvicente (1982), Ingram, Brooks, and Copeland (1983), Holthausen and Leftwich (1986), Hand, Holtausen, and Leftwich (1992), Goh and Ederington (1993), Nayar and Rozeff (1994), Kliger and Sarig (2000), Dichev and Piotroski (2001), Jorion, Liu, and Shi (2005), May (2010), Ellul, Jotikasthira, and Lundblad (2011), Henry, Kisgen, and Wu (2015), Agarwal, Chen, and Zhang (2016), and Spiegel and Starks (2016).

## 2 Theoretical Foundations and Hypotheses

In this section, we present the relevant theoretical background and formulate empirically testable hypotheses. The research question addressed in this paper is how changes in regulation interact with asset complexity in shaping the informativeness of credit ratings. The theoretical literature offers important economic mechanisms affecting informativeness by modeling the behavior of CRAs. Most models agree that rating-based regulation together with rating shopping by issuers leads to biased/less informative ratings (see, e.g., Skreta and Veldkamp (2009), Bolton, Freixas, and Shapiro (2012), Bar-Isaac and Shapiro (2013) or Opp, Opp, and Harris (2013)). Motivated by such theories, we aim to analyze the responses of CRAs to regulatory changes depending on asset complexity, and exploring the underlying mechanisms.[6]

To guide our arguments, we focus on Opp, Opp, and Harris (2013) as our point of reference, who directly model the relation between rating regulation and asset complexity. The feature of rating-based regulation is the first key ingredient of their mechanism, providing a regulatory advantage to rational investors when holding highly rated securities. This makes it optimal for issuers to pay for ratings, even when they are not providing any information, as investors value the regulatory advantage. In the absence of rating-contingent regulation, issuers would not pay for uninformative ratings, as investors are not fooled by inflated ratings and highly rated securities would not trade at higher prices. Thus, without rating-contingent regulation CRAs have to provide information to generate income, making regulation an essential driver of rating informativeness in the model.

The second ingredient is represented by asset-specific complexity. Before deciding on a rating, CRAs must determine the amount of costly private information they acquire about

[6]Most theoretical papers in this context appeal to the greater complexity of assets in the structured product market compared to other asset classes. However, these models are relevant for all cases, including corporate bonds, where certain securities are harder to rate, e.g., by inducing a higher cost of information acquisition.

the issuer of the security.[7] The more private information is acquired, the more informative the rating will be. The cost of information acquisition is heterogeneous across assets, as some issuers are more complex than others and hence more costly to rate.[8]

However, CRAs face a trade-off between costly information acquisition and issuing biased credit ratings because of the regulatory advantage. In other words, there is a threshold beyond which information acquisition by the CRAs is no longer optimal because its costs are outweighed by the benefits of biasing the rating induced by regulation. These elements allow for a rich set of possible outcomes after a change in regulation such as Dodd-Frank. This change due to Dodd-Frank can be thought of as a negative shock to the regulatory advantage which, ceteris paribus, will raise the threshold.[9] The impact of such a shock will depend on the model parameters. In particular, the heterogenous costs of information acquisition due to differences in asset complexity affect the possible outcomes. The shock could be large enough to incentivize CRAs to issue more informative ratings for all securities, or so low that CRAs still find it optimal not to acquire any additional information. Alternatively, informativeness could improve for assets with low complexity, but not for those with high complexity, as for such securities the shift in the threshold might not be large enough to incentivize CRAs to acquire more information. The final outcome is ultimately an empirical question that we aim to answer with our analysis.[10] This leads to the formulation of our main hypothesis:

[7] The information acquisition process is costly as it involves independent and time consuming analysis. For example, Bar-Isaac and Shapiro (2013) model the competition in the labor market for analysts.

[8] For example, a company operating in different business segments and multiple geographical locations is harder to analyze than another one operating in only one line of business in a single location.

[9] Ceteris paribus, CRAs have a lower incentive to issue uninformative ratings because of the larger litigation risk they face, while the gradual removal of rating-contingent regulation for some investors makes their regulatory advantage weaker.

[10] It is important to stress that such a comparison between regulatory regimes needs to be undertaken at similar points in the business cycle. Opp, Opp, and Harris (2013) but also other theoretical models (e.g., Bar-Isaac and Shapiro (2013)) indeed show that the impact of the regulatory advantage is generally much lower in crisis periods, mechanically leading to more informative ratings. We carefully take this into account in our empirical analysis.

*Hypothesis 1: Increasing litigation risk and removing rating-contingent regulation generally reduces the benefits from biasing ratings and improves the informativeness of credit ratings, but the effect may be lower or even not present for more complex securities with a high cost of information acquisition.*

Our main hypothesis relies on examining cross-sectional variation in asset complexity in the face of the same regulatory shock. An additional layer of heterogeneity can be explored if the magnitude of the regulatory shock varies across securities, because the regulatory reform has different consequences for different groups of investors. With Dodd-Frank, the objective of removing rating-based regulation from corporate bonds applied less to insurance companies and mutual funds (see Section 4.3 for further details), who both still have incentives to hold highly rated securities (see, e.g., Baghai, Becker, and Pitschner (2020), Becker, Opp, and Saidi (2021), and NAIC (2021)). Therefore, securities that are more dependent on those groups of investors, might face weaker regulatory shocks. This leads to our second hypothesis:

*Hypothesis 2: Assets held by investors that experience a weaker change in the regulatory advantage of highly rated securities show a lower effect on rating informativeness.*

While our hypotheses are based on Opp, Opp, and Harris (2013), comparing them with predictions of other models can be a particularly interesting exercise. Indeed, models that focus only on certain combinations of issuer-induced rating shopping, strategic information acquisition or rating inflation, would lead to more informative ratings for both simple and complex assets, often with stronger reactions for the latter. In particular, issuer-induced rating shopping alone (Skreta and Veldkamp (2009)) or in combination with CRAs deciding on costly information acquisition, but not actively biasing the ratings (Bar-Isaac and Shapiro (2013)), would result in an improvement for all securities. Only when allowing

CRAs to actively adjust their ratings, it is possible to obtain that regulatory changes lead to an improvement in informativeness for simple, but not for complex assets. Besides Opp, Opp, and Harris (2013), the model of Bolton, Freixas, and Shapiro (2012) offers such a mechanism, including a threshold that could be triggered for simple, but not complex bonds, after a regulatory change. However, Bolton, Freixas, and Shapiro (2012) do not explicitly model asset complexity. One could implicitly include asset complexity in their model by assuming a difference in the exogenously given rating precision across assets. We could consider such a difference to be the outcome of a technology choice, implicitly including a costly information acquisition mechanism. To conclude, the different reaction of complex assets after Dodd-Frank postulated by our hypotheses is only plausible when including regulatory advantage, asset complexity and rating inflation by CRAs, as in Opp, Opp, and Harris (2013) or indirectly in Bolton, Freixas, and Shapiro (2012). Instead, a general increase of informativeness can result from various combinations of different economic forces that appear in the other models, as well.

# 3 Main Variables and Data

## 3.1 Informativeness, Asset Complexity and Time Periods

Our main measure of credit rating informativeness is the bond price reaction after a rating change, based on trading data. We follow the past literature and focus on rating downgrades, which are shown to provide information to market participants, while upgrades do not (see, e.g., Chava, Ganduri, and Ornthanalai (2019) or Badoer and Demiroglu (2019)). We define the bond rating announcement return as the percentage change between the average price across the 5 days before the downgrade, and the average across the event day and the 5 days thereafter in excess of the corporate bond market return in the same time window when testing our hypotheses.[11] The market return is based on bonds with similar maturity and ratings compared to the downgraded asset. For details of the calculation and detailed definition of the rating-maturity match, see Appendix A. To validate our findings, we also measure the stock returns of the issuer around the observed rating changes. Similar to Dimitrov, Palia, and Tang (2015), we define the stock announcement return as the buy-and-hold return over the three-day period centered at the rating announcement date in excess of the corresponding return on the CRSP value-weighted index. Finally, we also employ two alternative measures of informativeness based on bond yield spreads. First, we measure the predictive power of traded bond yield spreads on future rating downgrades. Second, in the spirit of Becker and Milbourn (2011), we estimate the conditional correlation of offering yield spreads and credit ratings.

We employ three different measures of the complexity of bond issuers in our analysis. First, we follow Morgan (2002) and consider securities issued by financial firms to be more complex relative to those of non-financial issuers. The main reason is that the financial industry is opaque in terms of its risk exposure (which can often be swiftly altered with derivatives), the legal environment (especially in the face of costly lawsuits) and the value creation process, making credit analysis a challenging task. This is compounded by the uncertainty of rescue efforts by the central bank (e.g., quantitative easing) and the government (e.g., equity infusion or other types of bailouts) in the event of acute financial stress. Therefore, it is hard to predict the distress of financial institutions, and rate their securities with any precision. Further, in the spirit of Bushman, Piostrosku, and Smith (2004) and Cohen and Lou (2012), we use the number of business segments and the number of geographical segments as proxies for complexity, respectively. The idea behind these measures is that a company operating over multiple lines of business and/or geographical locations

[11] Similarly to Dimitrov, Palia, and Tang (2015) and consistent with Bessembinder, Kahle, Maxwell, and Xu (2009), we use a trading window from 5 days before to 5 days after the event to take into account the fact that corporate bonds might not trade every day. We use volume-weighted average prices to give more prominence to larger transactions.

is more complex to rate.[12] In our analysis, we are interested in the relative complexity across assets/issuers in the market, not in the raw number which might be influenced by trends over time. Hence, in each year, we sort all bond issuers present in our sample based on the number of business segments and geographic locations reported in the Compustat database in the previous year, and define as high (low) complexity those above (below) the median.

We consider three sub-periods in our analysis. The first covers rating events before the crisis, between January 2003 and November 2007. The second includes rating changes during the crisis, starting in December 2007, which we identify as the beginning of the financial crisis in accordance with the definition in National Bureau of Economic Research (2010), and ending on July 21, 2010, when the signing of the Dodd-Frank Act into federal law took place. The third period, after Dodd-Frank, covers all events after that date until May 2014. With this regulatory reform, increased liability for CRAs and the relaxation of pleading standards in private actions against them came into force immediately. The elimination of rating-contingent regulation was announced, but its implementation was assigned to federal agencies. The resulting heterogeneous implementation of the dismantling of rating-based regulation is discussed in Section 4.3, and will be exploited in our analysis based on bond ownership. When analyzing these three periods, we stress the importance of considering the crisis period separately in the empirical tests. Indeed Opp, Opp, and Harris (2013), but also other theoretical models (e.g., Bar-Isaac and Shapiro (2013)) show that rating informativeness changes depending on the evolution of the business cycle. When evaluating the impact of regulatory shocks, it is, therefore, important to control for economic conditions.

[12] General Electric is a representative example of a complex firm with more than 10 business/geographical segments.

## 3.2 Data

We obtain corporate bond ratings and characteristics from the Mergent Fixed Income Securities Database (FISD). We use the credit ratings of Standard & Poor's, Moody's, and Fitch, the three main CRAs.[13] We assign an integer to each rating level, with 1 being the best rating and 21 the worst one. With this scaling, the investment-speculative grade threshold is set between 10 and 11. We consider only fixed-coupon corporate bonds with an amount issued greater than or equal to $10 million. Convertibles, asset backed, exchangeable, foreign currency, perpetual and bonds with other complex optionalities are thus excluded from the final sample. We collect corporate bond traded prices and yields from TRACE, and apply standard cleansing procedures as in Dick-Nielsen (2009) and Friewald, Jankowitsch, and Subrahmanyam (2012). Similar to Jankowitsch, Nagler, and Subrahmanyam (2014), we require bonds to have a minimum amount of trading around the rating events.[14] Further, we use the Compustat Segment database to obtain issuer-specific information on the number of business and geographical segments. We match the bonds with the issuing companies from Compustat by using the 6 digits CUSIP number and subsequently manually check for mergers and acquisitions. Whenever information on business or geographical segments on a company is missing, we assign the average number of segments in the industry to which the issuer belongs.[15] Finally, we obtain information of quarterly corporate bond holdings by mutual funds and insurance companies from Lipper/eMAXX.

Our final sample goes from January 2003 to May 2014 and contains 1,180 downgrades.[16] Table 1 contains a detailed description of the distribution of downgrades over the rating

[13]We exclude default or close-to-default events (i.e., downgrades to CCC-, Caa3 or lower), which might be strongly influenced by asymmetric information and strategic behavior related to the default event.

[14]We require bonds to have, over the event day and the 5 days after, either an average cumulative daily volume of at least $1 million, or an average volume per trade of at least $100,000. Note that our main results hold even if we keep the excluded bonds in the sample.

[15]This justifies some issuers being assigned a number of segments which is not an integer.

[16]We consider the same rating changes on a bond on the same day by different CRAs as a single event.

grades and periods. The financial crisis period experienced a spike in the number of downgrades, when an extremely large number of them occurred in the financial sector. Table 2 presents summary statistics of the variables used in our tests. The vast majority of bonds experiences rating changes of about one notch (average 1.39) and is rated by all the three main agencies at the same time. The average downgraded bond in our sample is investment grade, has a maturity of around 7 years, has transaction costs of 62 bp and an outstanding amount of around $800 million. The average issuer in our sample has about 3 different business or geographical segments. However, there is large heterogeneity across the distribution, with the bottom decile having just one segment and the top decile having at least five. In addition, Figure 1 shows the average bond price evolution around a 181 days window centered at the event day for the different time periods and financial/non-financial issuers, as a representative example for differences in asset complexity. There are no clear price effects around downgrades before the crisis, while the price evolution for non-financial bonds indicates stronger reactions post Dodd-Frank.

# 4 Empirical Findings

## 4.1 Price Reactions around Rating Downgrades

In the first step of our analysis, we measure rating informativeness with bond prices from trades surrounding rating changes. Table 3 presents average bond announcement returns following credit rating downgrades. The sample is split across the three time periods and between complex vs simple bonds, as defined in Section 3.1. We use three different measures of complexity. In Panel A, we define bonds issued by financial firms (non-financial firms) as complex (simple). In Panel B, we sort bond issuers based on the number of business segments they reported in Compustat in the previous year and define as complex (simple) those above (below) the median. In Panel C we do the same by using the number of geographical segments. When analyzing the full sample distribution in Table 2, a relatively complex issuer would be one with a number of business (geographical) segments greater than 2.4 (2). Thus, simple/low complexity issuers would be either stand-alone firms or companies with one additional business/geographical segment. On the other hand, complex issuers combine three segments or more.

Three main patterns emerge, which are consistent across the different complexity measures. First, before the crisis, informativeness is relatively low for both simple and complex bonds. The two groups present similar price reactions, with the former having a drop in prices between -0.50% and -0.53%, while the latter ranging from -0.52% to -0.46%. We consider these price effects as being relatively low, since average transaction costs in the bond market are around 40 bp (Friewald, Jankowitsch, and Subrahmanyam (2012)).[17] Such a pattern is consistent with previous findings in the literature on ratings being inflated/uninformative during booms with rating contingent regulation in place (Cornaggia and Cornaggia (2013)). Second, during the crisis period, price reactions to credit rating downgrades are much stronger, ranging between -0.96% and -2.11% for simple bonds and between -1.43% and -2.33% for complex ones. These numbers support the idea that rating informativeness depends on the stage in the business cycle, and stress the importance of considering the crisis period separately. Third, post Dodd-Frank, the informativeness of credit ratings increases relative to the pre-crisis period for simple bonds (price reactions between -0.73% and -0.96%), while it does not improve for complex ones (returns between -0.31% and -0.10%). These pattern provide the first evidence that changes in informativeness vary in the cross-section of assets after Dodd-Frank.

Overall, the descriptive results presented in Table 3 are consistent with Hypothesis 1, supporting the idea that differences in asset complexity can trigger heterogeneous responses of rating informativeness to regulatory shocks. These univariate tests provide a

[17]Note that transaction costs around rating events are even higher with more than 60 bp on average in our sample.

first indication of this mechanism. In our regression analysis, we comprehensively assess the effect of asset complexity and regulatory changes on bond returns, explicitly controlling for confounding factors and, thus, providing a formal test of Hypothesis 1. We estimate the following model:

$$
\begin{aligned}
Y_{i,t} = {} & \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} \\
& + \beta_4 crisis_t + \beta_5 crisis_t \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{1}
$$

The dependent variable is the corporate bond return around the rating downgrade event in excess of the market return, as defined in Section 3.1. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate. $X_{i,t}$ is a vector of bond-, firm- and rating event-specific controls that are defined in Appendix A. Standard errors are heteroscedasticity consistent and clustered at the issuer and quarter level. This specification allows us to both control for confounding factors and directly test whether the time-series and cross-sectional patterns observed in Table 3 are statistically significant. Our coefficient of interest is $\beta_3$, which refers to the interaction term $doddfrank_t \times simple_{i,t}$ and measures whether the change in informativeness post Dodd-Frank compared to pre-crisis depends on the complexity of the downgraded bond. If, for example, there is a stronger positive impact on informativeness after Dodd-Frank for bonds with low complexity, $\beta_3$ should be negative and significant.

We present the results for Equation 1 in Table 4. In the first column, we show a variation of our regression analysis where we do not condition on asset complexity. The remaining three columns show the full model for the three different measures of complexity, where simple and complex bonds are as defined in Section 3.1. No matter which measure of complexity is adopted, the coefficient $\beta_3$ of $doddfrank_t \times simple_{i,t}$ is always negative and significant. Thus, credit ratings of bonds with low complexity increase their informativeness after Dodd-Frank compared to pre-crisis, whereas such an increase is not present for high complexity bonds. The economic magnitude of this effect is meaningful: the point estimate ranges from -0.71% up to -1.11%. If we consider the median bond return after downgrades of -0.31% or the average transaction costs of 40 bp as a reference point, the economic significance of these results is emphasized.[18] As already indicated, the coefficients of $\beta_2$ representing the after Dodd-Frank dummy are not statistically different from zero, meaning that ratings from complex issuers did not experience any improvement in informativeness following the regulatory shock. These results provide strong support for Hypothesis 1, implying that regulatory shocks could have heterogeneous effects in the cross-section of securities depending on issuer complexity. Further, they highlight the importance of conditioning on complexity when evaluating the impact of regulatory policies involving credit ratings. Without doing so, the impact might seem weaker or even ambiguous: Column 1 in Table 4 shows a marginally significant increase in informativeness across all bonds of about -0.40%, which is less than half the effect we record when conditioning on complexity.

If the effects we document are driven by information, they should be observed in stock prices, as well. Thus, we repeat our analysis based on stock returns, similar to Dimitrov, Palia, and Tang (2015). In general, stocks are more information-sensitive and their higher liquidity allows us to observe variation in prices in a narrower window around the event than we can for bonds. Hence, we estimate the regression model of Equation 1 by substituting the dependent variable with the stock announcement return of the downgraded issuer as defined in Section 3.1. The results are presented in Table 5. Again, the coefficient $\beta_3$ is negative and significant across all complexity measures, confirming the findings for bond returns. Also in this case, the effect is significant in economic terms and even stronger

[18] Starting from the median downgraded bond return (-0.31%), the effect measured by $\beta_3$ is equivalent to a shift to between the 28th and 23rd percentile of the distribution.

compared to the bond results, ranging from -1.82% to -2.46%.[19] As in Table 4, the estimates of $\beta_2$ are not statistically different from zero, confirming that credit ratings from complex issuers did not experience any improvement in informativeness following the regulatory shock.

Overall, our findings on bond and stock returns confirm Hypothesis 1. These results provide an empirical validation for recent theoretical studies concerning the strategic behavior of CRAs. In particular, the different reaction of complex assets after Dodd-Frank is only possible when including regulatory advantage, asset complexity and rating inflation by CRAs, as for example in Opp, Opp, and Harris (2013). Indeed, models that focus only on certain combinations of these economic forces, would lead to more informative ratings for simple and complex assets, often with stronger effects for the latter. Thus, our results indicate that rating inflation serving regulatory purposes, rather than rating inaccuracy or noise, drives rating informativeness and suggest that future regulatory policies targeting the rating industry should take such factors into account. In addition, it is worthwhile to note that most of the theoretical models considered have the higher costs of information acquisition for structured products in mind, when discussing heterogenous effects. Therefore, it is particularly interesting to find all the presented results even within the cross-section of the corporate bond market.

## 4.2 Measures of Informativeness based on Bond Yields

In this section, we present alternative empirical tests of Hypothesis 1, which employ informativeness measures based on corporate bond yield spreads.[20] Our first measure relies on the possible ability of traded yield spreads to predict future downgrades across assets

[19] Taking as a reference the median stock return around downgrades it is equivalent to a shift to between the 30th and 25th percentile of the distribution.

[20] When calculating the yield spread, we follow Gürkaynak, Sack, and Wright (2007) and model the zero-coupon yield curve with the Nelson-Siegel-Svensson functional form. We then compute discount rates that exactly match the cash flow structure of the corporate bond at that point in time.

and over time. If, ceteris paribus, bonds with higher yield spreads are more likely to be downgraded, it means that market prices already contain a relatively larger fraction of the increased credit risk and downgrades provide less information. An appealing feature of this approach is that it allows us to use a larger cross-section of corporate bonds, and base the empirical validation of our hypothesis not only on bonds at the time they experience a downgrade. We construct a monthly panel where we include all fixed-coupon corporate bonds that have an available traded yield in TRACE in a certain month and estimate the following predictive model:

$$\begin{aligned}\mathbb{1}_{Downg.\ i,t+1} = {} & \beta_1 yield\ spread_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times yield\ spread_{i,t} \\ & + \beta_4 crisis_t + \beta_5 crisis_t \times yield\ spread_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}\end{aligned} \tag{2}$$

The dependent variable in this regression is a dummy that equals 1 if in the following month $t+1$ bond $i$ is downgraded.[21] A positive relationship between this dependent variable and the yield spread implies that, ceteris paribus, traded yield spreads anticipate a future downgrade, making credit ratings less informative. Our coefficient of interest is $\beta_3$, which indicates the variation in this measure of informativeness after Dodd-Frank.

The results are presented in Table 6. The first column shows results for the full sample, while the following ones split the sample into simple and complex bonds according to the three different complexity measures defined before.[22] Analyzing the full sample, there is no change in informativeness after the regulatory shock, with the coefficient $\beta_3$ being negative but statistically insignificant. However, when splitting the sample between simple and complex bonds, a striking result emerges, which is consistent across all complexity

[21] We include issuer and quarter fixed effects as well. Summary statistics for the bond sample used in this regression can be found in Table IA1 in the Internet Appendix.

[22] The sample splits for business and geographical segments are based on the median issuer over the past year, as defined in Section 3.1. Note that the splits are based on the issuer and not on the bond, which means that the number of observations between the samples of complex and simple bonds need not be the same.

measures. While bonds from more complex issuers do not show any variation in their informativeness post Dodd-Frank ($\beta_3$ insignificant and close to zero), those from simple ones experience an increase, with $\beta_3$ being negative and statistically significant. Ceteris paribus, a 1% higher yield spread of a bond with low complexity is between 1.7% and 2.8% less likely to predict a downgrade after Dodd-Frank relative to pre-crisis. This result is also significant in economic terms, as it represent a reduction between 40% and 65% relative to the full sample pre-crisis coefficient $\beta_1$ of 4.3%. The results are the same for a longer predictability horizon, as shown in Table IA3 in the Internet Appendix.

Our second alternative measure of credit rating informativeness is in the spirit of Becker and Milbourn (2011), and is represented by the conditional correlation of bond offering yield spreads and credit ratings. A higher conditional correlation between yield spreads and credit ratings corresponds to higher rating informativeness, as primary market investors consider ratings more when pricing bonds. This measure allows us to directly link rating informativeness to issuance yields and, thus, captures the benefits of ratings accruing to issuers, which often correspond more directly to quantities used in theoretical models (e.g., Opp, Opp, and Harris (2013)). We consider all fixed-coupon corporate bonds issued between January 2003 and May 2014 with available offering yields and credit rating at issuance and estimate the following regression model:

$$\begin{aligned} OY_{i,t} = {} & \beta_1 rating_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times rating_{i,t} + \beta_4 crisis_t \\ & + \beta_5 crisis_t \times rating_{i,t} + \gamma' X_{i,t} + \epsilon_i \end{aligned} \tag{3}$$

The dependent variable in this regression is the offering yield spread of bond $i$.[23] The coefficient of interest is $\beta_3$, which indicates whether the conditional correlation between credit ratings and offering yield spreads changed following Dodd-Frank. The results are

[23]We also include issuer and quarter fixed effects. Summary statistics for the sample used in this regression can be found in Table IA2 in the Internet Appendix.

displayed in Table 7. Similarly to Table 6, the first column shows the full sample, while the following ones split the sample into simple and complex bonds according to the three different complexity measures. The coefficient $\beta_1$ is always positive and significant, confirming that, ceteris paribus, bonds with worse ratings have higher yields. The full sample analysis shows that, on average, the informativeness of credit ratings increases after Dodd-Frank, with the interaction term between Dodd-Frank and credit rating being positive and significant. However, when splitting the sample between simple and complex bonds, it is evident that this increase is driven solely by bonds with low complexity. For these bonds, the coefficient $\beta_3$ is positive and significant across all complexity measures, with a magnitude of around 0.11%. This effect is significant in economic terms, as it represents an increase by one third compared to pre-crisis levels captured in $\beta_1$. The interaction coefficient for complex bonds is instead much smaller and mostly insignificant. Overall, the tests with alternative yield-based informativeness measures confirm the findings of Section 4.1 and provide broad empirical support to Hypothesis 1. Further, they reinforce the importance of considering asset complexity when measuring the impact of regulatory shocks. Failing to do so, leads to contradictory or inconclusive results.

### 4.3 Heterogeneous Impact Across Institutional Investors

In this section, we explore an additional layer of heterogeneity, focusing on differences in the institutional ownership of bonds. Regulatory reforms, such as Dodd-Frank, provide many provisions that do not necessarily affect all investors in the same way. While the increased liability for CRAs came into force immediately (see, e.g., Dimitrov, Palia, and Tang (2015)), the removal of rating-based regulation was part of Dodd-Frank, but its effective implementation was assigned to individual federal agencies that regulated different financial institutions. The latter bore the responsibility for introducing new measures of creditworthiness that do not rely on ratings. This naturally led to an heterogeneous implementation across different groups of institutional investors. Two prominent examples among them, insurance companies and mutual funds, were basically unaffected by the removal of rating-based regulation for corporate bonds. The former keep using bond credit ratings to compute their capital charges based on NAIC rules (see, e.g., Becker, Opp, and Saidi (2021) and NAIC (2021)), while the latter still heavily rely on bond ratings to check the suitability of bonds within their investment mandates (see, e.g., Baghai, Becker, and Pitschner (2020)). Therefore, insurance companies and mutual funds are less affected by the regulatory shock of Dodd-Frank, i.e., both still have an incentive to hold highly rated securities. In this section, we empirically test whether credit ratings of bonds that are held by insurance companies and mutual funds show weaker reactions to the regulatory shock.[24]

We collect quarterly bond ownership data on insurance companies and mutual funds from Lipper/eMAXX and repeat our main analysis on price reactions to bond downgrades by estimating Equation 1. We split the sample into downgrades of bonds with high vs low ownership by these two groups of investors. For the downgrades in each year, we sort the bonds based on the fraction of the outstanding amount in the portfolio of insurance companies and mutual funds in the quarter preceding the event. We consider bonds with high ownership by insurance companies and mutual funds as those that have a value above the median. On average, the bonds in the sample of high (low) ownership have 54% (24%) of the outstanding amount in the portfolios of insurance companies and mutual funds.[25] For stocks, we perform a split on a firm-level by aggregating the holdings of all bonds of a firm in our sample per year.[26]

Tables 8 and 9 display the results for bond and stock returns around downgrades,

[24]Note that the ownership structure as an important bond-specific characteristic is already employed by Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008) in the context of measuring the latent liquidity of bonds.

[25]Our results are identical if we use alternative sample splits, such as defining high (low) ownership bonds as those with at least 60% (at most 40%) of the outstanding amount in the portfolio of insurance companies/mutual funds.

[26]Note that we repeat the analysis of the bond price reactions using this firm-level split. See Table IA9 in the Internet Appendix. The results are basically identical.

respectively. In both tables, in the group of bonds with low ownership by insurance companies and mutual funds, the coefficient of the interaction term $doddfrank_t \times simple_{i,t}$ provides a stronger effect compared to the baseline cases presented in Tables 4 and 5. On the other hand, bonds with high ownership by insurance companies and mutual funds show no significant change in informativeness following Dodd-Frank. In other words, the increase in informativeness for low complexity bonds documented in Tables 4 and 5 is largely driven by bonds with low ownership by insurance companies and mutual funds. The magnitude of this effect is significant in economic terms: the point estimate for $doddfrank_t \times simple_{i,t}$ with low ownership by insurance companies and mutual funds ranges from -0.87% up to -1.60% for bond returns, and from -2.28% to -3.50% for stock returns.

These findings are consistent with Hypothesis 2, confirming that heterogeneous implementation of regulation across investor groups can lead to a different impact on rating informativeness in the cross-section of assets depending on the ownership structure. In the Internet Appendix, we provide additional evidence in support of this mechanism. We repeat the analysis on the predictability of future downgrades by corporate bond yields with sample splits based on the ownership by insurance companies and mutual funds. The results are displayed in Table IA8 and confirm that the increase in informativeness for simple bonds after Dodd-Frank is concentrated in assets with low ownership by insurance companies and mutual funds.[27] Overall, we show that Dodd-Frank only improves the quality of ratings for securities with low complexity in the US corporate bond market. This indicates that stricter changes in regulation would have been necessary to improve the rating informativeness of all bonds. Our results in this section show that one possibility to approach this goal is to dismantle rating-contingent regulation by a similar degree for all investors. Thus, these results suggest that future regulatory policies targeting the rating industry should take such factors into account and attempt to alleviate the heterogeneity

[27]Note that we cannot perform the analysis on offering yields as we do not have data on primary market allocations, and therefore cannot observe institutional ownership at issuance.

in regulation.

While in line with our intuition, these findings come with some important caveats. First, we are able to measure institutional ownership only at the quarterly level, which means we could miss important ownership shifts during the quarter. Second and most importantly, we cannot observe the identity of the other owners that are not insurance companies and mutual funds. This introduces an important measurement limitation: the residual owners could be affected (e.g., banks) or unaffected (e.g., foreign institutions) by the removal of rating-based regulation.[28] We consider our results to be a first step towards investigating the heterogeneous impact of regulation across institutions in the same asset market. Additional research based on more granular data is needed to better understand the relevant implications.

## 4.4 Robustness

In this section we discuss an extensive set of robustness tests analyzing alternative specifications and factors that could explain our findings. The tables presenting the results of these checks are reported in the Internet Appendix to conserve space. We find that all our main results hold even within these robustness tests.

### 4.4.1 Confounding Events

Our first set of robustness checks analyzes whether the informativeness of the rating changes could be driven by other events relevant for bond prices when analyzing announcement returns. In particular, we analyze returns after excluding events that coincide with earnings announcements as well as mergers and acquisitions. The dates of earnings announcements are retrieved from Compustat, while those of mergers and acquisitions (M&A)

[28]For banks, the final rule was issued on August 2012, see FED Market Risk Capital Rule (2012). However, the removal of rating-based regulation was highly anticipated since the approval of Dodd-Frank.

are both obtained through the CRSP-Compustat merging table and hand-collected.[29] We exclude from the sample rating events when earnings announcements occur within 5-days, and when M&A activity (announcement and/or deal completion) are observed within 30 days before and after the events. We then repeat the analysis in Table 4 and find that our findings remain robust. The results are displayed in Table IA4.

#### 4.4.2 Regulatory Channel

The price impact around rating changes may reflect *both* information transmission and the effect of regulation, whenever a regulatory threshold is breached, and some investors may trade for this reason. If the regulatory channel is particularly strong, it might be that the observed impact is not due to informativeness alone, but regulation-induced fire sales. While we control for these events in our regressions, we try to further address this concern in an additional robustness check by re-estimating Equation 1 while excluding all downgrades where the investment-speculative threshold is crossed. The results are presented in Table IA5 and confirm that our findings are not driven by the regulatory channel.

#### 4.4.3 Distribution of Rating Events

This set of robustness checks considers differences in the distribution of rating events across rating classes when comparing different periods based on announcement returns, as Table 1 indicates that this distribution changes over time. The price impact of a rating change could be dependent on the rating class, e.g., a rating change from AA+ to AA might have a different effect compare to a change from BBB- to CCC+. Thus, the difference in informativeness could be driven, for example, by relatively more changes of speculative grade ratings compared to investment grade ratings across different periods. In the robustness test, we equally weight the observations in the first period (as in the

[29]For mergers and acquisitions, we consider both the announcement date and the date of deal completion as relevant.

regular analysis), while in the second and third period we weight the observations based on the relative frequency of rating changes in the rating classes in the first period. The results are presented in Table IA7 and confirm our findings.[30]

#### 4.4.4 Time-Varying Risk Premia

This set of robustness checks focuses on the time variation of the risk premium in the corporate bond market. The market price reaction to an event also reflects the risk-premium in the market at that specific point in time. If the risk premium varies significantly over time (e.g., through the business cycle), the market reaction to a rating change could be significantly different even if the informativeness of the rating stays constant. We address such a concern by including in our regressions the risk premium in the corporate bond market in the month of the rating event. The risk premium is estimated using Fama-Macbeth regressions on monthly corporate bond returns.[31] First we run, for each bond in the TRACE database over our sample period, a time-series regression of single corporate bond returns on the market return.[32] Second, in each month, we run cross-sectional regressions of corporate bond returns on the previously estimated bond-specific betas. The risk premium in each month is the estimated coefficient of the cross-sectional regression in that month. Including the risk premium as a control in the estimation of Equation 1 does not change our results, as shown in Table IA6.

[30]Note that such effects are directly considered at the event level in the regression setup by including rating-related variables. This robustness tests ensures that we are not overlooking any systmatic shift in the distribution of ratings across periods.

[31]A bond needs to have at least 12 monthly returns observations to be included in our sample.

[32]We take as market return the FINRA-Bloomberg Corporate Bond Investment Grade as well as High Yield Index. Considering that we are provided with an investment and speculative grade bond index, whenever a bond crosses the threshold in a month we equally weight the returns of the two indexes.

# 5 Conclusion

This paper shows that regulatory changes can result in a heterogeneous impact on credit rating informativeness, given cross-sectional differences in asset complexity. We provide empirical evidence in the context of the US corporate bond market, by exploiting the Dodd-Frank act as a negative shock to the regulatory advantage of credit ratings. Using various measures of complexity and rating informativeness, we find that following the regulatory changes, informativeness increased only for securities that have low complexity, while bonds from issuers that have high complexity do not see any improvement.

Our findings are consistent with recent theoretical models combining rating shopping of investors with strategic behavior by CRAs deciding on information acquisition and rating inflation, such as Opp, Opp, and Harris (2013). Alternative models that include only certain combinations of these economic mechanisms, would lead to more informative ratings for simple and complex assets, often with stronger effects for the latter. Thus, our results document that rating inflation that serves regulatory purposes, rather than rating inaccuracy or noise, drives rating informativeness. This result is further confirmed by the fact that the impact on informativeness is weaker for assets held by institutions less affected by Dodd-Frank.

Overall, our paper contributes to the important discussion on the role of asset characteristics in determining the impact of regulatory policies concerning credit ratings. Regulatory reforms are often targeted towards entire asset classes but their impact might not be homogeneous in the cross-section of securities. In our case, we show that Dodd-Frank only improves the quality of ratings for securities with low complexity in the US corporate bond market. Our results indicate that stricter changes in regulation would have been necessary to improve the rating informativeness of all bonds. In particular, if rating-contingent regulation is not dismantled by the same degree for all investors, then the risk of having heterogeneous outcomes increases. Regulators should take this possibility into account when designing future regulatory policies. Our results provide a first step in understanding the role of asset characteristics in shaping cross-sectional differences in rating informativeness. Our findings suggest that a prominent avenue for future research would be exploring the role of heterogeneous asset demand of different groups of institutional investors in shaping rating informativeness.

# A Appendix: Variable Definitions

| Variable | Definition |
|---|---|
| Bond Announcement Return | Percentage change between the average price across the 5 days before the event and the average across the event day and the 5 days thereafter. |
| Corporate Bond Market Return | Represents the rating and maturity matched corporate bond market return over the time window employed to analyze the reaction to rating changes. It is deducted from the price reaction of the bond affected by the rating change. Based on credit ratings, we divide the sample between investment and speculative grade, while for time to maturity, we consider long-term ($>$ 5 years) and short-term ($\leq$ 5 years) bonds. We exclude bonds that experience a rating change around the event. In the relevant group, we calculate the return for each bond based on the same methodology used to calculate the return on the downgraded bond, and employ an equally-weighted return as the market return of this group. For rating events ”crossing” the threshold between investment and speculative grade, we equally weight the returns of the two corresponding groups. |
| Stock Announcement Return | Percentage change over the three-day period centered at the rating announcement date in excess of the corresponding return on the CRSP value-weighted index. |
| After Dodd-Frank | Dummy equal to one if the rating change occurs between July 22, 2010 and May 2014. |
| Financial Crisis | Dummy equal to one if the rating change occurs between December 2007 and July 21, 2010. |
| Simple | Dummy equal to one if the issuer of the bond is of low complexity. We use three alternative definitions for high vs low complexity: financial (high complexity) vs non-financial (low complexity) issuers, number of business segments above (high complexity) vs below (low complexity) the median of issuers in the past year, number of geographical segments above (high complexity) vs below (low complexity) the median of issuers in the past year. |

| Variable | Definition |
|---|---|
| Time to Maturity | Number of years left before maturity at the time of the rating change. |
| Issue Size | Natural logarithm of the outstanding amount of a bond at the time of the rating change. |
| Liquidity | Represents one plus the natural logarithm of Roll's illiquidity measure for the bond around the rating change using the past 20 trading days as the estimation window. |
| Yield | Yield to maturity of the bond around the rating change. |
| Total Assets | Natural logarithm of the issuer's total assets. |
| Rating Number | Integer value representing the rating grade, starting from 1 for the highest to 21 for the lowest (*Fitch*, *Moody's*, *Standard and Poor's*). |
| Rating Dispersion | Average absolute difference in the ratings of the three different agencies on the day the rating change occurred. |
| Number of Agencies | Number of CRAs rating the bond at the time of the rating change. |
| Notches | Difference between the rating number before and that after the event. |
| Invest./Specul. Threshold | Dummy variable equal to 1 when investment-speculative grade threshold is crossed. |

# References


Agarwal, Sumit, Vincent Chen, and Weina Zhang, 2016, The information value of credit rating action reports: A textual analysis, *Management Science* 62, 2218–2240.

Badoer, Dominique, and Cem Demiroglu, 2019, The relevance of credit ratings in transparent bond markets, *The Review of Financial Studies* 32, 42–74.

Baghai, Ramin, Bo Becker, and Stefan Pitschner, 2020, The use of credit ratings in financial markets, *Working Paper, Stockholm School of Economics.*

Bar-Isaac, Heski, and Joel Shapiro, 2013, Ratings quality over the business cycle, *Journal of Financial Economics* 108, 62–78.

Becker, Bo, and Todd Milbourn, 2011, How did increased competition affect credit ratings?, *Journal of Financial Economics* 101, 493–514.

Becker, Bo, Marcus Opp, and Farzad Saidi, 2021, Regulatory forbearance in the U.S. insurance industry: The effects of removing capital requirements for an asset class, *The Review of Financial Studies* Forthcoming.

Behr, Patrick, Darren Kisgen, and Jerome Taillard, 2018, Did government regulations lead to inflated ratings?, *Management Science* 64, 983–1476.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *The Review of Financial Studies* 22, 4219–4258.

Bolton, Patrick, Xavier Freixas, and Joel Shapiro, 2012, The credit ratings game, *The Journal of Finance* 67, 85–111.

Bushman, Robert M., Joseph D. Piostrosku, and Abbie J. Smith, 2004, What determines corporate transparency?, *Journal of Accounting Research* 42, 207–252.

Chava, Sudeer, Rohan Ganduri, and Chayawat Ornthanalai, 2019, Do credit default swaps mitigate the impact of credit rating downgrades?, *Review of Finance* 23, 471–511.

Cohen, Lauren, and Dong Lou, 2012, Complicated firms, *Journal of Financial Economics* 104, 383–400.

Cornaggia, Jess, and Kimberly J. Cornaggia, 2013, Estimating the costs of issuer-paid credit ratings, *The Review of Financial Studies* 26, 2229–2269.

Dichev, Ilia D., and Joseph D. Piotroski, 2001, The long-run stock returns following bond ratings changes, *The Journal of Finance* 56, 173–203.

Dick-Nielsen, Jens, 2009, Liquidity biases in TRACE, *The Journal of Fixed Income* 19, 43–55.

Dimitrov, Valentin, Darius Palia, and Leo Tang, 2015, Impact of the Dodd-Frank act on credit ratings, *Journal of Financial Economics* 115, 505–520.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

FED Market Risk Capital Rule, 2012, http://www.gpo.gov/fdsys/pkg/FR-2012-08-30/pdf/2012-16759.pdf.

Friewald, Nils, Rainer Jankowitsch, and Marti G. Subrahmanyam, 2012, Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crises, *Journal of Financial Economics* 105, 18–36.

Goh, Jeremy C., and Louis H. Ederington, 1993, Is a bond rating downgrade bad news, good news, or no news for stockholders?, *The Journal of Finance* 48, 2001–2008.

Griffin, Paul A., and Antonio Z. Sanvicente, 1982, Common stock returns and rating changes: A methodological comparison, *The Journal of Finance* 37, 103–119.

Gürkaynak, Refet S., Brian Sack, and Jonathan H. Wright, 2007, The US treasury yield curve: 1961 to the present, *Journal of Monetary Economics* 54, 2291–2304.

Hand, John R. M., Robert W. Holtausen, and Richard W. Leftwich, 1992, The effect of bond rating agency announcements on bond and stock prices, *The Journal of Finance* 47, 733–752.

Henry, Tyler R., Darren J. Kisgen, and Juan Wu, 2015, Equity short selling and bond rating downgrades, *Journal of Financial Intermediation* 24, 89–111.

Holthausen, Robert W., and Richard W. Leftwich, 1986, The effect of bond rating changes on common stock prices, *Journal of Financial Economics* 17, 57–89.

Ingram, Robert W., Leroy D. Brooks, and Ronald M. Copeland, 1983, The information content of municipal bond rating changes: A note, *The Journal of Finance* 38, 997–1003.

Jankowitsch, Rainer, Florian Nagler, and Marti G. Subrahmanyam, 2014, The determinants of recovery rates in the US corporate bond market, *Journal of Financial Economics* 114, 155–177.

Jorion, Philippe, Alfred Zhu Liu, and Charles Shi, 2005, Informational effects of regulation FD: Evidence from rating agencies, *Journal of Financial Economics* 76, 309–330.

Katz, Steven, 1974, The price adjustment process of bonds to rating reclassifications, *The Journal of Finance* 29, 551–559.

Kliger, Doron, and Oden Sarig, 2000, The information value of bond ratings, *The Journal of Finance* 55, 2879–2902.

Mahanti, Sriketan, Amrut Nashikkar, Marti Subrahmanyam, George Chacko, and Gaurav Mallik, 2008, Latent liquidity: A new measure of liquidity, with an application to corporate bonds, *Journal of Financial Economics* 88, 272–298.

May, Anthony D., 2010, The impact of bond rating changes on corporate bond prices: New evidence from the over-the-counter market, *Journal of Banking and Finance* 34, 2822–2836.

Morgan, Donald P., 2002, Rating banks: Risk and uncertainty in an opaque industry, *American Economic Review* 92, 874–888.

NAIC, 2021, NAIC report on rating agencies, http://www.naic.org/cipr_topics/topic_rating_agencies.htm.

National Bureau of Economic Research, 2010, http://www.nber.org/cycles/sept2010.pdf.

Nayar, Nandukmar, and Michael S. Rozeff, 1994, Ratings, commercial paper and equity returns, *The Journal of Finance* 49, 1431–1449.

Opp, Christian C., Marcus M. Opp, and Milton Harris, 2013, Rating agencies in the face of regulation, *Journal of Financial Economics* 108, 46–61.

Skreta, Vasiliki, and Laura Veldkamp, 2009, Ratings shopping and asset complexity: A theory of ratings inflation, *The Journal of Monetary Economics* 56, 678–695.

Spiegel, Matthew, and Laura Starks, 2016, Institutional rigidities and bond returns around rating changes, *Working Paper*.

Toscano, Francesca, 2020, Does the Dodd-Frank act reduce the conflict of interests of credit rating agencies?, *Journal of Corporate Finance* 62.

Wakeman, L., 1978, Bond rating agencies and the capital markets, *Working Paper, University of Rochester NY*.

Weinstein, Mark I., 1977, The effect of a rating change announcement on bond price, *Journal of Financial Economics* 5, 329–350.

**Table 1: Distribution of Downgrades.**
This table shows how the rating events are distributed in our sample. The table reports the ratings of the bonds after the downgrade. Rating is a variable that assigns integer values to the different rating grades, starting from 1 for the highest and extending down to 21 for the lowest rating grade. The table is divided by rating grades and time periods. Our sample represents downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. We obtain bond characteristics from Mergent FISD and bond transactions from TRACE. The sample period is divided into before the crisis (January 2003 - November 2007), during the crisis (December 2007 - July 21, 2010) and after Dodd-Frank (July 22, 2010 - May 2014).

| **Rating** | **Downgrades** | | | | **All Events** |
|---|---|---|---|---|---|
| | **Before** | **During** | **After** | **All Periods** | **All Periods** |
| **AAA/Aaa/1** | 0 | 0 | 0 | 0 | 0 |
| **AA+/Aa1/2** | 2 | 3 | 3 | 8 | 16 |
| **AA/Aa2/3** | 5 | 17 | 3 | 25 | 50 |
| **AA-/Aa3/4** | 7 | 36 | 11 | 54 | 108 |
| **A+/A1/5** | 32 | 70 | 29 | 131 | 262 |
| **A/A2/6** | 56 | 81 | 43 | 180 | 360 |
| **A-/A3/7** | 31 | 66 | 63 | 160 | 320 |
| **BBB+/Baa1/8** | 22 | 53 | 47 | 122 | 244 |
| **BBB/Baa2/9** | 31 | 52 | 34 | 117 | 234 |
| **BBB-/Baa3/10** | 37 | 31 | 24 | 92 | 184 |
| **BB+/Ba1/11** | 34 | 12 | 21 | 67 | 134 |
| **BB/Ba2/12** | 24 | 11 | 5 | 40 | 80 |
| **BB-/Ba3/13** | 25 | 9 | 9 | 43 | 86 |
| **B+/B1/14** | 17 | 17 | 6 | 40 | 80 |
| **B/B2/15** | 15 | 11 | 3 | 29 | 58 |
| **B-/B3/16** | 13 | 15 | 2 | 30 | 60 |
| **CCC+/Caa1/17** | 16 | 9 | 3 | 28 | 56 |
| **CCC/Caa2/18** | 4 | 5 | 5 | 14 | 28 |
| **CCC-/Caa3/19** | 0 | 0 | 0 | 0 | 0 |
| **CC/Ca/20** | 0 | 0 | 0 | 0 | 0 |
| **C/C/21** | 0 | 0 | 0 | 0 | 0 |
| **All Ratings** | 371 | 498 | 311 | 1180 | 1180 |

**Table 2: Summary Statistics.**
This table shows summary statistics of the main variables used in the analysis. Time to maturity and issue size are given in years and millions of dollars, respectively. Liquidity is in basis points, whereas yield is measured in percentage points of face value. Firm size is given in billions of dollars. Rating is a variable that assigns integer values to the different rating grades, starting from 1 for the highest and extending down to 21 for the lowest rating grade. Rating dispersion, number of agencies, notches, business segment and geo segments are all given in integers. Our sample represents 1,180 downgrades events of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. We obtain bond characteristics from Mergent FISD and bond transactions from TRACE. The sample period is divided into before the crisis (January 2003 - November 2007), during the crisis (December 2007 - July 21, 2010) and after Dodd-Frank (July 22, 2010 - May 2014).

| Variable | Unit | Mean | Stdv | q10 | q50 | q90 | $\text{Mean}_{pre}$ | $\text{Mean}_{crisis}$ | $\text{Mean}_{postDF}$ |
|---|---|---|---|---|---|---|---|---|---|
| Maturity | [years] | 7.26 | 6.87 | 1.22 | 4.82 | 17.62 | 8.64 | 6.12 | 7.46 |
| Issue Size | [millions] | 808.49 | 590.09 | 250.00 | 599.97 | 1752.50 | 609.32 | 807.42 | 1047.81 |
| Liquidity | [bp] | 61.81 | 62.92 | 8.80 | 43.91 | 140.98 | 56.72 | 85.21 | 30.40 |
| Yield | [%] | 7.06 | 5.12 | 2.79 | 6.02 | 11.45 | 6.61 | 9.23 | 4.14 |
| Total Assets | [billions] | 480.23 | 687.20 | 7.19 | 149.45 | 1681.31 | 146.07 | 587.58 | 706.97 |
| Rating | [integer] | 8.55 | 3.54 | 5.00 | 8.00 | 14.00 | 9.67 | 7.97 | 8.15 |
| Rating Disp. | [integer] | 1.13 | 1.09 | 0.00 | 1.00 | 2.00 | 1.02 | 1.12 | 1.28 |
| N. of Agencies | [integer] | 2.96 | 0.18 | 3.00 | 3.00 | 3.00 | 2.94 | 2.97 | 2.99 |
| Notches | [integer] | 1.39 | 0.91 | 1.00 | 1.00 | 2.00 | 1.51 | 1.38 | 1.26 |
| Business Seg. | [integer] | 3.03 | 1.99 | 1.00 | 2.40 | 5.00 | 3.05 | 2.91 | 3.17 |
| Geo Seg. | [integer] | 2.93 | 2.16 | 1.00 | 2.00 | 5.00 | 2.94 | 3.02 | 2.78 |

**Table 3: Bond Returns around Downgrades and Asset Complexity.**
This table shows returns surrounding US corporate bond rating changes that occurred between January 2003 and May 2014. The sample period is divided into before the crisis (January 2003 - November 2007), during the crisis (December 2007 - July 21, 2010) and after Dodd-Frank (July 22, 2010 - May 2014). The returns are calculated as the percentage change between the average volume weighted daily price across the 5 days before the event, and the average across the event day and the 5 days after it. Returns are tested to analyze whether their mean is statistically different from zero. The sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The analysis is performed separately for simple and complex bonds in each of the periods. Panel A, B and C represent this split based on complexity measured by financials/non-financials, number of business segments and number of geographical segments, respectively. The table reports the mean of the returns, and the value of the two-sided t-test. The significance is indicated as follows: * < 0.1, ** < 0.05, *** < 0.01.

| | Simple | | Complex | |
|---|---|---|---|---|
| Period | Mean | T-test | Mean | T-test |
| Panel A: Fin/Nofin | | | | |
| Before the Crisis | −0.53 | −6.42*** | −0.51 | −3.87*** |
| During the Crisis | −0.96 | −2.12** | −1.63 | −5.28*** |
| After Dodd-Frank | −0.83 | −4.63*** | −0.30 | −2.85*** |
| Panel B: Business Segments | | | | |
| Before the Crisis | −0.53 | −5.44*** | −0.46 | −2.62** |
| During the Crisis | −1.28 | −4.57*** | −2.33 | −3.50*** |
| After Dodd-Frank | −0.73 | −5.20*** | −0.10 | −0.93 |
| Panel C: Geo Segments | | | | |
| Before the Crisis | −0.50 | −5.79*** | −0.52 | −4.36*** |
| During the Crisis | −2.11 | −2.00* | −1.43 | −5.32*** |
| After Dodd-Frank | −0.96 | −4.91*** | −0.31 | −3.06*** |

**Table 4: Bond Returns around Downgrades and Asset Complexity: Regression Analysis.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} \\ + \beta_4 crisis_t + \beta_5 crisis_t \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the corporate bond return in excess of the market return during a 10 days trading day window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches and regulatory threshold dummy). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Dodd-Frank | $-0.398^{*}$ | $-0.116$ | 0.335 | $-0.140$ |
| | $(-1.833)$ | $(-0.400)$ | (0.964) | $(-0.622)$ |
| Simple | | 0.437 | 0.342 | 0.387 |
| | | (1.633) | (1.050) | (1.543) |
| Dodd-Frank × Simple | | $-0.710^{**}$ | $-1.106^{**}$ | $-1.091^{***}$ |
| | | $(-1.793)$ | $(-2.520)$ | $(-2.588)$ |
| Intercept | $-1.959^{*}$ | $-2.791^{**}$ | $-1.615$ | $-1.904^{*}$ |
| | $(-1.785)$ | $(-2.815)$ | $(-1.643)$ | $(-1.725)$ |
| Observations | 1,180 | 1,180 | 1,180 | 1,180 |
| Controls | Yes | Yes | Yes | Yes |
| $R^2$ | 0.079 | 0.084 | 0.083 | 0.080 |

**Table 5: Stock Returns around Downgrades and Asset Complexity: Regression Analysis.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} + \beta_4 crisis_t + \beta_5 crisis_t \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the excess stock return during a 3 days trading window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches and regulatory threshold dummy). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Dodd-Frank | 0.222 | 1.339 | 1.633 | 0.770 |
| | (0.240) | (1.340) | (1.222) | (0.754) |
| Simple | | 0.961 | 0.469 | 1.881** |
| | | (1.241) | (0.725) | (2.537) |
| Dodd-Frank × Simple | | −2.268** | −1.819* | −2.459** |
| | | (−2.019) | (−1.710) | (−2.473) |
| Intercept | −1.226 | −1.187 | 0.934 | −1.450 |
| | (−0.394) | (−0.427) | (0.311) | (−0.430) |
| Observations | 1,126 | 1,126 | 1,126 | 1,126 |
| Controls | Yes | Yes | Yes | Yes |
| $R^2$ | 0.004 | 0.006 | 0.015 | 0.010 |

**Table 6: Predictability of Rating Downgrades, Bond Yields and Asset Complexity.** We present results for variations of the following regression

$$\mathbb{1}_{Downg.\ i,t+1} = \beta_1 yield\ spread_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times yield\ spread_{i,t} + \beta_4 crisis_t + \beta_5 crisis_t \times yield\ spread_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is a dummy that equals 1 if in the following month $t+1$ bond $i$ is downgraded. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $yield\ spread_{i,t}$ is the average daily yield spread of bond $i$ in month $t$. $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, rating number, rating dispersion, number of agencies, issuer fixed effects and quarter fixed effects). The regression sample includes fixed-coupon US corporate bonds that traded between January 2003 and May 2014. The first column reports the results on the full sample. The remaining columns show results where the sample is split between simple and complex bonds, using three different measures of complexity (financials/non-financials, number of business segments, number of geographical segments). Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | | Business Segments | | Geo Segments | |
|---|---|---|---|---|---|---|---|
| | | Complex | Simple | Complex | Simple | Complex | Simple |
| Yield Spread | 0.043*** | 0.054*** | 0.027*** | 0.030*** | 0.048*** | 0.038*** | 0.041*** |
| | (5.149) | (4.068) | (3.916) | (6.337) | (4.250) | (4.858) | (3.300) |
| Dodd-Frank | 0.023** | 0.039** | 0.011 | −0.001 | 0.032** | 0.022 | 0.023** |
| | (2.140) | (2.514) | (1.194) | (−0.068) | (2.235) | (1.559) | (2.012) |
| Yield Spread × Dodd-Frank | −0.015 | −0.016 | −0.017** | 0.003 | −0.024** | −0.001 | −0.028** |
| | (−1.530) | (−0.980) | (−2.422) | (0.376) | (−2.063) | (−0.048) | (−2.538) |
| Observations | 136,824 | 74,548 | 62,276 | 62,974 | 73,850 | 83,615 | 53,209 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.097 | 0.103 | 0.096 | 0.096 | 0.115 | 0.104 | 0.104 |

**Table 7: Bond Offering Yields, Credit Ratings and Asset Complexity.** We present results for variations of the following regression

$$OY_{i,t} = \beta_1 rating_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times rating_{i,t} + \beta_4 crisis_t + \beta_5 crisis_t \times rating_{i,t} + \gamma' X_{i,t} + \epsilon_i$$

The dependent variable is the offering yield spread of bond $i$. $crisis_t$ and $doddfrank_q$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $rating_{i,t}$ is the initial credit rating at issuance of bond $i$. $X_{i,t}$ is a vector of controls (time to maturity, issue size, rating dispersion, number of agencies, issuer fixed effects and quarter fixed effects). The regression sample includes fixed-coupon US corporate bond offerings between January 2003 and May 2014. The first column reports the results on the full sample. The remaining columns show results where the sample is split between simple and complex bonds, using three different measures of complexity (financials/non-financials, number of business segments, number of geographical segments). Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | | Business Segments | | Geo Segments | |
|---|---|---|---|---|---|---|---|
| | | Complex | Simple | Complex | Simple | Complex | Simple |
| Credit Rating | 0.254*** | 0.175** | 0.386*** | 0.210*** | 0.214*** | 0.135** | 0.310*** |
| | (5.537) | (2.199) | (5.197) | (4.341) | (3.789) | (2.170) | (4.471) |
| Dodd-Frank | −0.499** | −0.244 | −0.487 | −0.097 | −0.665** | −0.114 | −0.592** |
| | (−2.441) | (−0.629) | (−1.617) | (−0.371) | (−2.284) | (−0.335) | (−2.025) |
| Credit Rating × Dodd-Frank | 0.104*** | 0.074 | 0.106*** | 0.071* | 0.112*** | 0.067 | 0.107** |
| | (3.361) | (0.947) | (2.810) | (1.895) | (2.691) | (1.391) | (2.373) |
| Observations | 2,858 | 1,475 | 1,383 | 1,415 | 1,443 | 1,527 | 1,331 |
| $R^2$ | 0.794 | 0.556 | 0.910 | 0.750 | 0.851 | 0.747 | 0.897 |

**Table 8: Bond Returns around Downgrades: the Role of Institutional Ownership.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t}$$
$$+ \beta_4 crisis_t + \beta_5 crisis_t \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the corporate bond return in excess of the market return during a 10 days trading day window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches and regulatory threshold dummy). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Panel A (Panel B) presents results for bonds with low (high) ownership by insurance companies and mutual funds. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Panel A: Low Ownership of Insurance Companies and Mutual Funds | | | | |
| Dodd-Frank | −0.415 | −0.173 | 0.740 | −0.058 |
| | (−1.520) | (−0.521) | (1.402) | (−0.194) |
| Simple | | 0.349 | 0.823* | 0.558 |
| | | (1.060) | (1.722) | (1.621) |
| Dodd-Frank × Simple | | −0.873 | −1.598*** | −1.514** |
| | | (−1.580) | (−2.602) | (−2.527) |
| Panel B: High Ownership of Insurance Companies and Mutual Funds | | | | |
| Dodd-Frank | −0.630 | −0.507 | −0.437 | −0.541 |
| | (−1.486) | (−0.710) | (−0.703) | (−1.205) |
| Simple | | 0.297 | −0.225 | 0.106 |
| | | (0.786) | (−0.615) | (0.303) |
| Dodd-Frank × Simple | | −0.274 | −0.352 | −0.378 |
| | | (−0.501) | (−0.630) | (−0.859) |
| Observations Panel A | 637 | 637 | 637 | 637 |
| Controls Panel A | Yes | Yes | Yes | Yes |
| $R^2$ Panel A | 0.097 | 0.102 | 0.109 | 0.107 |
| Observations Panel B | 543 | 543 | 543 | 543 |
| Controls Panel B | Yes | Yes | Yes | Yes |
| $R^2$ Panel B | 0.105 | 0.113 | 0.107 | 0.106 |

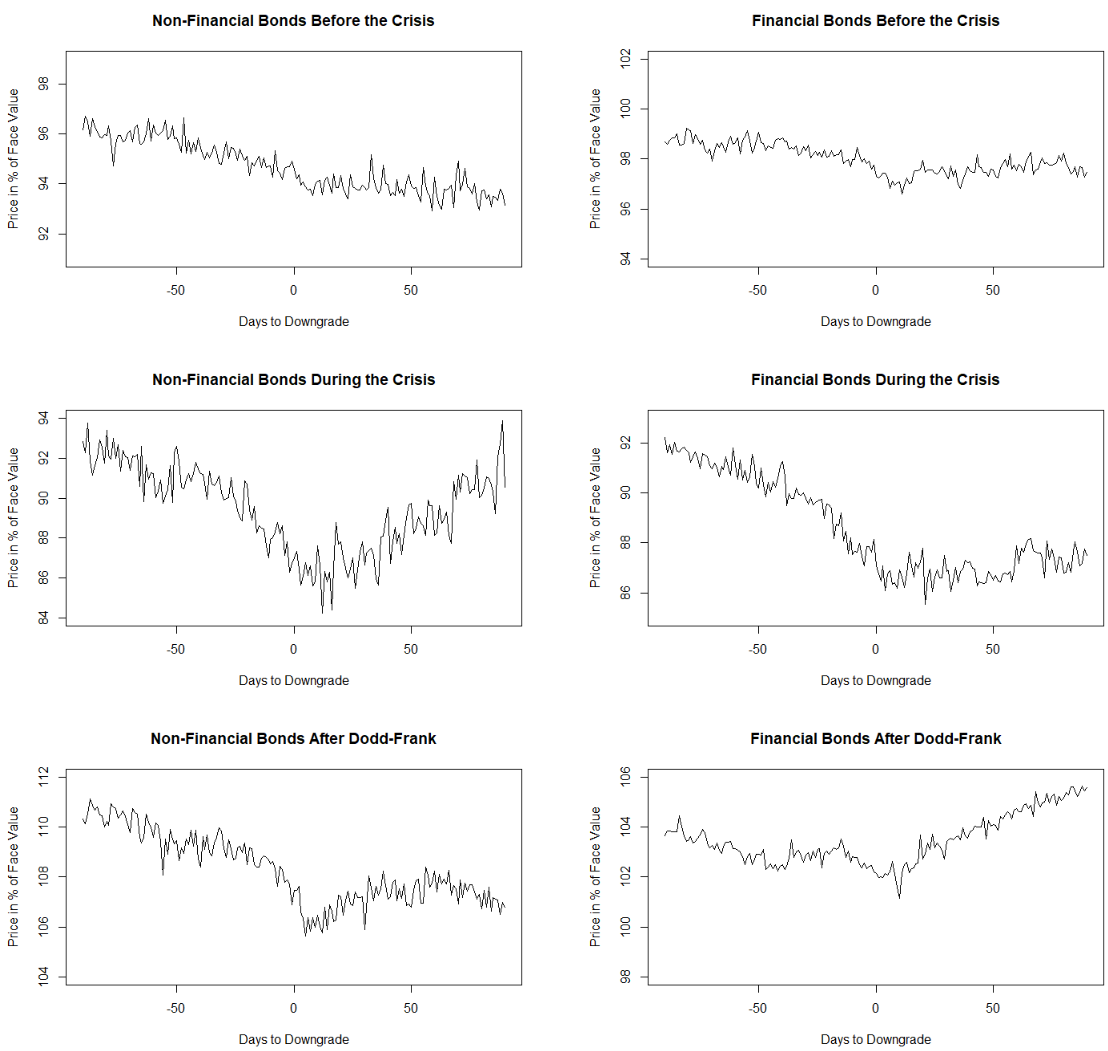
**Table 9: Stock Returns around Downgrades: the Role of Institutional Ownership.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} \\ + \beta_4 crisis + \beta_5 crisis \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the excess stock return during a 3 days trading window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches and regulatory threshold dummy). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Panel A (Panel B) presents results for stocks with low (high) bond ownership by insurance companies and mutual funds measured at the firm-level. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Panel A: Low Ownership of Insurance Companies and Mutual Funds | | | | |
| Dodd-Frank | 0.190 | 1.189 | 2.865 | 0.719 |
| | (0.099) | (0.609) | (1.200) | (0.368) |
| Simple | | 1.141 | 2.060 | 1.490* |
| | | (1.006) | (1.630) | (1.656) |
| Dodd-Frank × Simple | | −3.111* | −3.497** | −2.276* |
| | | (−1.846) | (−2.056) | (−1.733) |
| Panel B: High Ownership of Insurance Companies and Mutual Funds | | | | |
| Dodd-Frank | −0.248 | 0.746 | 0.315 | 0.340 |
| | (−0.249) | (0.488) | (0.226 | (0.305) |
| Simple | | 0.799 | −0.380 | 1.860 |
| | | (0.622) | (−0.424) | (1.554) |
| Dodd-Frank × Simple | | −1.293 | −0.636 | −1.620 |
| | | (−0.876) | (−0.518) | (−1.131) |
| Observations Panel A | 589 | 589 | 589 | 589 |
| Controls Panel A | Yes | Yes | Yes | Yes |
| $R^2$ Panel A | 0.010 | 0.012 | 0.027 | 0.011 |
| Observations Panel B | 537 | 537 | 537 | 537 |
| Controls Panel B | Yes | Yes | Yes | Yes |
| $R^2$ Panel B | 0.011 | 0.012 | 0.018 | 0.028 |

**Figure 1: Time Series for Downgrades.**
This figure presents, for each of the three sample periods, the time series of the daily average bond price. Each is calculated across all events within the time interval from 90 days before to 90 days after the event. The left hand column shows the results for non-financial bonds, and the right hand one those for financials, as a representative example for differences in asset complexity. Our sample represents downgrades that occurred in the US corporate bond market between January 2003 and May 2014. We obtain bond characteristics from Mergent FISD and bond transactions from TRACE. The sample period is divided into before the crisis (January 2003 - November 2007), during the crisis (December 2007 - July 21, 2010) and after Dodd-Frank (July 22, 2010 - May 2014).



# B Internet Appendix

Internet Appendix to

**Regulation, Asset Complexity, and the Informativeness of Credit Ratings**

**Table IA1: Summary Statistics: Yield Predictability.**

This table shows summary statistics of the main variables used in the yield predictability regressions. Time to maturity and issue size are given in years and millions of dollars, respectively. Liquidity is in basis points. Rating is a variable that assigns integer values to the different rating grades, starting from 1 for the highest and extending down to 21 for the lowest rating grade. Rating dispersion, number of agencies, business segments and geo segments are all given in integers. Yield spread is measured in percentage points of face value. The dummies for downgrades in the next month or within two months are both given in percentage points. Our sample represents traded fixed-coupon US corporate bonds between January 2003 and May 2014. We obtain bond characteristics from Mergent FISD and traded yields from TRACE. The sample period is divided into before the crisis (January 2003 - November 2007), during the crisis (December 2007 - July 21, 2010) and after Dodd-Frank (July 22, 2010 - May 2014).

| Variable | Unit | Mean | Stdv | q10 | q50 | q90 | N |
|---|---|---|---|---|---|---|---|
| Time to Maturity | [years] | 8.23 | 8.88 | 1.17 | 4.83 | 23.50 | 136,824 |
| Issue Size | [millions] | 808.49 | 590.09 | 250.00 | 599.97 | 1,752.50 | 136,824 |
| Liquidity | [bp] | 81.20 | 282.61 | 19.84 | 55.16 | 146.23 | 136,824 |
| Rating | [integer] | 6.63 | 2.87 | 3.67 | 6.00 | 10.00 | 136,824 |
| Rating Dispersion | [integer] | 0.64 | 0.58 | 0.00 | 0.58 | 1.41 | 136,824 |
| Number of Agencies | [integer] | 2.79 | 0.43 | 2.00 | 3.00 | 3.00 | 136,824 |
| Business Segments | [integer] | 3.68 | 3.12 | 1.00 | 2.65 | 7.00 | 136,824 |
| Geo Segments | [integer] | 3.22 | 2.94 | 1.00 | 2.23 | 6.00 | 136,824 |
| Yield Spread | [%] | 1.76 | 1.96 | 0.41 | 1.13 | 3.77 | 136,824 |
| $\mathbb{1}_{Downg.\ t+1}$ | [%] | 3.87 | 19.29 | 0.00 | 0.00 | 0.00 | 136,824 |
| $\mathbb{1}_{Downg.\ t+2}$ | [%] | 6.99 | 25.50 | 0.00 | 0.00 | 0.00 | 136,824 |

**Table IA2: Summary Statistics: Offering Yields.**

This table shows summary statistics of the main variables used in the offering yield regressions. Time to maturity and issue size are given in years and millions of dollars, respectively. Rating is a variable that assigns integer values to the different rating grades, starting from 1 for the highest and extending down to 21 for the lowest rating grade. Rating dispersion, number of agencies, business segments and geo segments are all given in integers. Yield spread is measured in percentage points of face value. Our sample represents offerings of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. We obtain bond characteristics and offering yields from Mergent FISD. The sample period is divided into before the crisis (January 2003 - November 2007), during the crisis (December 2007 - July 21, 2010) and after Dodd-Frank (July 22, 2010 - May 2014).

| Variable | Unit | Mean | Stdv | q10 | q50 | q90 | N |
|---|---|---|---|---|---|---|---|
| Time to Maturity | [years] | 9.83 | 8.23 | 3.00 | 8.08 | 30.00 | 2,858 |
| Issue Size | [millions] | 585.15 | 728.79 | 50.00 | 400.00 | 1,250.00 | 2,858 |
| Rating | [integer] | 7.27 | 3.80 | 3.33 | 6.00 | 13.50 | 2,858 |
| Rating Dispersion | [integer] | 0.44 | 0.51 | 0.00 | 0.58 | 1.16 | 2,858 |
| Number of Agencies | [integer] | 2.20 | 0.70 | 1.00 | 2.00 | 3.00 | 2,858 |
| Business Segments | [integer] | 3.43 | 2.73 | 1.00 | 2.79 | 6.00 | 2,858 |
| Geo Segments | [integer] | 3.04 | 2.83 | 1.00 | 2.16 | 6.00 | 2,858 |
| Yield Spread | [%] | 1.79 | 1.95 | 0.40 | 1.13 | 4.45 | 2,858 |

**Table IA3: Predictability of Rating Downgrades, Bond Yields and Asset Complexity: 2 Month Horizon.** We present results for variations of the following regression

$$\mathbb{1}_{Downg.\ i,t+2} = \beta_1 yield\ spread_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times yield\ spread_{i,t} + \beta_4 crisis_t + \beta_5 crisis_t \times yield\ spread_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is a dummy that equals 1 if in the following months $t+1$ or $t+2$ bond $i$ is downgraded. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $yield\ spread_{i,t}$ is the average daily yield spread of bond $i$ in month $t$. $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, rating number, rating dispersion, number of agencies, issuer fixed effects and quarter fixed effects). The regression sample includes fixed-coupon US corporate bonds that traded between January 2003 and May 2014. The first column reports the results on the full sample. The remaining columns show results where the sample is split between simple and complex bonds, using three different measures of complexity (financials/non-financials, number of business segments, number of geographical segments). Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | | Business Segments | | Geo Segments | |
|---|---|---|---|---|---|---|---|
| | | Complex | Simple | Complex | Simple | Complex | Simple |
| Yield Spread | 0.066*** | 0.082*** | 0.041*** | 0.052*** | 0.071*** | 0.058*** | 0.060*** |
| | (6.107) | (4.483) | (4.723) | (7.380) | (4.791) | (5.529) | (3.915) |
| Dodd-Frank | 0.043*** | 0.079*** | 0.015 | 0.011 | 0.052** | 0.049** | 0.032* |
| | (2.755) | (3.553) | (0.985) | (0.518) | (2.400) | (2.386) | (1.821) |
| Yield Spread × Dodd-Frank | −0.021* | −0.022 | −0.024** | −0.0001 | −0.031** | 0.001 | −0.041*** |
| | (−1.706) | (−1.028) | (−2.433) | (−0.005) | (−1.980) | (0.094) | (−2.654) |
| Observations | 136,824 | 74,548 | 62,276 | 62,974 | 73,850 | 83,615 | 53,209 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.147 | 0.161 | 0.141 | 0.155 | 0.170 | 0.161 | 0.161 |

**Table IA4: Bond Returns around Downgrades and Asset Complexity: Excluding Confounding Events.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} \\ + \beta_4 crisis + \beta_5 crisis \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the corporate bond return in excess of the market return during a 10 days trading day window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches and regulatory threshold dummy). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. We exclude rating changes that overlap with earning announcements (M&A) over an 11 (61) days window centered at the earning announcement day (M&A announcement and completion date). The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Dodd-Frank | −0.424 | −0.152 | 0.358 | −0.166 |
| | (−1.622) | (−0.498) | (0.756) | (−0.430) |
| Simple | | 0.348 | 0.416 | 0.450 |
| | | (1.250) | (0.924) | (1.345) |
| Dodd-Frank × Simple | | −0.767** | −1.174** | −0.899* |
| | | (−2.059) | (−2.438) | (−1.806) |
| Intercept | −2.036** | −2.632** | −1.775* | −0.637 |
| | (−2.127) | (−2.015) | (−1.871) | (−0.429) |
| Observations | 931 | 931 | 931 | 931 |
| Controls | Yes | Yes | Yes | Yes |
| $R^2$ | 0.122 | 0.127 | 0.129 | 0.099 |

**Table IA5: Bond Returns around Downgrades and Asset Complexity: Excluding Events Crossing IG/SP Threshold.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} + \beta_4 crisis + \beta_5 crisis \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the corporate bond return in excess of the market return during a 10 days trading day window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies and notches). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. We exclude rating changes that cross the investment/speculative grade threshold. The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Dodd-Frank | −0.384 | −0.126 | 0.437 | −0.139 |
| | (−1.565) | (−0.420) | (1.329) | (−0.566) |
| Simple | | 0.382 | 0.404 | 0.309 |
| | | (1.397) | (1.272) | (1.436) |
| Dodd-Frank × Simple | | $-0.706^{**}$ | $-1.262^{***}$ | $-1.069^{***}$ |
| | | (−1.983) | (−2.767) | (−2.676) |
| Intercept | −1.774 | −2.620 | −1.397 | −1.705 |
| | (−1.542) | (−1.540) | (−1.335) | (−1.456) |
| Observations | 1,084 | 1,084 | 1,084 | 1,084 |
| Controls | Yes | Yes | Yes | Yes |
| $R^2$ | 0.071 | 0.078 | 0.077 | 0.073 |

**Table IA6: Bond Returns around Downgrades and Asset Complexity: Controlling for Time-Varying Risk Premia.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} \\ + \beta_4 crisis + \beta_5 crisis \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the corporate bond return in excess of the market return during a 10 days trading day window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches, regulatory threshold dummy and corporate bond market risk premium in the month of the rating event). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: * < 0.1, ** < 0.05, *** < 0.01.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Dodd-Frank | −0.292 | −0.139 | 0.396 | −0.037 |
| | (−1.454) | (−0.514) | (1.249) | (−0.173) |
| Simple | | 0.225 | 0.302 | 0.388 |
| | | (0.879) | (0.959) | (1.496) |
| Dodd-Frank × Simple | | −0.575* | −1.049*** | −1.107** |
| | | (−1.760) | (−2.663) | (−2.506) |
| Intercept | −1.341 | −1.994 | −1.007 | −1.290 |
| | (−1.626) | (−1.291) | (−1.133) | (−1.555) |
| Observations | 1,180 | 1,180 | 1,180 | 1,180 |
| Controls | Yes | Yes | Yes | Yes |
| $R^2$ | 0.137 | 0.145 | 0.142 | 0.139 |

**Table IA7: Bond Returns around Downgrades and Asset Complexity: Weighting by the Initial Rating Distribution.** We present results for variations of the following regression

$$Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} + \beta_4 crisis + \beta_5 crisis \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t}$$

The dependent variable is the corporate bond return in excess of the market return during a 10 days trading day window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches and regulatory threshold dummy). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The returns during the crisis and after Dodd-Frank are weighted according to the distribution of rating events in the period before the crisis. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Dodd-Frank | $-0.518^{*}$ | $-0.162$ | 0.255 | $-0.182$ |
| | $(-1.889)$ | $(-0.423)$ | (0.835) | $(-0.716)$ |
| Simple | | 0.497 | 0.297 | $0.478^{**}$ |
| | | (1.315) | (1.147) | (2.023) |
| Dodd-Frank × Simple | | $-0.880^{*}$ | $-1.179^{***}$ | $-1.403^{***}$ |
| | | $(-1.854)$ | $(-2.714)$ | $(-3.223)$ |
| Intercept | $-2.284$ | $-3.126^{*}$ | $-1.822$ | $-2.195$ |
| | $(-1.369)$ | $(-1.726)$ | $(-1.297)$ | $(-1.310)$ |
| Observations | 1,180 | 1,180 | 1,180 | 1,180 |
| Controls | Yes | Yes | Yes | Yes |
| $R^2$ | 0.071 | 0.076 | 0.077 | 0.075 |

**Table IA8: Predictability of Rating Downgrades, Bond Yields and Asset Complexity: the Role of Institutional Ownership** We present results for variations of the following regression

$$\mathbb{1}_{Downg.\ i,q+1} = \beta_1 yield\ spread_{i,q} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times yield\ spread_{i,q} + \beta_4 crisis_t + \beta_5 crisis_t \times yield\ spread_{i,q} + \gamma' X_{i,q} + \epsilon_{i,q}$$

The dependent variable is a dummy that equals 1 if in the following quarter $q+1$ bond $i$ is downgraded. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $yield\ spread_{i,q}$ is the average daily yield spread of bond $i$ in quarter $q$. $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, rating number, rating dispersion, number of agencies, issuer fixed effects and quarter fixed effects). The regression sample includes fixed-coupon US corporate bonds that traded between January 2003 and May 2014. The first column reports the results on the full sample. The remaining columns show results where the sample is split between simple and complex bonds, using three different measures of complexity (financials/non-financials, number of business segments, number of geographical segments). Panel A (Panel B) presents results for bonds with low (high) ownership by insurance companies and mutual funds. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | | Business Segments | | Geo Segments | |
|---|---|---|---|---|---|---|---|
| | | Complex | Simple | Complex | Simple | Complex | Simple |
| **Panel A: Low Ownership of Insurance Companies and Mutual Funds** | | | | | | | |
| Yield Spread | 0.086*** | 0.093*** | 0.066*** | 0.073*** | 0.088*** | 0.084*** | 0.081*** |
| | (9.392) | (6.020) | (7.768) | (5.324) | (7.397) | (8.338) | (5.734) |
| Dodd-Frank | 0.127*** | 0.165*** | 0.038 | 0.129*** | 0.099*** | 0.146*** | 0.100*** |
| | (5.875) | (5.543) | (1.540) | (2.662) | (4.424) | (4.301) | (4.130) |
| Yield Spread × Dodd-Frank | −0.030*** | −0.027 | −0.030*** | −0.025 | −0.026* | −0.012 | −0.047*** |
| | (−2.884) | (−1.593) | (−2.577) | (−1.511) | (−1.944) | (−0.909) | (−3.253) |
| **Panel B: High Ownership of Insurance Companies and Mutual Funds** | | | | | | | |
| Yield Spread | 0.057*** | 0.103*** | 0.033*** | 0.044*** | 0.071*** | 0.075*** | 0.024 |
| | (5.434) | (4.278) | (3.037) | (3.910) | (3.924) | (5.043) | (1.550) |
| Dodd-Frank | | 0.111*** | 0.020 | 0.011 | 0.049** | 0.038 | 0.028 |
| | (1.528) | (3.337) | (1.418) | (0.463) | (2.235) | (1.511) | (1.610) |
| Yield Spread × Dodd-Frank | −0.014 | −0.032 | −0.028** | 0.0002 | −0.027 | −0.001 | −0.025 |
| | (−1.087) | (−1.184) | (−2.196) | (0.009) | (−1.299) | (−0.055) | (−1.498) |
| Observations Panel A | 22,781 | 15,886 | 6,895 | 10,934 | 11,847 | 12,916 | 9,865 |
| Controls Panel A | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ Panel A | 0.214 | 0.206 | 0.257 | 0.232 | 0.248 | 0.246 | 0.251 |
| Observations Panel B | 9,956 | 3,346 | 6,610 | 4,473 | 5,483 | 4,789 | 5,167 |
| Controls Panel B | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ Panel B | 0.195 | 0.233 | 0.184 | 0.221 | 0.224 | 0.217 | 0.215 |

**Table IA9: Bond Returns and Institutional Ownership with Issuer-Based Sorts.** We present results for variations of the following regression

$$\begin{aligned} Y_{i,t} = \alpha_{i,t} + \beta_1 simple_{i,t} + \beta_2 doddfrank_t + \beta_3 doddfrank_t \times simple_{i,t} \\ + \beta_4 crisis_t + \beta_5 crisis_t \times simple_{i,t} + \gamma' X_{i,t} + \epsilon_{i,t} \end{aligned}$$

The dependent variable is the corporate bond return in excess of the market return during a 10 days trading day window centered on the announcement date of bond rating downgrades. $crisis_t$ and $doddfrank_t$ are dummies indicating the crisis (December 2007 - July 21, 2010) and post Dodd-Frank (July 22, 2010 - May 2014) periods, respectively. $simple_{i,t}$ is a dummy indicating whether the issuer of the bond is classified as simple to rate based on three different complexity measures (financials/non-financials, number of business segments, number of geographical segments). $X_{i,t}$ is a vector of controls (time to maturity, issue size, liquidity, yield, issuer's total assets, rating number, rating dispersion, number of agencies, notches and regulatory threshold dummy). The regression sample includes downgrades of fixed-coupon US corporate bonds that occurred between January 2003 and May 2014. The first column reports the results without interactions. The last three columns report the results based on different definitions of the dummy $simple_{i,t}$. Panel A (Panel B) presents results for bonds with low (high) bond ownership by insurance companies and mutual funds measured at the firm-level. Standard errors are corrected for heteroscedasticity and clustered at the issuer and quarter level. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

| | All | Fin/Nofin | Business Segments | Geo Segments |
|---|---|---|---|---|
| Panel A: Low Ownership of Insurance Companies and Mutual Funds | | | | |
| Dodd-Frank | −0.271 | −0.117 | 0.981** | −0.338 |
| | (−0.856) | (−0.329) | (2.058) | (−0.991) |
| Simple | | 0.346 | 0.945** | 0.321 |
| | | (0.878) | (2.498) | (0.690) |
| Dodd-Frank × Simple | | −0.801 | −1.731*** | −1.265* |
| | | (−1.152) | (−3.155) | (−1.810) |
| Panel B: High Ownership of Insurance Companies and Mutual Funds | | | | |
| Dodd-Frank | −0.747* | −0.786 | −0.577 | −0.592 |
| | (−1.762) | (−1.204) | (−0.996) | (−1.262) |
| Simple | | 0.046 | −0.277 | 0.251 |
| | | (0.128) | (−0.759) | (0.764) |
| Dodd-Frank × Simple | | −0.070 | −0.334 | −0.589 |
| | | (−0.139) | (−0.712) | (−1.485) |
| Observations Panel A | 626 | 626 | 626 | 626 |
| Controls Panel A | Yes | Yes | Yes | Yes |
| $R^2$ Panel A | 0.094 | 0.100 | 0.107 | 0.093 |
| Observations Panel B | 554 | 554 | 554 | 543 |
| Controls Panel B | Yes | Yes | Yes | Yes |
| $R^2$ Panel B | 0.108 | 0.115 | 0.109 | 0.108 |