Credit Ratings across Asset Classes

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Abstract

We employ a comprehensive database of credit rating histories to compare the performance of credit ratings across broad asset classes and across types of structured products. We observe significant differences in default rates by rating, transition statistics, instantaneous upgrade and downgrade intensities, accuracy ratios, and other metrics. Some of these differences persist over our entire 30-year sample period. These results imply not only that outcomes of the rating process differ across asset classes, but also that asset classes have fundamentally different underlying rating processes. These results are important in light of the Dodd-Frank mandate to standardize credit ratings.

JEL classification: G14, G24, G28, G32

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"We have always had one scale, a consistent scale that we have tried to adopt across all our asset classes."

-- Deven Sharma, President, Standard & Poor's (S&P), July 27, 2011[1]

Credit rating agencies have persistently maintained that ratings are comparable across sectors and asset classes.[2] This assumption underlies the rating process itself. For example, raters relied on corporate bond rating transition distributions and default histories to estimate the credit risk of like-rated sovereign bonds and components of structured finance products prior to the recent financial crisis (S&P, 2005). The assumption that like-rated assets have comparable credit risk further underlies a host of financial regulations and investment policies, irrespective of whether the issuers are corporations, financial institutions, school districts, asset-backed securities, government sponsored entities or sovereign nations.

However, the market observed substantially different downgrade intensities of structured finance products during the recent financial crisis. Following the crisis, pension funds, municipalities, and even 'sophisticated' global financial institutions testified that they relied on ratings without distinction across asset classes.[3,4] In response, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (hereafter, Dodd-Frank) mandated comparability of default risk for like-rated securities (see §938). Toward this end, new rules proposed by the SEC (2011) require "*consistent application of ratings symbols and definitions*" across asset classes. The goal of these initiatives is for credit ratings to behave similarly across like-rated securities, regardless of their asset class.

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[1] Testimony before the U.S. House of Representatives, Committee on Financial Services, Oversight and Investigations Subcommittee, 2129 Rayburn Office Building, Washington DC, July 27, 2011.

[2] Appendix A exhibits these assertions by Moody's Investor Service (Moody's), Standard & Poor's (S&P), and Fitch Ratings (Fitch), collectively referred to as the Big 3 credit rating agencies (CRAs). An exception, discussed in Section 1 below, is Moody's municipal ratings dichotomy.

[3] A U.S. District Court denied Moody's and S&P dismissal of a claim brought by investors alleging that fraudulent ratings resulted in misallocated capital; No. 08 Civ. 7508, 2009 U.S. Dist. LEXIS 79607 (S.D.N.Y. Sept. 2, 2009). More recently, Australian Federal Court held Moody's and S&P liable for the misallocation of public funds attributable to inaccurate and misleading credit ratings; Bathurst Regional Council v Local Government Financial Services Pty Ltd (No 5) 2012 FCA 1200; Federal Court of Australia, ruling November 5, 2012.

[4] UBS Shareholder Report on Write-Downs explains "*Over-reliance on ratings: MRC relied on the AAA rating of certain Subprime positions, although the CDOs were built from lower rated tranches of RMBS. This appears to have been common across the industry...*"April 18, 2008, page 39.

We believe these initiatives will prove challenging to implement. There exists substantial variation in risk profiles of like-rated assets and credit quality shocks often affect different sectors in different ways. Expanding economies, for example, increase tax receipts and thus increase municipal bond (muni) ratings. Corporations similarly benefit in economic expansions, but often borrow money to repurchase shares in order to maintain financial leverage. In such a case, one might expect muni bonds to upgrade relative to like-rated corporate bonds. The most recent financial crisis offers another example. The crisis began with deterioration in RMBS, was then compounded in the CDOs formed from poorly–performing RMBS, and then affected corporation financing through distressed financial institutions. Because these sectors respond differently (in time and magnitude) to changes in underlying state variables, it is not obvious that ordinal rankings of credit risk in different asset classes can be expected to evolve similarly.

In this paper, we examine the performance of credit ratings across asset classes. We use a comprehensive database of credit ratings histories over the past 30 years for corporate bonds, sovereign bonds, municipal bonds, bonds issued by financial institutions, and the universe of structured products. A critical aspect of our approach is that although we document substantial differences across asset classes in common metrics like default rates and accuracy ratios, we focus most of our attention on how different asset classes exhibit different rating dynamics. We adapt migration statistics from the credit-VAR literature to establish that different asset classes have statistically different transition matrices year-by-year over our sample period. For example, we find that the ratings of corporate bonds tend to migrate down relative to those of like-rated municipal (sovereign) bonds in 24 of 25 (23 of 24) vintages.[5] Additionally, we show that different asset classes have significantly different instantaneous upgrade and downgrade intensities for both their total rating change histories and their initial rating changes. These results imply not only that the outcomes of the rating process (rating levels and subsequent

[5] Our sample of municipal (sovereign) bond ratings runs 1981 – 2010 (1982 – 2010). We require five years to gauge transitions, resulting in 25 five-year transition statistics comparing munis and corporate bonds.

default rates) differ across asset classes, but that asset classes have fundamentally different underlying rating processes.

Prior papers document problems in the ratings process for individual sectors of structured products.[6] We are the first to compare ratings across types of structured products and we find striking differences. Based on the magnitudes of downgrades during the crisis, we find tranches of Collateralized Debt Obligations (CDOs) and Residential Mortgage Backed Securities (RMBS) exhibited the greatest rating inflation at issuance, followed by Asset Backed Securities (ABS). However, Commercial Mortgage Backed Securities (CMBS) did not generally exhibit the optimistic ratings enjoyed by the RMBS. The ratings of Public Finance (PF) tranches were the least generous, performing more like the ratings of sovereign and municipal bonds than the ratings of other structured products.

In addition to examining ratings across the broad structured universe, our data allow us to examine the behavior of structured products' ratings over a longer time series than other papers. We find that some patterns persist throughout the sample, including the years before the crisis. For example, we find that CDOs tend to downgrade relative to like-rated corporate bonds throughout the entire history of CDOs, beginning with vintages issued in the 1990s. We also find that PF tranches tend to upgrade relative to like-rated corporate bonds throughout the entire history of PF tranches, including the crisis years.

The persistent differences in ratings migration and default risk we observe for like-rated assets from different classes lead us to conclude that there exist persistent differences in ratings standards. Variation in rating standards may result for multiple reasons. Asset opacity is one potential factor. For example, synthetic CDOs are more opaque than corporations with audited financial statements. If this opacity results in greater dispersion among credit assessment by competing raters, then it should result in greater opportunity for ratings shopping by the issuers of the CDOs. In the model of Skreta and Veldkamp (2009), ratings inflation results from issuer

[6] For work on CDOs, see Coval, et al. (2009), Griffin and Tang (2012) and Griffin, et al. (2013). For work on CMBS, see Stanton and Wallace (2013).

opacity even when all CRAs endeavor to produce accurate ratings. Further, Mathis, McAndrews, and Rochert (2009) suggest that CRAs' concerns over reputation capital diminish in issuer opacity.

However, issuer opacity cannot fully explain our results. The rating inflation of structured products is not confined to synthetic CDOs backed by credit default swaps. We find significant ratings inflation among RMBS and ABS. Pools of mortgages and credit card receivables are less opaque than corporate issuers with synthetic leases and other exotic off-balance-sheet liabilities.[7] We find even these more transparent structured products exhibit significant ratings inflation relative to corporate bonds. Moreover, we find no evidence of ratings inflation among the highly opaque municipal and sovereign issuers.[8] To the contrary, municipal and sovereign bonds' ratings are lower at issuance relative to ratings of corporate bonds with comparable risk.

Alternatively, our results could obtain because of the conflict of interest inherent in the issuer-pays compensation structure.[9] In the model of Fulghieri, Strobl, and Xia (2010), raters enhance their revenues and their reputations by issuing lower (pessimistic) ratings to non-paying issuers. If pessimistic ratings enhance rater reputation, raters rationally apply more stringent standards to issuers collectively paying the least. This hypothesis is similar to that tested by He, Qian, and Strahan (2012). These authors document significant ratings inflation among the CRAs' largest clients. Consistent with this conflict of interest, we find ratings optimism (inflation) increases with revenues by asset class. Revenues generated from structured products are significantly higher than those generated from corporate issuers which are, in turn, higher than those generated from sovereign issuers and municipalities. Unfortunately, we lack sufficient data

[7] See Beatty et al. (2010) and Zechman (2010) regarding financial reporting quality and off-balance-sheet financing.

[8] Moody's (2008) Sovereign Analytics Report describes the variety of risks associated with sovereign debt. The report reviews case studies of sovereign crises, discusses deposit freezes and debt moratoria, transfer and convertibility risk, country debt ceilings, the distinction between sovereign and country risk, changing legal provisions, correlation of sovereign default and banking crises, and Moody's qualitative approach to bond ratings.

[9] A parallel literature explores these conflicts of interest and the potential benefits of alternative CRA business models; e.g., Sangiorgi, Sokobin, and Spatt (2009), Strobl and Xia (2012), Bongaerts (2013), and Kashyap and Kovrijnykh (2013).

to document variation in profit margin, which would be more compelling than correlations with revenues (i.e., deal volume).

The third factor potentially leading to variation in rating standards is regulatory reliance on credit ratings to establish reserve requirements and prudent investment standards (Opp, Opp and Harris, 2012; Stanton and Wallace, 2013). Lax rating standards for structured finance products, relative to other asset classes, allow regulated institutional investors to chase yield without facing higher regulatory capital requirements (Becker and Ivashina, 2013). This regulatory reliance on ratings is likely to remain a factor despite the Dodd-Frank mandate to replace credit ratings with alternative risk metrics in federal regulation. To date, such attempts have not been successful (Becker and Opp, 2013). We likewise predict that the mandate to standardize ratings is infeasible, even given best efforts by the rating agencies toward this end. (See Kartasheva and Yilmaz, 2013, who also question the efficacy of this Dodd-Frank mandate.) We recommend instead a regulatory framework that distinguishes risk across asset classes.

As a final exercise, we explore the extent to which security prices vary by asset class. A thorough analysis of potential mispricing is beyond the scope of this paper, but we do find significant differences in offer yields after controlling for ratings. As such, the only conclusion we draw regarding the misallocation of capital is the potential circumvention of regulatory constraints suggested by Opp, et al. (2012). Although the pricing tests are limited, our main contribution – a comprehensive analysis of credit risk associated with each rating category across asset classes – should prove useful for establishing regulatory capital requirements, for fixed income portfolio management, and for the design of risk management systems.

1. Institutional Detail

1.1 Economic Importance of Credit Ratings

Credit ratings produced by Nationally Recognized Statistical Ratings Organizations (NRSROs) play an essential role in the U.S. economy. Ratings that are publicly observable and easy to interpret reduce contracting costs for creditors and other counterparties and provide

information to a host of market participants (Kliger and Sarig, 1999; Boot, Milbourn, and Schmeits, 2006). Ratings affect cost of capital (Faulkender and Petersen, 2006; Kisgen, 2006; Kisgen and Strahan, 2010) and corporate financing decisions (Hovakimian, Kayhan, and Titman, 2009; Kisgen, 2009; Sufi, 2009). Issuers who do not receive investment grade ratings face liquidity premiums (in addition to higher credit risk premiums) in part because regulators impose costs on banks, pension funds, and insurance companies holding speculative grade debt.[10] Because regulated institutions dominate fixed income markets (SIFMA, 2007) ratings-based regulations have important implications for capital allocation.[11]

Investment- versus speculative-grade is the most prominent threshold, but some regulations draw lines elsewhere along the rating scale. For example, the SEC has historically required money market funds to hold Aaa-rated commercial paper, and bank reserves vary with borrower ratings as per Basel II. Given variation in absolute credit risk, regulated institutional investors can to some extent circumvent regulatory constraints by directing funds to the higher risk asset classes with lower (risk-adjusted) capital requirements. For example, consider NAIC guidelines for insurance company reserves over our sample period:[12]

Credit ratings	Capital charge
AAA, AA, A	0.30%
BBB	0.96% (3.2 x Category 1)
BB	3.39% (11.3 x Category 1)
B	7.38% (24.6 x Category 1)
CCC	16.96% (56.5 x Category 1)
CC or lower	19.50% (65.0 x Category 1)

A hypothetical insurance company holding A rated RMBS (45.7% default in our 1980-2010 sample) face the same capital reserve requirements as an insurance company holding A rated municipal bonds (0.5% default) or A rated corporate bonds (1.8% default). Assuming that

[10] See Chen, et al. (2007) regarding liquidity premiums; see White (2010) regarding the pervasive regulatory reliance on ratings; see Ellul, et al. (2011) for evidence of fire sales induced by regulatory compliance.

[11] Dodd-Frank calls for the removal of ratings in SEC rules and other federal regulations. However, state (i.e., insurance) and international (i.e., Basel) regulators are not subject to Dodd-Frank mandates.

[12] Post-tax capital requirements are from the National Association of Insurance Commissioners (NAIC) Risk-Based Capital Newsletter (10/12/2001).

sophisticated risk assessment and securities prices reflect information beyond credit ratings (e.g., Cornaggia and Cornaggia, 2013) the first hypothetical insurance company in our example circumvents the spirit of the regulatory constraints. Becker and Ivashina (2013) document such yield chasing among insurance companies before *and after* the financial crisis of 2008. This post-crisis evidence indicates intentional yield chasing rather than naïve reliance on ratings prior to the crisis. To the extent that variation in ratings standards across asset classes reflects pressure from regulated institutions, we should not expect standards to converge following the crisis.

1.2 Recalibrating Ratings after Dodd-Frank

In contrast to Moody's public assertion of comparable ratings (Appendix A), its analysts made clear that they have historically rated municipal bonds on a more stringent scale; Moody's (2002a).[13] This 2002 report explains that while Moody's muni bond rating scale is distinct, its corporate bond rating scale is applicable to sovereign issuers and structured products. Moody's (2007) refers to this latter scale "used to rate all bonds outside of the U.S. public finance market" as the *Global Rating Scale*.

Moody's attributes this ratings dichotomy in part to munis' tax-exempt status (for U.S. investors) and in part to a finer gradation in the more stringent muni rating scale.[14] Unlike the *Global Rating Scale* that reflects expected loss, the muni scale reflects the probability that the municipality will need support from higher levels of government. Historically, state governments cover bond payments for distressed municipalities resulting in trivial expected losses among muni bonds which suggest Aaa ratings according to the *Global Rating Scale*.

Following Dodd-Frank (which mandates ratings comparability), Moody's announced a recalibration of its muni bond ratings onto the *Global Rating Scale*. This recalibration resulted in upgrades to $1.7 trillion muni bonds, with a range of one to five notches (Cornaggia, Cornaggia,

[13] Moody's reports a 0.0420% ten-year cumulative default rate for the entire population of muni bonds over 1970-2000. This total rate is lower than the 0.6750% default rate for Aaa corporate bonds over the same period.

[14] Regarding the coarseness and refinement of bond rating scales, see Goel and Thakor (2013) and Tang (2009), respectively.

and Israelsen, 2013). Likewise, S&P (2009) discusses changes in their rating criteria for CDOs and RMBS intended to improve the comparability of ratings.

However, the fact that Moody's ratings reflect expected losses, rather than unconditional default probabilities, complicates comparison even after recalibration. Taxing authority and implied support from higher levels of government reduces the probability of a municipal default, relative to corporations. However, conditional on default, the illiquidity of assets funded by municipal bonds (sewage systems, transportation, public schools, athletic arenas, etc.) results in lower expected recovery (Trzcinka, 1982). Moreover, muni bonds are commonly wrapped with third party insurance to protect their tax exempt cash flows; see Nanda and Singh (2004). Together, these differences lead us to question the premise underlying the Dodd-Frank mandate and SEC proposal that ratings can be effectively standardized.

2. Data

A primary contribution of this paper to the ratings literature is comprehensive data. We obtain complete ratings histories for obligations issued between 1980 and 2010 by corporations (industrials and transportation companies), financial institutions (U.S. banks, U.S. bank holding companies, securities companies, and insurance companies), sovereign nations, and local and regional governments from Moody's Default and Recovery Database (DRD). We only include regular bonds in order to make straightforward comparisons across asset classes (e.g., we exclude convertible or callable bonds). We further obtain complete ratings histories for structured finance products issued between 1980 and 2010 including ABS (backed by various receivables including credit cards, auto loans, student loans, and equipment leases), CDOs, CMBS, PF deals, and RMBS from Moody's Structured Finance Default Risk Service Database (SFD). The SFD contains a comprehensive universe of Moody's rated structured products and the DRD a comprehensive universe of corporations, financial institutions, and sovereign nations. However, the DRD contains only a sample (N = 6,410) of municipal issues which is the only sample Moody's makes available to us. We contemplate potential selection biases and conclude

that if issues contained in the DRD were 'cherry picked' such a selection bias should work against our general finding that these bonds receive abnormally low ratings.[15] We describe and compare these different issue types in Section 2.1 below.

We map Moody's ratings to a 21-point numeric scale where Aaa is 21 and C is 1. The scale ranges from most to least creditworthy, so our rating measure increases in credit quality and decreases in credit risk. Obligations with ratings equal to Baa3 or higher (12 – 21) are investment grade and obligations with ratings of Ba1 or lower (1 – 11) are speculative grade.

2.1 Sample Description

We describe the sample, by asset class, in Table 1. Because our data are comprehensive, this section constitutes the most exhaustive such comparison in the literature. The median face value of corporate bonds ($132M) is more than twice the size of the median municipal issue ($64M). Sovereign issues are the largest by a wide margin; median $769M. Financial issues and structured tranches are considerably smaller; $25M and $19M at the median, respectively. However, as noted above, the broad structured finance category includes securities backed by a variety of underlying assets. Within structured products, the face value of ABS tranches are the largest ($36M median) followed by CDOs ($30M), CMBS ($24M), RMBS ($13M); PF tranches are the smallest ($3M median).[16] We observe large differences in maturity. Structured product tranches have an average maturity of 24.3 years with a median 29 years. Other classes have means and medians in the range of 5 to 9 years.

Initial ratings vary by class, as do frequencies of ratings changes. The median corporate issue is initially rated A3 (15), which is investment grade. Further, these bonds are more likely to be downgraded (36% probability over the life of the bond) than upgraded (15%). Conversely, the sample of muni bonds are almost three times more likely to be upgraded than downgraded (30% versus 12%), and are more likely to be upgraded than corporate bonds – even though the median

[15] Without resource constraints, we would examine all NRSROs. Because ratings by the Big 3 are highly correlated (Bongaerts, Cremers, and Goetzman, 2012) results for S&P or Fitch would likely be similar to those reported here.

[16] Results by subcategory of structured products are tabulated in the Internet Appendix.

muni is issued at a higher rating (Aa1) than the median corporate bond. Sovereign issues' ratings are similar to muni bond ratings in this regard. They are almost twice as likely to be upgraded than downgraded, even though the median sovereign bond has a higher rating at issuance (Aa3) than the median corporate bond. Financial issues' ratings are similar to, but more volatile than, corporate bond ratings (41% downgrade and 23% upgrade). The median structured tranche is issued with the Aaa rating, which curtails upgrade potential for this class; structured tranches exhibit a downgrade frequency (40%) which is comparable to corporate and financials, but a much smaller upgrade frequency (6%). Frequency of default also varies by asset class. Four percent of corporate bonds default over the sample period. Less than 1% of munis default. Two percent of sovereign and financial bonds default and 15% of structured tranches default. This percentage varies widely by the underlying asset type: 20% of ABS, 29% of CDOs, 15% RMBS and 4% of CMBS default. No tranches of PF deals default in our sample period.

We plot annual issuance volume in our sample by asset class in Figure 1. Because the sample of munis is incomplete, this figure represents our sample and not necessarily the entire market. However, we have complete ratings history for all structured products and Figure 1 clearly indicates the growth in this sector. Figure 2 provides greater detail of initial ratings for each asset class and how these evolve over time. In each panel, the proportions are cumulative with the issues rated Aaa appearing at the top, Aa second from top, and so on.

Several interesting patterns emerge from Figure 2. Sovereign issues (Panel C) were generally investment grade (Baa or higher) prior to the wave of sovereign crises beginning in the mid-1990's.[17] Panel E contains tranches of all structured issues showing the dynamics in initial ratings of these products over time. Proportionally, the greatest increase is in the Baa tranches, which have the lowest investment grade ratings. As explained above, the investment grade threshold has important implications for regulatory compliance. Virtually nonexistent prior to the

[17] See Bartram, Brown, and Hund, (2007) for details on the Mexican crisis (December 1994), Asian crisis (July 1997), Russian crisis (August 1998), LTCM crisis (September 1998), Brazilian crisis (January 1999) and the disruption to the financial system following the attacks on the U.S. in September 2001.

mid-1990's, the Baa tranches represent 10.2% of structured issues in 1999, grow to 15% in 2000 and peak at 26% in 2006 before declining to 5% and 7% in 2009 and 2010, respectively. In the earlier years of the sample, 95% to 100% of tranches received Aaa ratings. This proportion declined to 52% in 1995, ranging from 50% to 65% thereafter.[18] Results by subcategory are available in the Internet Appendix.

2.2 Moody's Revenue by Asset Class

In Figure 3, we plot annual revenue by asset class as reported in Moody's 10-K filings.[19] By 2005, revenues from rating structured products ($709M) are 2.5 times revenues from rating corporate bonds ($277M). By 2008, the difference is smaller ($405M and $307M, respectively). By 2009 corporate bond revenue once again surpasses structured products. Taken together, Figures 1, 2, and 3 suggest that Moody's greatest reliance on issuers of structured products occurred between 2000 and 2007. Following the collapse of the structured finance market in 2008 (Figure 2), corporate issuers are again the primary source of revenue (Figure 3). Public Finance is always the least relevant source of Moody's revenue.

3. Ratings Performance and Comparability across Asset Classes

In this section, we show that like-rated bonds in different asset classes exhibit significant variation in credit quality using a variety of performance metrics. To ease interpretation, we employ corporate bond ratings as our benchmark. We analyze structured finance deals at the tranche level because Moody's can downgrade one tranche (e.g., a Ba1 rated tranche) without

[18] Although the proportion of Aaa decreased over our sample period, the total volume of Aaa rated structured products increased (combine Figure 1 and Figure 2) consistent with the predictions of Opp, Opp, and Harris (2012).

[19] Prior to 2007, Moody's combined revenue from financial and sovereign issuers into one asset class. In 2007, Moody's began including sovereign issuers in "Public Finance" along with local governments. To display consistent classifications through time, we estimate the revenues attributable to sovereign issuers in 2007-2010 and add it to financial institutions to estimate "Financials and Sovereigns" as reported prior to 2007. Specifically, we note that in 2006, the last year before the switch, revenue from sovereign (financial) issuers constituted 10.5 (89.5) percent of "Financials and Sovereigns". Assuming a constant proportion, we reconstitute "Financials and Sovereigns" for the years 2007 through 2010 by dividing "Financial Institutions" by 0.895. For the same years, we subtract from "Public Finance" an amount of revenue equal to the difference between our estimate of "Financials and Sovereigns" and "Financial Institutions" as reported. Ignoring the reclassification does not alter relative rankings throughout the entire 2000-2010 period; public finance remains the lowest source of revenues with or without the sovereign segment and corporate issues and structured products remain the top-two revenue generating asset classes.

downgrading others (e.g., the Aaa rated tranche) in the same deal. However, we recognize that the tranches of any particular deal are not entirely independent. Thus, we cluster standard errors in regression models at the issuer level (for corporate, municipal, sovereign, and financial issues) and deal level (for tranches of structured products). Because distinct types of underlying assets vary in terms of complexity, and various issuer types contribute differently to CRA revenue, we partition structured products into various types in most analyses.

3.1 Default Percentages by Asset Class and Initial Credit Ratings

We document the frequency of default by initial rating across asset classes in Table 2.[20] That is, we report the percentage of bonds issued Aaa (or Aa, etc.) that later default within our sample period separately for each class. To avoid small sample biases, we require at least 100 issues per asset class-initial rating category for admission to this analysis. Moody's (2002b) intends its ratings to be ordinal in nature; we should thus find the default frequency strictly decreasing in credit ratings. This pattern appears to be the case for the corporate, municipal, and sovereign issues. However, the 4.13% default rate among A rated financial bonds exceeds the 2.18% for the Baa rated bonds in that class. Moreover, the default rate (39.52%) among the Baa rated structured products mirrors those of the speculative grade tranches (38.00% among B rated and 36.58% among C rated tranches).

Table 2 clearly indicates a material difference in the default risk implied by any given rating across asset classes over the entire sample period. For example, consider the default frequencies in the A range: corporations 0.51%, municipals 0.00%, sovereigns 0.00%, financials 4.13%, and structured tranches 26.97%. The segmented structured products better indicate the defaulting issue types. The pervasive defaults of investment grade tranches are primarily among ABS, RMBS, and CDO tranches. In contrast to RMBS, the defaulting CMBS tranches were largely issued with speculative grade ratings. There are no defaults among the PF tranches.

[20] In the DRD, Moody's defines missed interest payments and bankruptcy filings as default events. In the SFD, Moody's defines interest impairment and principal impairment as default events.

3.2 Transition Matrices

A growing theoretical and empirical literature concludes that Moody's issuer-paid compensation results in an optimistic bias in favor of issuers as going concerns (e.g., Jiang, Stanford, and Yuan, 2012) and in favor of particular issuers that constitute a disproportionate amount of Moody's revenue (e.g., He, Qian, and Strahan, 2012). Moody's (2002b, page 7) and Manso (2013) attribute the optimistic bias to the self-fulfilling nature of credit ratings. We test for differences in rating bias at the time of issuance across asset classes by observing aggregate ratings migration. For example, if Moody's errs on the side of optimism for corporate issuers, we should observe greater downgrade propensities than upgrade propensities over the lives of these bonds. If this bias is stronger for issuers of structured products, then we should observe greater discrepancy in the upgrade and downgrade propensities of these issues, relative to corporate bonds. Evidence of equal upgrade and downgrade propensities in any particular asset class is inconsistent with the notion that Moody's awards optimistic ratings at issuance for that class of issuers.

We test for differences in ratings optimism by comparing transition matrices in Table 3. We report the number of issues in each ratings bin, rather than percentages of the initial rating, five years after the date of issue. Numbers make it easier to visualize the relative mass across asset classes and across ratings bins within each class. The sum column conveys the relative likelihood of each initial rating allowing comparison across classes. We summarize the percentages of upgrades and downgrades by initial rating in the rightmost columns.

We begin by reporting migration among corporate issues (Panel A) which serve as our benchmark. The disparity between upgrade (6.63%) and downgrade (19.06%) frequencies is consistent with an optimistic bias at the time of issuance.[21] Given upper and lower bounds, unbiased ratings should exhibit greater upward (downward) migration among the lowest (highest) rated bonds. We find that bonds in every rating category are more likely downgraded.

[21] These rating changes are observed over five years and thus do not match lifetime change frequencies in Table 1.

Moreover, the highest upgrade frequency is among the bonds issued just below the critical investment grade threshold. Overall, these results support the conclusion that Moody's is sensitive to issuing firms from whom it receives its primary compensation (see also Kraft, 2010; Bruno, et al., 2013; and Xia, 2013).

The migration of municipal bond ratings in Panel B is very different from that of corporate bonds. Although munis have a higher percentage of initial ratings in the upper echelon (33.65% Aaa and 50.80% Aa), they are far less likely to downgrade (2.64%) than corporates and more likely to upgrade (9.14%). The upgrade frequency is particularly high among the A and Baa rated muni bonds; 48% and 23%, respectively.[22] However, the small fraction of munis issued speculative grade exhibit higher downgrade frequency.

The migration of sovereign issues in Panel C resembles that of munis with an 8.40% (11.08%) frequency of downgrades (upgrades) and a relatively high incidence of upgrades among the upper echelons (13.90% of Aa rated issues and 19.90% of A rated issues). Financial issues in Panel D behave similarly to corporates (23.11% downgrade), although the frequency of upgrades is higher (12.00%). The ratings migration in Panel E suggests that structured finance products enjoyed the most inflated initial ratings of the broad asset classes. Within this category, rating inflation appears most severe among the CDOs (62.39% downgraded versus 2.20% upgraded) followed by RMBS (45.61% vs. 3.45%) and ABS (36.30% vs. 2.53%).[23] The inflation among CMBS (32.23% downgraded vs. 8.78% upgraded) is less pronounced, and the PF tranches are closest to symmetric (15.04% vs. 6.03%).

Because municipal bonds (structured products) constitute a relatively low (high) proportion of Moody's revenue, these results are consistent with the conclusion by He, et al. (2012) that rating bias is a function of rater revenue.

3.3 Transition Statistics

[22] These upgrades in 1980-2010 do not reflect Moody's recalibration, which followed Dodd-Frank Act of 2010.

[23] Results for subcategories of structured products are tabulated in the Internet Appendix.

A drawback of transition matrices is that they aggregate ratings performance over the sample period. That analysis demonstrates differential behavior among asset classes over the last three decades, but it does not allow us to specify the periods of time in which the individual asset classes experienced the greatest and least amounts of transition, nor whether the differences in transitions are statistically significant. This section extends the analysis by using an innovative methodology based on Trück and Rachev (2005) to compute annual transition statistics – scalars that summarize the amount of transition exhibited by the ratings of each asset class and each year of issuance – and their associated standard errors to assess statistical significance.

We begin by creating five-year transition matrices similar to those in Table 3, but for each asset class in each year of issuance. For example, instead of creating one five-year transition matrix for all corporate issues as in Panel A of Table 3, we separately create 26 five-year transition matrices for corporate issues. That is, we construct matrices that reveal how the credit ratings of each cohort of corporate bonds issued each year from 1980 to 2005 transition over the course of five years after issuance. We convert these matrices into probability matrices according to the proportions of ratings that migrate off the diagonal for each initial rating.[24]

The next step implements a weighting procedure similar to that in Trück and Rachev (2005). We multiply each probability by the difference between its corresponding row and column in the matrix. This procedure accomplishes two objectives. First, it attaches a positive sign to upward transitions and a negative sign to downward transitions. Second, distant migrations receive more weight than proximal migrations.

Finally, we sum the weighted probabilities for each row of the matrix and value weight each row by the number of bonds in each rating to calculate the final metric. The domain of this metric is [-9, 8]. A metric of -9 requires all bonds to be issued with Aaa ratings, and all of them must default within five years (i.e., they must migrate down nine notches). A metric of 8 requires

[24] Please refer to the Internet Appendix for a detailed numeric example.

all bonds to be issued with C ratings, and Moody's must upgrade all of them to Aaa within five years (i.e., they must migrate up eight notches).

We calculate these statistics for each asset class and each year of issuance and plot them in Figure 4. To avoid clutter, we plot each asset class' time series of transition statistics separately against the transition statistics for corporate issues for comparison. We calculate bootstrapped standard errors for each transition metric. We perform 1,000 bootstrap replications for each transition metric, each drawing with replacement a sample size equal to the number of bonds issued in a given year for a given asset class.

We first plot the transition statistics for municipal and corporate bonds. The results indicate Moody's tends to downgrade corporate bonds more than it downgrades munis over the entire sample period. Only for the 1986 vintage do municipal issues experience greater downgrades, and the difference is not statistically significant. In 18 of 25 years with complete data, corporate bonds exhibit significantly greater downward transitions than munis. We next plot the transition statistics for sovereign bonds. Similar to the results for munis, the results indicate Moody's tends to downgrade corporate bonds more than it downgrades sovereign issues for all but one cohort (1992). The difference between sovereign and corporate transition statistics is statistically significant in ten of 24 years with complete data. Taken together, the results indicate corporate bonds receive more generous ratings at issuance than municipal or sovereign issues, and this pattern is pervasive throughout the sample period. The plot of transition statistics for financial issues does not suggest systematic rating differences between corporate and financial issues—in some years corporate bonds downgrade more, in other years less.

We analyze individual types of structured products (ABS, CDO, CMBS, PF, and RMBS) in the final plots of Figure 4. We observe significant differences between each type of structured product and the corporate benchmark. Moreover, we observe differences across the different structured products. The plots of ABS and RMBS suggest little change in credit quality (or little ratings surveillance) among the early vintages of these structured products. Downgrades of the

ABS and RMBS begin with deals issued after 2002. The CMBS plot resembles the RMBS plot, although the migration of the CMBS is significantly smaller than the migration of the RMBS; the transition statistic for the final 2005-2010 vintage is -1.2 for CMBS and -4.4 for RMBS. Only the CDO plot is consistently below the corporate benchmark in each period (from the earliest 1996 vintage).

In stark contrast to the other structured products, the plot for PF tranches resembles the plots for munis and sovereign issues; it is always above the plot for corporate bonds. This result further indicates that ratings migration reflects the risk of underlying assets, and that public assets are fundamentally different than the more liquid assets backing corporate bonds and conventional ABS backed by mortgages and credit card receivables.

3.4 Hazard Rate Models

Results in Section 3.3 show that different asset classes have statistically different ratings transition statistics. This would result if different asset classes have different rating change intensities. This section formally tests differences in probabilities of ratings changes across asset classes by comparing hazard rates for downgrades and upgrades. Specifically, we denote the instantaneous downgrade (or upgrade) rate for bond j as $h_j(t)$ and estimate:

$$h_j(t) = h_0(t)\exp(\beta X) \tag{1}$$

for a vector of covariates X. This approach is a single-failure Cox proportional hazard model with "failure" denoting a downgrade (upgrade), the unit of observation being the time until a downgrade (upgrade) for each rating change, and allowing observations to exit or censor upon upgrade (downgrade), maturity, default, or the end of the sample period. For the vector of covariates X representing dummy variables corresponding to membership in various asset classes, the coefficient β represents the proportional shift in the instantaneous baseline downgrade/upgrade intensity, which we set to correspond to corporate bonds. For example, $\beta_i = 2$ indicates that asset class i has a downgrade rate which is twice that of corporate bonds; $\beta_i = 0.5$ indicates that asset class i has a downgrade rate half that of corporate bonds. This specification

implies that significance testing is versus the null of $\beta_i = 1$. Coefficients for all asset classes statistically indistinguishable from 1 imply ratings comparability in the sense that the distributions of ratings changes are indistinguishable from those of corporate issues. An advantage of this approach is that it allows us to look at asymmetry in the upgrade and downgrade process, focusing on the variation in this asymmetry across asset classes and within the broad structured finance universe.

Table 4 presents the results of Cox regressions over the full sample period for all ratings changes and for subsamples of ratings changes originating from investment and speculative grades. We recognize that ratings changes are not independent within or across asset classes and cluster standard errors separately by year, by issue, by issuer, and report the most conservative (largest standard errors are obtained by clustering at the issue level). We observe that ratings change intensities differ significantly across asset classes. All but two coefficients in the table are significant, most are different from the baseline (corporate bonds) at the 1% level.

The pattern across the full sample indicates low relative downgrade intensities and high relative upgrade intensities for municipal and sovereign bonds and exactly the opposite pattern for structured products, with ABS and CDOs exhibiting especially high downgrade intensities. The 98.6% of municipals and 84.3% of sovereign issues that are issued with investment grade ratings (see Table 3) clearly drive the results observed in the full sample. We observe insignificant coefficients only for the 1.4% of municipal bonds (column 6) and the 15.7% of sovereign issues (column 3) that are issued with speculative grade ratings.

Instances where upgrade and downgrade intensities are both greater than the baseline point to highly volatile yet unbiased (relative to corporate issues) ratings changes, which is the case for the financial institutions. Such a pattern might reflect greater opacity of financial institutions compared to corporate issuers. Overall, this table suggests that initial ratings for municipal and sovereign bonds are low (harsher) relative to corporate bonds, ratings for

structured products are high (optimistic) relative to corporate bonds, and financial institutions are simply more volatile.

A potential drawback of using all ratings changes as observations is that the estimation could be skewed by differences in ratings momentum across asset classes.[25] In Table 5 we limit the sample to the first rating change after issuance to more directly measure the potential implied bias in the initial rating. The results for municipal, sovereign, and financial issuers are similar to those in Table 4. The evidence still strongly suggests initial ratings biased in favor of CDO issuers. Results for other structured products differ. Downgrade propensities of ABS and RMBS remain higher than their upgrade propensities. However, ABS and RMBS are less likely than corporates to experience a downgrade as their *first* rating change. We infer that the higher propensity to downgrade observed among ABS and RMBS in Table 4 is driven by ratings changes that occur later in the life of these securities. This result is less consistent with systematic rating inflation at issuance (as observed in the CDOs) among non-CDO structured products. In contrast to RMBS, CMBS are as likely as corporates to experience an upgrade as their first ratings change. Tranches from the public finance deals have greater symmetry between upgrade and downgrade intensities, and are less volatile than corporates.

As in Table 4, the results in Table 5 strongly reject the idea that ratings changes are comparable across asset classes. By focusing on the first rating change, we infer ratings bias only among municipal and sovereign issues (harsher than corporates) and CDOs (more optimistic than corporates). Other asset classes exhibit greater or lesser ratings volatility, but do not appear biased based on the Cox proportional hazard regression models in Table 5.

Prior results indicate variation in credit standards for corporate bonds over time.[26] We are particularly interested in testing for differences in standards across asset classes during the growth of structured finance markets and, separately, the recent financial crisis. We conduct

[25] Lando and Skodeberg (2002) document ratings momentum using a method similar to our Cox regressions.

[26] See Blume, et al. (1998), Jorion, et al. (2009), Becker and Milbourn (2011), Baghai, et al. (2012), Alp (2013), and Bar-Isaac and Shapiro (2013).

separate regressions using observations from 1980–2000, 2001–2006, and 2007-2010 in Table 6. We find that differential ratings changes are greatest during – but not exclusive to – the crisis period of 2007-2010. Nearly half of the ratings changes occur after 2006, reflecting both the massive waves of issuance in the 2000-2006 period and the rush to downgrade during the financial crisis. During the crisis, all structured products and financial institutions face far higher downgrade intensities than the baseline corporate intensity. Municipal and sovereign bonds maintain significantly lower downgrade intensities than corporate bonds across all periods. Munis' relative upgrade intensity varies, but sovereign issues also face higher upgrade intensities in all periods. Only CDOs appear more optimistically rated than corporate bonds in the pre-crisis period between 1980 and 1999. CDO downgrade intensity only decreases toward that of corporates during the "boom" of 2000-2006. CDOs' upgrade intensities remain significantly lower than that of corporate bonds throughout the entire sample period.

Perhaps most interesting are the results for the non-CDO structured products (ABS, CMBS, and RMBS, in particular). The early vintages of these issues exhibited less inflation than corporate bonds (as evidenced by downgrades prior to 2007). Recall from Figure 2 that early vintages of structured products did not account for as much CRA business as the later vintages. The coinciding increase in volume and revenue and decrease in rating standards for these assets is further consistent with the conclusion by He, et al. (2012) that rating bias is a function of rater revenue.

Finally, we note that differences between CMBS and RMBS upgrade intensities are evident in each time period and strongest prior to 2007. We infer that differences between commercial and residential mortgage risk are not confined to the real estate bubble or the expanded subprime lending in the 2000-2006 period.

Results from the Cox proportional regression framework overwhelmingly reject the hypothesis of ratings comparability. Asset classes differ not only in levels of ratings and default behavior, but also in their distributions of ratings changes and their volatility. Credit risk models

(such as J.P. Morgan's CreditMetrics™) that use ratings transition matrices as an input yet ignore asset classes will not only under- or over-estimate ratings volatility, they will also have biased distributions of rating change intensities.[27]

3.5 Rating Change Regressions

We further test for differences in ratings changes across asset classes in the regression models found in Table 7. The regression models in Panel A capture the magnitude as well as the direction of ratings changes as opposed to the Cox proportional hazard regressions which model only the relative probabilities of upgrades and downgrades. The Probit models in Panel B test for differences in the highly consequential downgrades that cross the investment grade threshold.

Additionally, we include control variables and year-of-issue fixed effects in Table 7. We include the size of the issue (*Face*), the market's initial pricing of the issue (*Coupon*), and the issue maturity (*Maturity*). Table 1 indicates differences across asset classes along these dimensions. We also control for credit ratings at issuance. Because many tranches of structured products received Aaa ratings at issuance, these ratings can only migrate down. Controlling for initial ratings mitigates the influence of these highly-rated securities. The inclusion of year-of-issue fixed effects mitigates the influence of macroeconomic trends.

In Panel A, ratings changes are measured in rating notches for each issue from the time of issuance until the bond matures, defaults, or until the end of available data. Our numeric conversions of ratings are increasing in credit quality; i.e. Aaa = 21 and C = 1. Therefore, if a bond was issued with a rating of Aaa (21) and matured with a rating of Aa2 (19), its rating change would be -2. This specification means that variables with positive (negative) coefficients contribute upward (downward) rating migration over the course of the bonds' lives. We omit the dummy variable for corporate bonds; these are captured by the constant and serve as our

[27] Technical documentation of the CreditMetrics methodology is available from the RiskMetrics Group here: http://www.msci.com/resources/technical_documentation/CMTD1.pdf

benchmark. Thus, asset classes' coefficient estimates represent changes in the dependent variable relative to changes among corporate bonds. We cluster the standard errors at the issuer level.

The baseline model (1) in Panel A indicates that relative to corporates, the ratings of munis and sovereign bonds migrate upward after issuance. In contrast, structured products' ratings migrate downward. The ratings of bonds issued by financial institutions do not update significantly differently than the corporate bond ratings. In models (2) through (7) we partition structured finance products into subcategories. These results indicate that the significant downgrade of structured products relative to corporate issues is driven by CDOs, and to a lesser extent ABS and RMBS. Conversely, CMBS and PF tranches upgrade relative to corporate issues. Perhaps it is not surprising to find the PF deals update similarly to municipal and sovereign bonds. We find it remarkable, however, that CMBS should update so differently than RMBS. Securities backed by commercial real estate loans are rated less optimistically than securities backed by residential real estate loans and this difference is significant at 1%.[28]

We consider next downgrades that cross the investment grade threshold. Panel B of Table 7 displays results for Probit models with dependent variables that take the value of one when a security is downgraded from investment grade to speculative grade and zero otherwise. As in Panel A, these regressions control for issue characteristics and year-of-issue fixed effects. The only difference is the exclusion of Face, which adds no explanatory power in Panel A. As in Panel A, the constant captures corporate bonds which serve as our benchmark.

In each model, munis are significantly less likely to downgrade below investment grade, relative to corporate bonds. Coefficients on sovereign issues are also negative, but significant only in model (3). PF and CMBS tranches are also less likely than corporates to cross the investment grade threshold from above; PF significantly different at 1% and CMBS significant (at 5%) only in model (2). In contrast, coefficients are significantly positive for ABS, CDO, and RMBS even after controlling for *Initial rating* in model (5). These structured products are more

[28] Column (7) contains the most stringent model. Here, the coefficient on CMBS is 2.762 and the coefficient on RMBS is -0.766. The difference between the two is 3.528 and is significant at 1% (standard error = 0.812).

likely than corporate bonds to receive investment grade ratings at issuance and subsequently downgrade to speculative territory.

Overall, the results reported in Table 7 are consistent with more stringent ratings of both municipal and sovereign issues at issuance and more generous rating of structured products, especially ABS, RMBS and CDOs. PF tranches are more similar to municipal and sovereign issues than to other structured products. There are also significant differences between CMBS and RMBS. Specifically, CMBS do not exhibit the optimistic ratings enjoyed by RMBS. Results are generally robust to the inclusion of bond characteristics, initial credit rating, and year-of-issue fixed effects. As such, we cannot attribute these results to macroeconomic conditions at issuance.

3.6 Cumulative Distributions of Default Prediction Ability and Accuracy Ratios

Perhaps the most common metrics of ratings performance are empirical cumulative distributions of default prediction and accuracy ratios (e.g., Moody's, 2003, and Cornaggia and Cornaggia, 2013). Figure 5 displays cumulative distributions of default for the five main asset classes in our sample (Panel A), as well as individual structured product types (Panel B). For each asset class and type of structured product, we count the number of bonds with a given credit rating as of January 1 of any year of the sample and the number of those bonds that default over the following year. For each credit rating, we divide the full sample count of defaulted bonds by the full sample count of bonds. This approach calculates a default percentage associated with each rating. Panels A and B plot the cumulative distribution of these percentages for each asset class and type of structured product, moving from the lowest credit rating to the highest. The solid black line in both panels represents the cumulative distribution of ratings that have no predictive content. In other words, if Moody's randomly assigned ratings, then we would expect equal percentages of defaults among the rating categories, and the solid black line representing a uniform cumulative distribution function would emerge.

In Panel A, the cumulative distribution for municipal bonds lies higher and further to the left than the other four asset classes. Table 1 indicates that the default rate among our municipal bonds is less than 1%. Figure 5 suggests that Moody's does a better job identifying defaults among munis compared to other asset classes. Closest to the cumulative distribution for munis is that of corporate bonds. The cumulative distribution for tranches of structured products lies closest to the hypothetical "randomly assigned" diagonal. This pattern obtains because more of the highest-rated tranches of structured products default than similarly rated bonds of other asset classes. We compute accuracy ratios in order to formally express the difference between these cumulative distributions. An asset class's accuracy ratio measures the area between its cumulative distribution and the diagonal line. The larger the ratio, the more accurate the ratings are in an ordinal sense. To be concrete, we calculate the accuracy ratios as follows:

$$\textit{Accuracy ratio} = \sum_{k=1}^{N}\left[\sum_{j=1}^{k}\left[\frac{\dfrac{\textit{Number of issues that default over the next year}_j}{\textit{Number of issues}_j}}{\sum_{i=1}^{N}\dfrac{\textit{Number of issues that default over the next year}_i}{\textit{Number of issues}_i}} - \frac{j}{N}\right]\right] \qquad (2)$$

N = the number of credit rating classifications (we combine ratings of Caa1, Caa2, Caa3, Ca, and C since so few bonds have these ratings) and i, j, and k are numerical translations of issues' credit ratings. The accuracy ratios for the five asset classes are as follows: municipal bonds = 0.44, corporate bonds = 0.40, sovereign bonds = 0.36, financial bonds = 0.30, and tranches of structured products = 0.16. The accuracy ratios of the individual structured products are as follows: CMBS = 0.33, ABS = 0.17, RMBS = 0.14, and CDO = 0.09. We cannot calculate an accuracy ratio for PF tranches because none default in our sample.

Taken together, the accuracy ratios provide additional evidence that credit ratings behave differently across asset classes over our 1980 - 2010 sample period. Ratings of municipal bonds perform best in terms of ordinal performance, with those of corporate bonds performing second best. Ratings of structured products perform worst in an ordinal sense, with those of CDOs exhibiting the worst performance of the asset class.

3.7 Offer yields

Because a host of financial regulations employ credit ratings as benchmarks, the differences we document have important implications for the allocations of regulated capital. However, this does not imply that securities are mispriced. Indeed, regulated institutional investors may perceive a benefit (i.e., higher yields with lower capital requirements) from inflated ratings of structured products; see Opp, et al. (2012) and Becker and Ivashina (2013). The extent to which investors identify the variation in credit risk implied by any particular credit rating remains an open question – a question being considered by multiple courts of law (see footnote 3).

Although a thorough analysis of potential mispricing is beyond the scope of this paper, we obtain data to explore the extent to which security prices reflect information beyond credit ratings across asset classes.[29] Table 8 displays OLS regressions of offer yields on dummy variables indicating asset classes and credit ratings at issuance. This approach allows us to test whether the market prices like-rated bonds similarly across asset classes. As in prior tables, the constant captures corporate bonds which serve as our benchmark.

Because the DRD and SFD databases do not provide yields, the analysis in Table 8 employs data from Thomson Reuters' SDC Platinum (SDC).[30] SDC provides information including issue date, offer yield, credit rating at issuance, principle, proceeds, and maturity. Because SDC sometimes reports principal and proceeds in different units (e.g., principal may be reported in millions and proceeds in hundreds of thousands for the same observation) we drop all observations for which principal is less than "100" and keep only those observations for which

[29] See Driessen and Van Hemert (2011) for a more rigorous empirical analysis of CMBX pricing.

[30] This sample period spans January 1, 1980 to November 21, 2012. Observations categorized as Structured Finance include ABS and MBS (issue types AB and MB). Observations categorized as Public Finance are drawn from "Agency Supranational Sovereign" (issue type AS). We include nations (e.g., Italy), provinces (e.g., Ontario), and cities (e.g., Berlin) and exclude supranational issuers (e.g., European Union) and Government-backed corporate debt (e.g., Morgan Stanley debt backed by the FDIC Temporary Liquidity Guarantee Program). Observations categorized as Corporate are drawn from non-convertible bonds and medium term notes (MTNs) and include both investment grade and high yield (issue types IG and HY). We categorize issuers in SIC codes 6000-6999 as Financial Institutions.

proceeds are within 0.80 and 1.20 of principal. This approach mitigates the potential for the inclusion of observations with misreported issue size.

Controlling for initial ratings and year-of-issue fixed effects, model (1) indicates that public finance issues (bonds issued by nations, provinces, states, cities, and other state-owned enterprises) are priced similarly to corporate bonds. However, structured products and bonds issued by financial institutions have higher offer yields than similarly rated corporate bonds. These results are robust to the inclusion of maturity and principal in models (2) and (3). As in Table 7, principal adds no explanatory power.

The results are highly sensitive to the inclusion of issuer fixed effects in model (4). The results in model (4) indicate significantly lower offer yields (at 1%) among the public finance issues, relative to like-rated corporate bonds. The coefficient on structured finance increases fivefold suggesting much greater differences in the pricing of structured products, relative to similarly rated corporate bonds. Including issuer fixed effects removes variation in idiosyncratic issuer characteristics leaving variation in macroeconomic conditions and asset classes.[31] Bonds issued by financial institutions appear to be priced similarly to like-rated corporate bonds in model (4). The results in model (4) are more closely in line with an efficient bond market, given the results we report in Tables 3–6.

We leave for future research formal asset pricing models allowing inferences about efficient pricing. We merely conclude from Table 8 that the market prices additional information beyond credit ratings across asset classes. As such, the only conclusion we can draw regarding the misallocation of capital is the potential circumvention of regulatory constraints.

4. Conclusion

[31] We consider regression models including both year-of-issue and issuer-fixed effects. However, including both substantially limits the amount of variation available to identify coefficients. (Specifically, the coefficients would identify off of variation within issuers over time or within issuer-years. Only 26.5% of the issuers in the sample issue debt in multiple years and only 5.5% of the issuers ever issue debt more than once in any year.)

We examine credit ratings across asset classes from 1980 - 2010. We document substantial differences in default rates, accuracy ratios, and rating dynamics across asset classes and within the broad structured finance universe. We adapt migration metrics from the credit-VAR literature and document statistically different transition statistics, year-by-year over our sample period. Hazard models further indicate that different asset classes have significantly different instantaneous upgrade and downgrade intensities for both their initial rating change and their total rating history. Our results imply not only that the outcomes of the rating process (rating levels and subsequent default rates) differ across asset classes, but that these asset classes have fundamentally different underlying rating processes. Although prior research documents inflated ratings of structured products and their contribution to the financial crisis, we are the first to provide a comprehensive analysis of ratings across asset classes over time. Our novel results indicate significant differences in ratings transition metrics outside of the crisis period. Our results further indicate significant differences among structured product types.

Our results contribute to the debate surrounding regulatory reliance on credit ratings that do not reflect absolute credit risk. Failure of regulators to distinguish risk associated with A rated CDOs (31.26% default frequency) compared to A rated corporate bonds (0.51% default frequency) and A rated municipals (no defaults in our sample) potentially allows banks, money market and pension funds, and insurance companies to circumvent regulatory safeguards.

Rating agency incentives notwithstanding, there exists substantial variation in risk profiles of the assets underlying various security types. For example, we find that PF tranches migrate more similarly to municipal bonds than to other structured products. Furthermore, credit-quality shocks are often specific to (or highly concentrated in) particular sectors. We therefore conclude that the Dodd-Frank mandate and SEC proposal to standardize ratings across asset classes will prove difficult to enforce. Instead, we advocate a regulatory framework that distinguishes regulatory capital and prudent investment requirements across asset classes. The analysis we provide should prove useful for these purposes.

References

Alp, Aysun, 2013, Structural shifts in credit ratings, *Journal of Finance,* forthcoming.

Baghai, Ramin, Henri Servaes, and Ane Tamayo, 2012, Have rating agencies become more conservative? Implications for capital structure and debt pricing, working paper.

Bar-Isaac, Heski., and Joel Shapiro, 2013. Ratings quality over the business cycle, *Journal of Financial Economics* 108(1), 62-78.

Bartram, Sohnke, Greg Brown, and John E. Hund, 2007, Estimating systemic risk in the international financial system, *Journal of Financial Economics* 86, 835-869.

Beatty, Anne, Scott Liao, and Joseph Weber, 2010, Financial reporting quality, private information, monitoring, and the lease-versus-buy decision. *The Accounting Review* 85, 1215-1238.

Becker, Bo and Victoria Ivashina, 2012, Reaching for yield in the bond market, Harvard Business School working paper 12-103.

Becker, Bo and Todd Milbourn, 2011. How did increased competition affect credit ratings?, *Journal of Financial Economics* 101(3), 493-514.

Becker, Bo, and Marcus Opp. 2013. Replacing ratings. Working paper.

Blume, Marshall E., Felix Lim, and A. Craig MacKinlay, 1998, The declining credit quality of U.S. corporate debt: Myth or reality?, *Journal of Finance* 53(4), 1389-1413.

Bongaerts, Dion, Martijn Cremers, and William Goetzman, 2012, Tiebreaker: certification and multiple credit ratings, *Journal of Finance* 67, 113-152.

Bongaerts, Dion, 2013. Can alternative business models discipline credit rating agencies? Working paper.

Boot, Arnoud W.A., Todd T. Milbourn, and Anjolein Schmeits, 2006, Credit ratings as coordination mechanisms, *Review of Financial Studies* 19(1), 81-118.

Bruno, Valentina, Jess Cornaggia, and Kimberly J. Cornaggia, 2013, Does certification affect the information content of credit ratings?, working paper.

Chen, Long, David A. Lesmond, and Jason Wei, 2007, Corporate yield spreads and bond liquidity, *Journal of Finance* 62(1), 119-49.

Cornaggia, Jess, and Kimberly J. Cornaggia, 2013, Estimating the costs of issuer-paid credit ratings, *Review of Financial Studies* 26(10) 2229-2269.

Cornaggia, Jess, Kimberly J. Cornaggia, and Ryan Israelsen, 2013, Are Credit Rating Agencies Still Relevant Information Intermediaries?, working paper.

Coval, Joshua, Jakub Jurek, and Erik Stafford, 2009, The economics of structured finance, *Journal of Economic Perspectives* 23(1), 3–25.

Driessen, Joost, and Otto Van Hemert, 2011, Pricing of commercial real estate securities during the 2007-2009 financial crisis, working paper.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond markets, *Journal of Financial Economics* 101(3), 596-620.

Faulkender. Michael, and Mitchell A. Petersen, 2006, Does the source of capital affect capital structure? *Review of Financial Studies* 19(1), 45-79.

Fons, Jerome S., 2008, Congressional Testimony Before the Committee on Oversight and Government Reform, U.S. House of Representatives, October 22.

Fulghieri, Paolo, Gunter Strobl, and Han Xia, 2010, The economics of solicited and unsolicited credit ratings, working paper.

Goel, A.M. and A.V. Thakor. 2013. Why are credit ratings coarse? Working paper.

Griffin, J.M., Tang, D., 2012. Did subjectivity play a role in CDO credit ratings? Journal of Finance 67(4), 1293-1328.

Griffin, J.M., J. Nickerson, and D.Y. Tang, 2013, Rating shopping or catering? An examination of the response to competitive pressure for CDO ratings, *Review of Financial Studies* 26 (9) 2270-2310.

He, Jie, Jun Qian, and Philip E. Strahan, 2012, Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities, *Journal of Finance*, forthcoming.

Hovakimian, Armen, Ayla Kayhan, and Sheridan Titman, 2009, Credit rating targets, working paper.

Ingram, Robert W., Leroy D. Brooks, and Ronald M. Copeland, 1983, The information content of municipal bond rating changes: A note, *Journal of Finance* 38(3), 997-1003.

Jiang, J.X., Stanford, M., Yuan, X., 2012. Does it matter who pays for bond ratings? Historical evidence. *Journal of Financial Economics* 105(3), 607-621.

Jorion, Philippe, Charles Shi, and Sanjian Zhang, 2009, Tightening credit standards: the role of accounting quality, *Review of Accounting Studies* 14, 123-160.

Kashyap, A. K. and N. Kovrijnykh. 2013. Who should pay for credit ratings and how? NBER working paper 18923.

Kartasheva, A.V. and B. Yilmaz. 2013. Precision of Ratings. Working paper.

Kisgen, D.J., 2006. Credit ratings and capital structure, *Journal of Finance* 61(3), 1035-72.

Kisgen, D.J., 2009. Do firms target credit ratings or leverage levels?, *Journal of Financial and Quantitative Analysis*, 44(6), 1323-1344.

Kisgen, Darren J. and Philip E. Strahan. 2010. Do Regulations Based on Credit Ratings Affect a Firm's Cost of Capital?, *Review of Financial Studies* 23(12), 4324-47.

Kliger, D., Sarig, O., 1999. The information value of bond ratings, *Journal of Finance*, 55(6), 2879-2903.

Kraft, Pepa, 2010, Do rating agencies cater? Evidence from rating-based contracts, working paper.

Lando, David, and Torben M. Skødeberg, 2002, Analyzing rating transitions and rating drift with continuous observations, *Journal of Banking and Finance* 26(2), 423-444

Manso, G., 2013. Feedback effects of credit ratings, *Journal of Financial Economics,* forthcoming.

Mathis, Jerome, James McAndrews, and Jean-Charles Rochet, 2009, Rating the raters: Are reputation concerns powerful enough to discipline rating agencies?, *Journal of Monetary Economics* 56, 657-674.

Moody's, 2002a, Special Comment: Moody's US municipal bond rating scale, November.

Moody's, 2002b, Special Comment: Understanding Moody's corporate bond ratings and rating process, May.

Moody's, 2003, Special Comment: Measuring the performance of corporate bond ratings, April.

Moody's, 2007, Rating Methodology: The U.S. Municipal Bond Rating Scale: Mapping to the Global Rating Scale and assigning Global Ratings to municipal obligations, March.

Moody's, 2008, Sovereign Analytics: Sovereign defaults and interference: Perspectives on government risks, August.

Nanda, Vikram, and Rajdeep Singh, 2004, Bond insurance: What is special about munis?, *Journal of Finance* 59 (5), 2253-2279.

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

Sangiorgi, Francesco, Jonathan Sokobin, and Chseter Spatt, 2009,. Credit-rating shopping, selection and the equilibrium structure of ratings, working paper.

SIFMA, 2007, *SIFMA/EPDA/EHYA response to CESR call for evidence on non-equity markets transparency*, March 6.

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

Standard & Poor's, 2005, CDO Evaluator Version 3.0: Technical Document, December 19.

Standard & Poor's, 2009, Big changes in Standard & Poor's Rating Criteria, November 3.

Stanton, Richard, and Nancy Wallace, 2013, CMBS subordination, ratings inflation, and regulatory capital arbitrage. Working paper.

Strobl, Gunter and Han Xia, 2012. The issuer-pays rating model and ratings inflation: Evidence from corporate credit ratings, working paper.

Sufi, Amir, 2009. The real effects of debt certification: Evidence from the introduction of bank loan ratings, *Review of Financial Studies* 22(4), 1659-91.

Tang, Tony T., 2009. Information asymmetry and firms' credit market access: Evidence from Moody's credit rating format refinement, *Journal of Financial Economics* 93, 325-51.

Trück, Stefan, and Svetlozar T. Rachev, 2005, Changes in migration matrices and credit VaR – a new class of difference indices, Working paper.

Trzcinka, Charles, 1982, The pricing of tax-exempt bonds and the miller hypothesis, *Journal of Finance* 37 (4), 907-923.

U.S. Securities and Exchange Commission, 2011, Summary report of commission staff's examinations of each NRSRO: As required by Section 15E(p)(3)(c) of the Securities Exchange Act of 1934.

White, Lawrence J. 2010. Markets: The credit rating agencies, *Journal of Economic Perspectives*, 24(2), 211-26.

Xia, Han, 2013. Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?, working paper.

Zechman, Sarah, 2010, The relation between voluntary disclosure and financial reporting: Evidence from synthetic leases. *Journal of Accounting Research* 48, 725-765.

Appendix A

CRA assertion of comparable rating standards across asset classes[32]

"Standard & Poor's strives to make its rating symbols reflect a broadly comparable view of creditworthiness wherever they appear. Standard & Poor's believes that maximizing comparability makes Standard & Poor's' ratings more useful to investors. Thus, when Standard & Poor's assigns a given rating symbol to multiple issuers, it intends to connote roughly the same opinion of creditworthiness, irrespective of whether the issuers are a Canadian mining company, a Japanese financial institution, an Illinois school district, a British mortgage-backed security, or a sovereign nation."

- Deven Sharma, President, Standard & Poor's, February 7, 2011

"To meet needs over time, credit ratings have developed important attributes including insightful, robust and independent analysis, symbols that succinctly communicate opinions, and broad coverage across markets, industries and asset classes. These attributes have enabled credit ratings to serve as a point of reference and common language of credit that is used by financial market professionals worldwide to compare risk across jurisdictions, industries and asset classes, thereby facilitating the efficient flow of capital worldwide."

- Farisa Zarin, Managing Director, Moody's Investors Service, February 18, 2011.

"Fitch's first and primary goal is that over the longer term, default rates will be broadly similar for like-rated securities across all asset classes. As a secondary goal, Fitch aspires to greater comparability of ratings transition/volatility across asset classes, especially at the highest end of the rating scale."

- John S. Olert, Chief Credit Officer, Fitch Ratings, March 7, 2011. (Reference is taken from appended "Ratings Comparability" Special Report dated June 21, 2010, and co-authored by Mr. Olert.)

[32] We collect these quotes from comment letters written in response to the SEC's proposed Credit Rating Standardization: www.sec.gov/comments/4-622/4-622.shtml

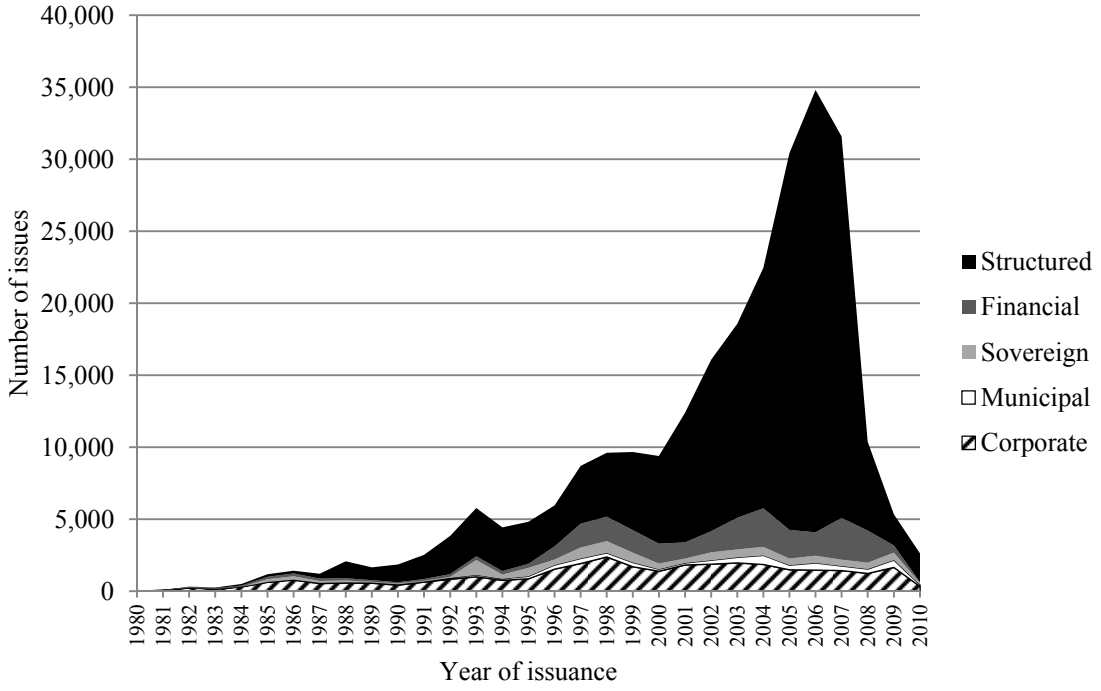
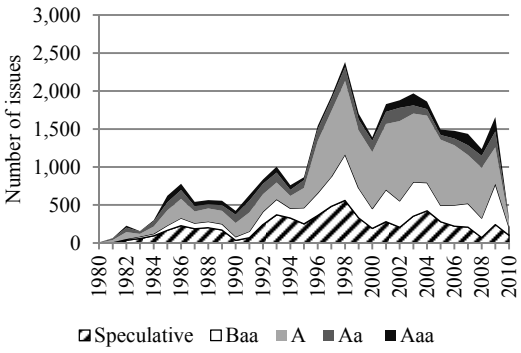
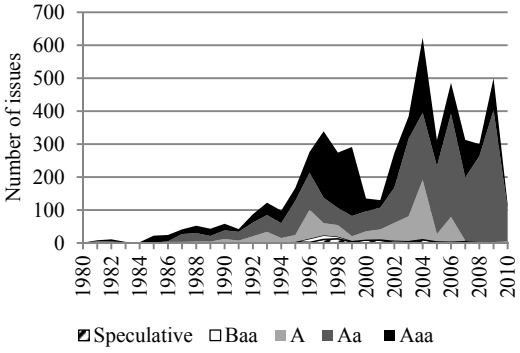


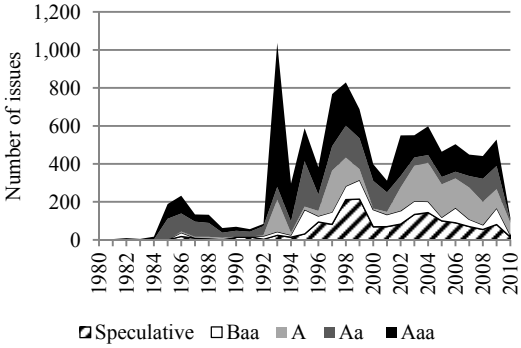
Figure 1
Number of issues by asset class through time
This figure displays the number of issues in our sample rated by Moody's Investors Service every year from 1980 to 2010 partitioned by asset class. The asset classes include tranches of structured products, bonds issued by financial institutions (U.S. banks, U.S. bank holding companies, securities companies, and insurance companies), bonds issued by sovereign nations, bonds issued by municipalities, and bonds issued by corporations (industrials and transportation companies). The data come from Moody's Default and Recovery Database, and Moody's Structured Finance Default Risk Service Database.



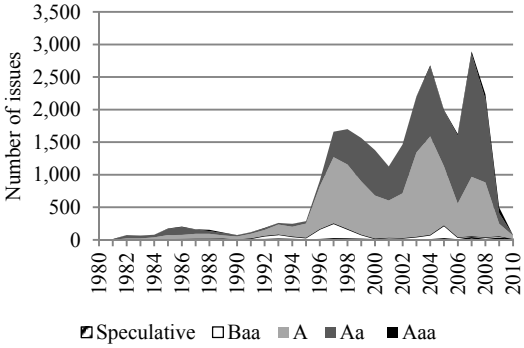
Panel A. Corporate issues



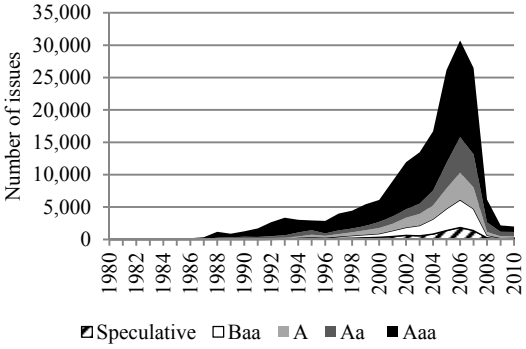
Panel B. Municipal issues



Panel C. Sovereign issues



Panel D. Financial issues



Panel E. Structured issues

Figure 2
Number of new issues per year by initial credit rating and asset class

Panels A through E display the number of new issues rated by Moody's every year from 1980 to 2010 for each asset class and initial credit rating. The asset classes include tranches of structured products, bonds issued by financial companies (U.S. banks, U.S. bank holding companies, securities companies, and insurance companies), bonds issued by sovereign nations, bonds issued by local and regional governments, and bonds issued by corporations (industrials and transportation companies). The data come from Moody's Default and Recovery Database, and Moody's Structured Finance Default Risk Service Database. The rating scale in this figure is a simplified version of Moody's traditional 21-point alphanumeric scale. For example, we combine initial issues with credit ratings of Aa1, Aa2, and Aa3 into one bin, Aa. Additional panels displaying structured products partitioned according to their underlying assets (i.e., ABS, CDOs, CMBS, PF, and RMBS) are available in the Internet Appendix.

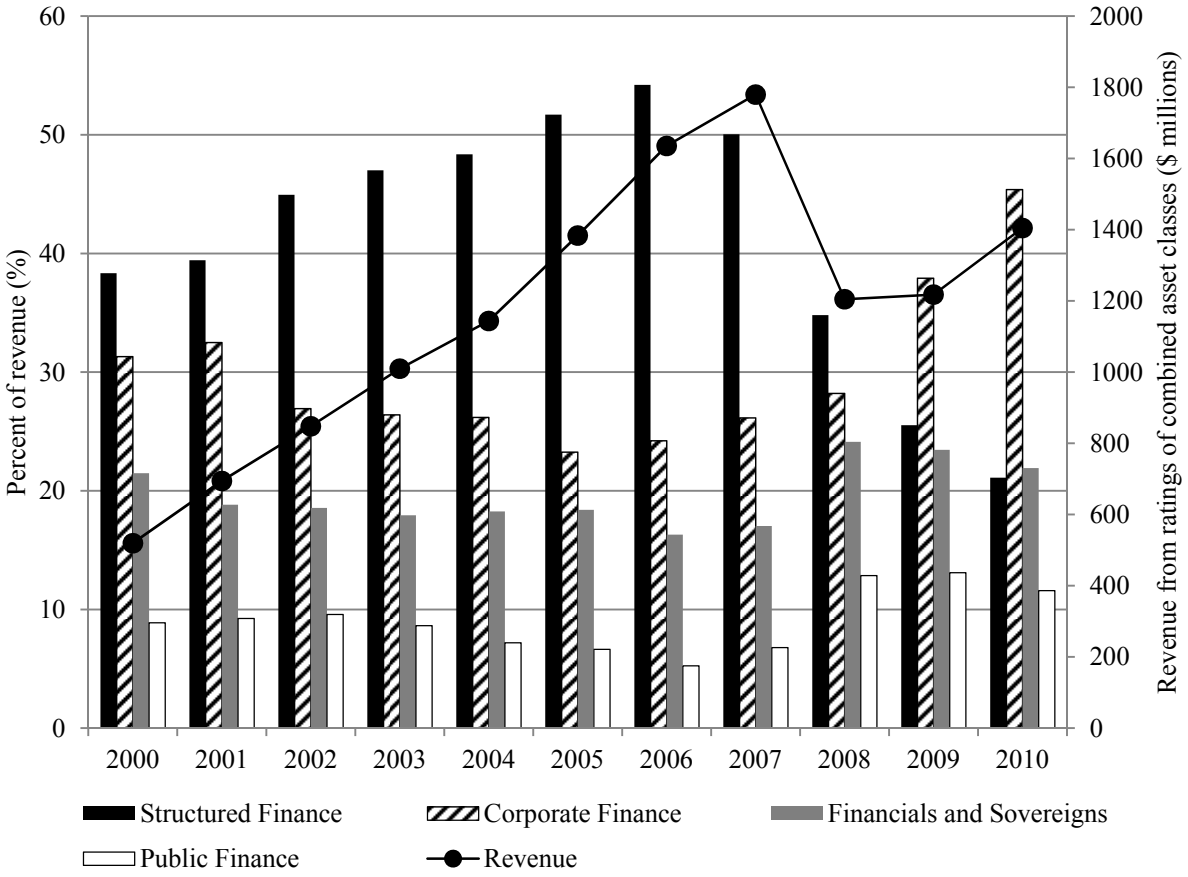
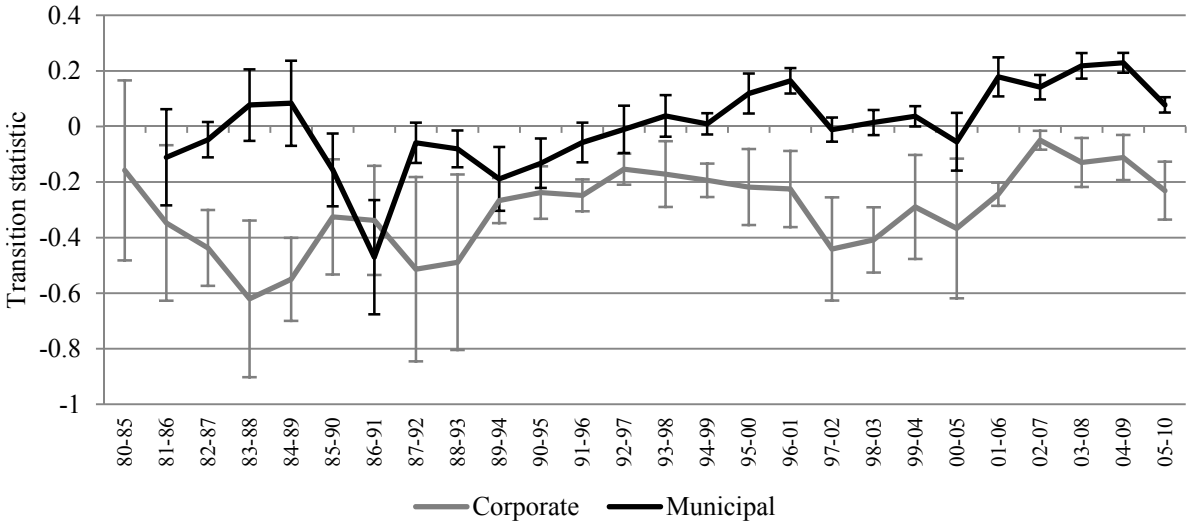


Figure 3
Moody's revenue by asset class through time
This figure displays revenue generated by Moody's from 2000 to 2010 partitioned by asset class. We collect this information from Moody's 10-k filings. Prior to 2007, Moody's combined revenue from financial and sovereign issuers into one asset class, "Financials and Sovereigns". In 2007, Moody's began including revenue from sovereign issuers in "Public Finance" along with revenues from local governments. In an effort to display consistent revenue classifications through time, we estimate the revenues attributable to sovereign issuers in 2007-2010 and add it to financial institutions to estimate "Financials and Sovereigns" as reported by Moody's prior to 2007. Specifically, we note that in 2006, the last year before the switch, revenue from sovereign (financial) issuers constituted 10.5 (89.5) percent of "Financials and Sovereigns". Assuming a constant proportion going forward, we reconstitute "Financials and Sovereigns" for the years 2007 through 2010 by dividing "Financial Institutions" by 0.895. For the same years, we subtract from "Public Finance" an amount of revenue equal to the difference between our estimate of "Financials and Sovereigns" and "Financial Institutions" as reported by Moody's.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Corporate
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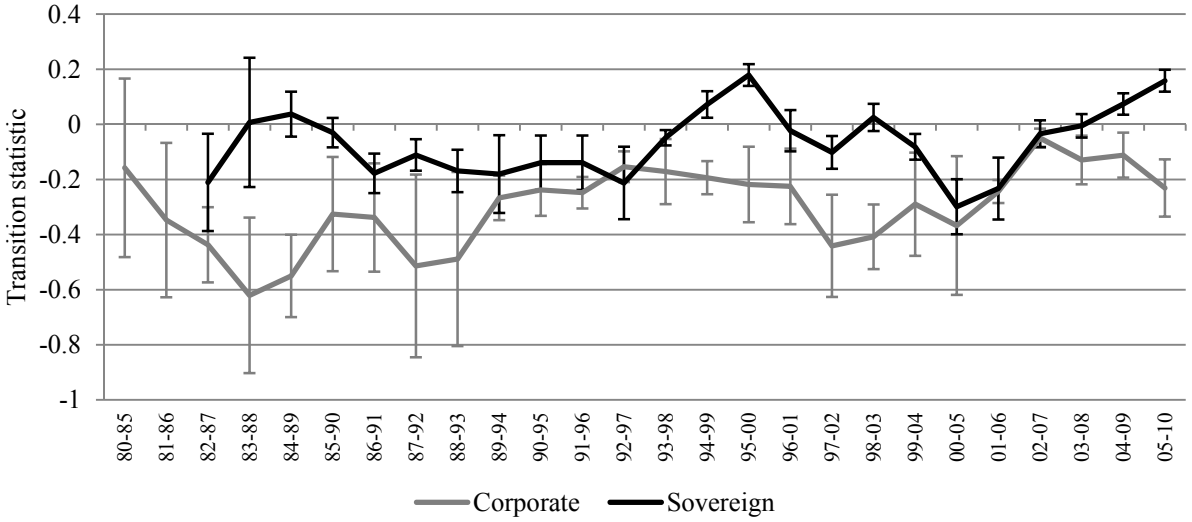
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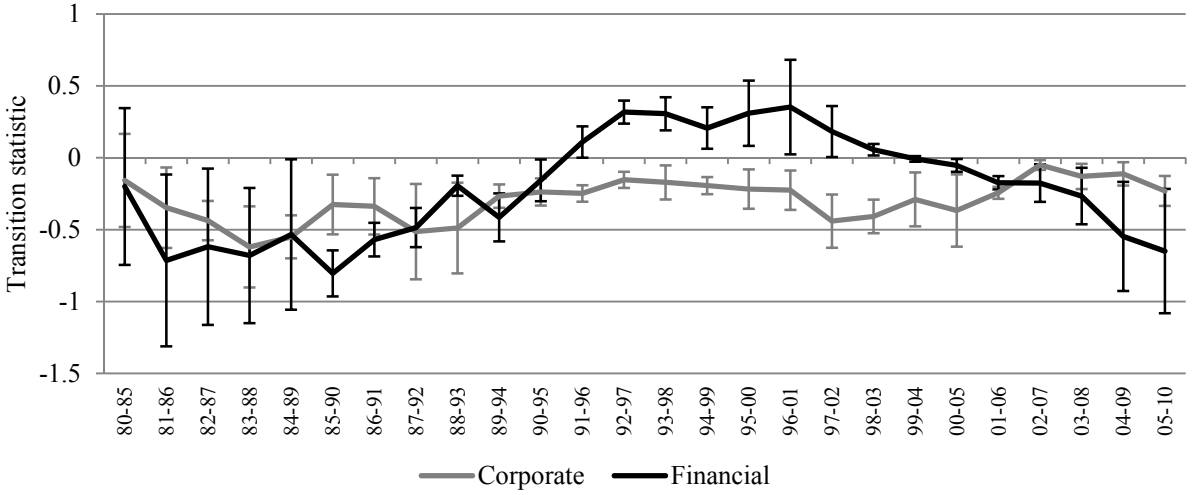
Corporate
Sovereign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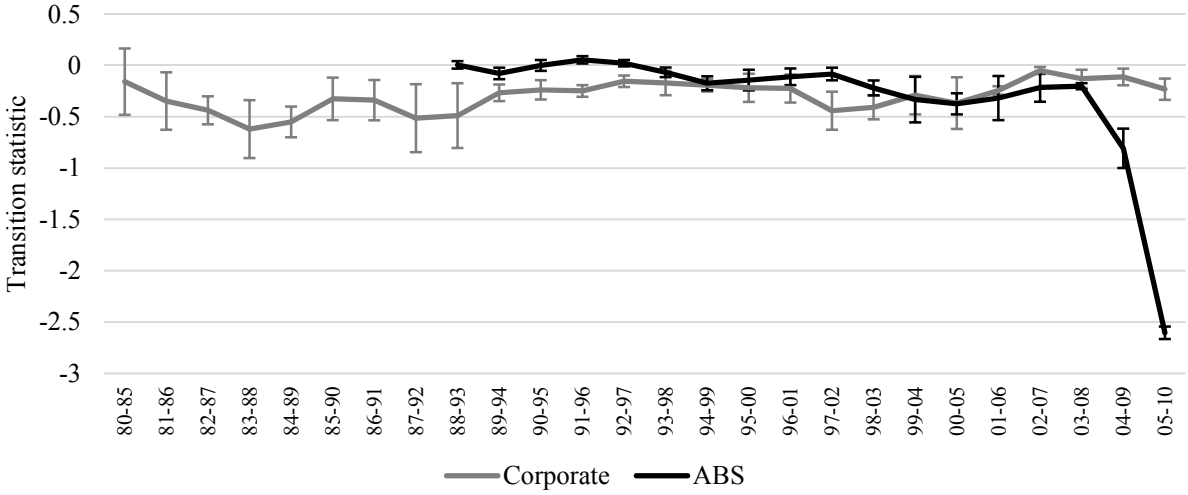
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Corporate
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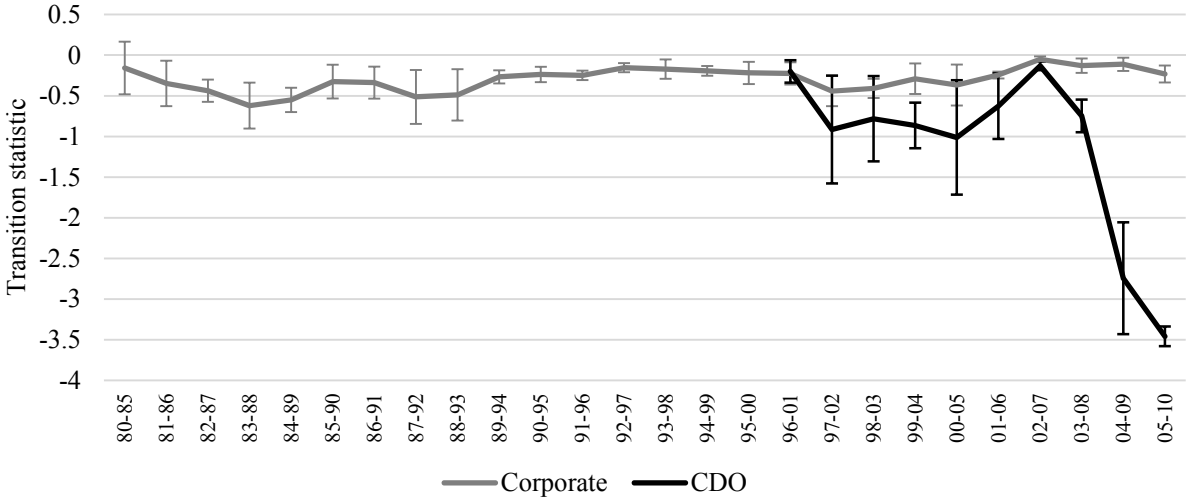
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Corporate
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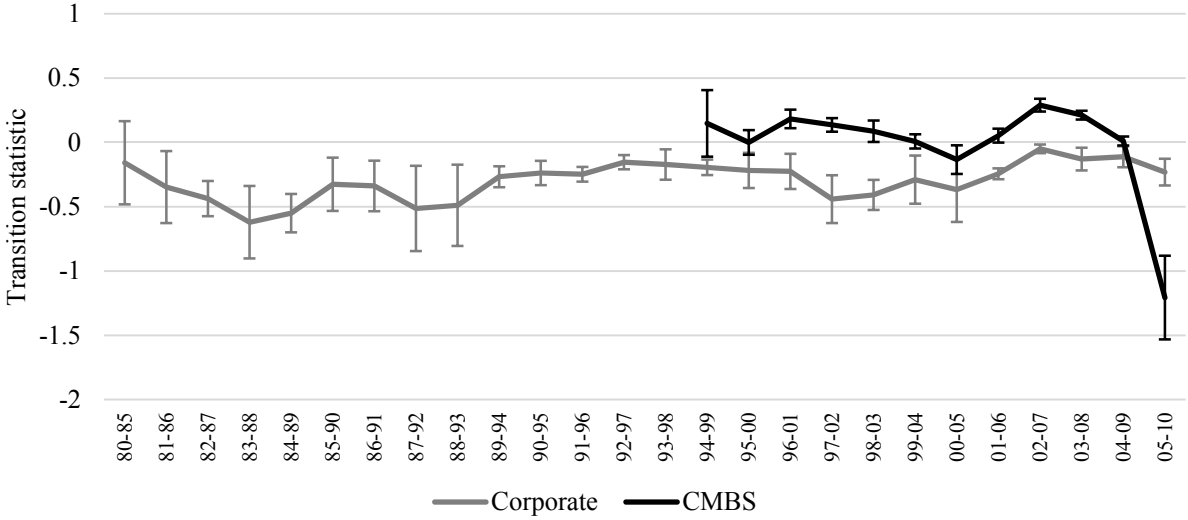
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Corporate
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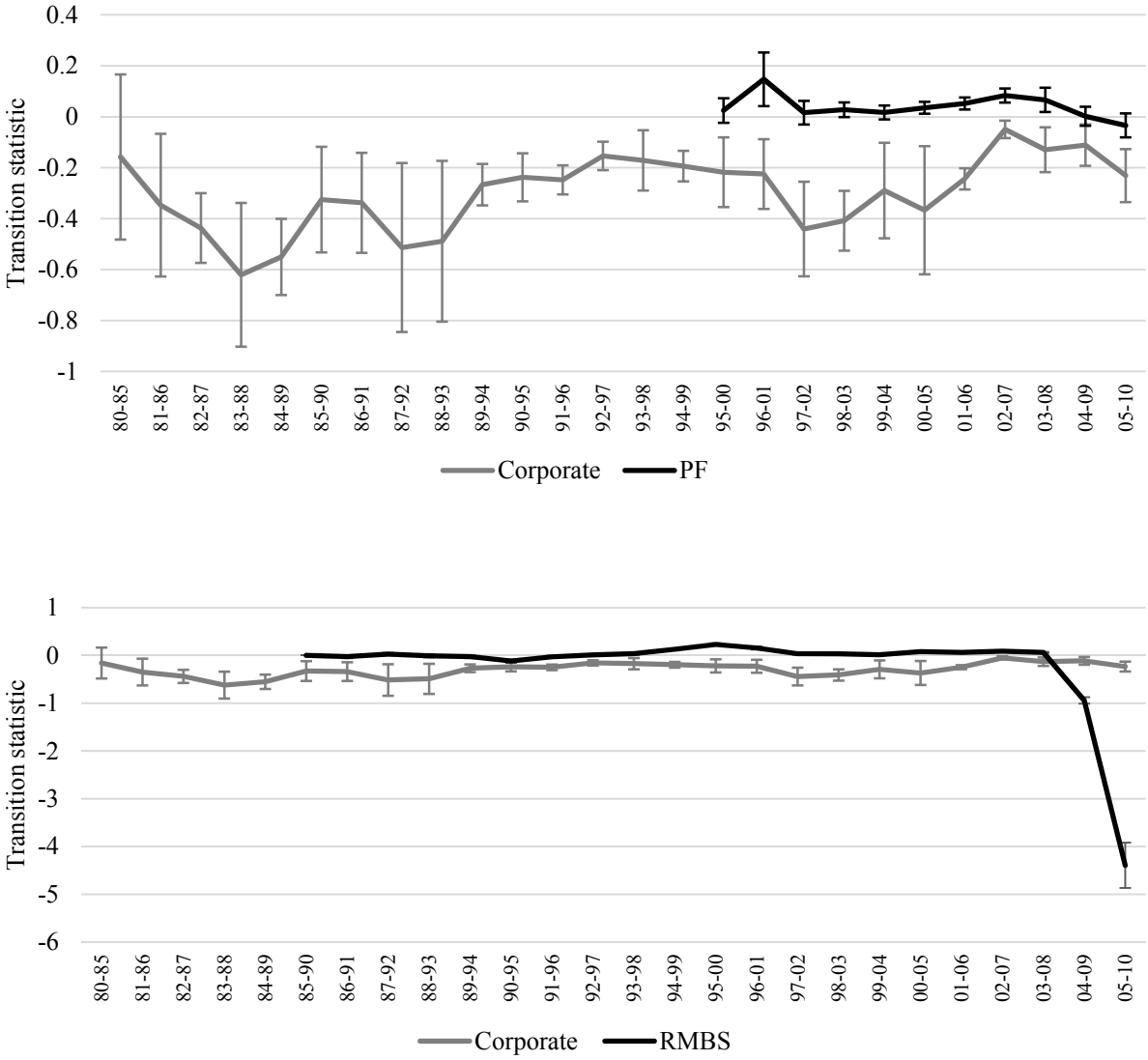
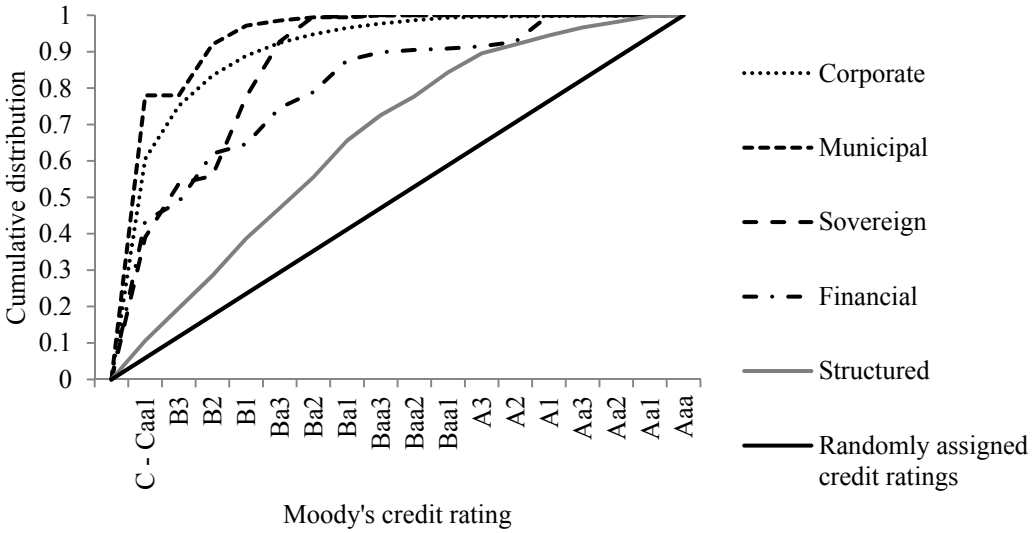
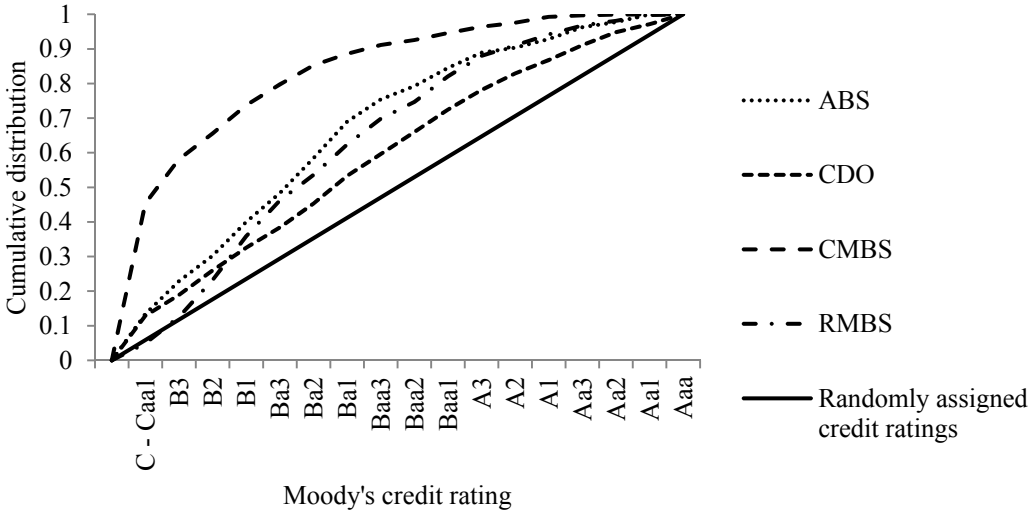


Figure 4
Transition statistics by asset class and year of issuance
This figure displays transition metrics that summarize the information in five-year transition matrices. The transition period is year of issuance to five years hence. We compute these transition statistics for bonds belonging to each asset class and year of issuance. Each plot includes corporate issues' transition statistics for comparison. Vertical bars represent 95 percent confidence intervals. We describe the computations behind the transition metrics and their standard errors in the text.



Panel A. Cumulative distributions of default prediction ability by asset class



Panel B. Cumulative distributions of default prediction ability for structured issues partitioned by product type

Figure 5
Cumulative distributions of default prediction ability

Panel A of this figure plots empirical cumulative distributions of default prediction ability for each asset class (corporate bonds; bonds issued by local and regional governments; sovereign bonds; bonds issued by U.S. banks, U.S. bank holding companies, insurance companies, and securities firms; and tranches of structured products). For each asset class we count the number of bonds with a given credit rating as of January 1 of any year of the sample and the number of those bonds that default over the following year. For each credit rating classification, we then divide the full sample count of defaulted bonds by the full sample count of bonds. The figure plots the cumulative sum of these values, moving from the lowest credit rating to the highest. Panel B plots the same for different types of structured products (Asset Backed Securities, Collateralized Debt Obligations, Commercial Mortgage Backed Securities, and Residential Mortgage Backed Securities).

Table 1
Summary statistics

This table displays mean *(median)* values of issue characteristics by asset class for obligations issued from 1980 - 2010. More extensive descriptive statistics are available in the Internet Appendix. *Face* represents the face value of debt obligations measured in millions of dollars. *Maturity* represents the number of years between when the debt obligation was issued and when it matures, assuming it does not default. *Coupon* represents the coupon rate expressed as a percentage. *Initial rating* is a numeric translation of an obligation's first Moody's credit rating. The highest credit rating, Aaa, equals 21 and the lowest credit rating, C, equals 1. *Downgrade* (*Upgrade*) is a dummy variable taking a value of one if Moody's downgrades (upgrades) the issue between the date of issuance and the earlier of the issue's maturity date, default date, or the end of the sample, and zero otherwise. *Rating change* represents the difference between the numeric translation of an issue's credit rating when the issue matures, defaults, or the sample ends and the initial rating. *Default* is a dummy variable taking a value of one if the issue defaults, and zero if it matures or has not defaulted by the end of the sample period. For structured products, we report the preceding variables at the tranche level. We report additional statistics at the deal level including the number of tranches per deal, the percentage of tranches per deal that receive Aaa ratings at issuance, the face value of deals measured in millions of dollars, and the percentage of deals' face values that receive Aaa ratings at issuance. The data come from Moody's Default and Recovery Database and Moody's Structured Finance Default Risk Service Database.

	Corporate	Municipal	Sovereign	Financial	Structured
Face	282.8 *(132)*	221.0 *(64)*	3,137.4 *(769)*	156.2 *(25)*	193.2 *(19)*
Maturity	9 *(7)*	9.1 *(7)*	9.3 *(7)*	7.1 *(5)*	24.3 *(29)*
Coupon	6.7 *(6.5)*	5.5 *(5.3)*	5.7 *(5.6)*	5.1 *(5.6)*	--
Initial rating	14.2 ≈ Baa1 *(15 = A3)*	19.2 ≈ Aa2 *(20 = A1)*	16.9 ≈ A1 *(18 = Aa3)*	17.1 ≈ A1 *(17 = A1)*	18.6 ≈ Aa2 *(21 = Aaa)*
Downgrade	36%	12%	14%	41%	40%
Upgrade	15%	30%	26%	23%	6%
Rating change	-0.7 *(0)*	0.4 *(0)*	0.1 *(0)*	-1.1 *(0)*	-3.5 *(0)*
Default	4%	0%	2%	2%	15%
N tranches per deal					4.8 *(2)*
% N tranches rated Aaa					53.2% *(50%)*
Total Deal Face					929.6 *(151)*
% Face rated Aaa					61.8% *(87.8%)*

Table 2
Default percentages by asset class and initial credit rating

The table displays default percentages for issues by asset class and initial Moody's credit rating. We require at least 100 issues per asset class-initial rating for admission to this table. The rating scale in this table is a simplified version of Moody's traditional 21-point scale. For example, we combine initial credit ratings of A1, A2, and A3 into one bin, A. The data come from Moody's Default and Recovery Database, and Moody's Structured Finance Default Risk Service Database.

Panel A. Major asset classes

	Corporate		Municipal		Sovereign		Financial		Structured	
Initial rating	N	Dflt %	N	Dflt %	N	Dflt %	N	Dflt %	N	Dflt %
Aaa	1,867	0.16	1,862	0.05	3,541	0.00	395	0.25	102,680	3.64
Aa	3,480	0.34	2,811	0.00	2,251	0.00	11,113	0.56	30,063	20.21
A	13,635	0.51	715	0.00	1,965	0.00	12,750	4.13	21,682	26.97
Baa	6,875	1.69			1,092	2.29	1,562	2.18	19,578	39.52
Ba	2,140	7.52			941	5.74	322	5.59	7,013	40.98
B	3,798	21.30			612	10.95			2,629	38.00
Caa	560	26.79							661	50.53
Ca									408	48.28
C									626	36.58

Panel B. Tranches of structured products partitioned by product type

	ABS		CDO		CMBS		PF		RMBS	
Initial rating	N	Dflt %	N	Dflt %	N	Dflt %	N	Dflt %	N	Dflt %
Aaa	30,815	2.02	6,651	20.52	5,197	0.12	13,621	0.00	46,396	3.75
Aa	7,311	28.71	3,759	26.76	2,043	0.34	8,074	0.00	8,876	33.38
A	9,203	29.02	3,484	31.26	2,145	2.70	2,315	0.00	4,535	44.76
Baa	8,204	51.46	3,554	34.86	2,981	3.22	363	0.00	4,476	48.73
Ba	2,171	71.58	1,765	36.43	1,589	8.56	113	0.00	1,375	39.35
B	516	71.32	262	62.21	1,152	22.40	92	0.00	607	34.60
Caa	231	67.53	179	81.01			143	0.00		
Ca	132	66.67	115	90.43			114	0.00		
C	305	69.51					199	0.00		

Table 3
Transition matrices
This table displays five-year transition matrices for issues by asset class. The rating scale in this table is a simplified version of Moody's traditional 21-point scale. For example, we combine credit ratings of A1, A2, and A3 into one bin, A. The vertical axis represents the issues' initial credit ratings and the horizontal axis represents the issues' credit ratings five years later. The data come from Moody's Default and Recovery Database, and Moody's Structured Finance Default Risk Service Database.

Panel A. Corporate issues

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C	Default	Sum	% Down	% Up
Aaa	1,162	508	55	120	18	1	1			2	1,867	37.76	
Aa	123	2,440	799	77	16	15	6			4	3,480	26.35	3.53
A	47	377	11,097	1,741	237	81	29	4		22	13,635	15.50	3.11
Baa	1	27	630	5,368	592	151	38	21	4	43	6,875	12.35	9.57
Ba	1	3	28	421	1,238	254	70	25	12	88	2,140	20.98	21.17
B	2		13	76	321	2,407	318	106	11	544	3,798	25.78	10.85
Caa				8	3	62	342	22	6	117	560	25.89	13.04
Ca					3	3	1	47	2	23	79	31.65	8.86
C									5	1	6	16.67	0.00
Sum											32,440	19.06	6.63

Panel B. Municipal issues

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C	Default	Sum	% Down	% Up
Aaa	1,781	81									1,862	4.35	
Aa	141	2,633	37								2,811	1.32	5.02
A		346	367	2							715	0.28	48.39
Baa		1	14	51							66	0.00	22.73
Ba				3	11		6	2			22	36.36	13.64
B						24	1	17			42	42.86	0.00
Caa					1		7				8	0.00	12.50
Ca								6			6	0.00	0.00
C									2		2	0.00	0.00
Sum											5,534	2.64	9.14

Panel C. Sovereign issues

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C	Default	Sum	% Down	% Up
Aaa	3,247	269	21	4							3,541	8.30	
Aa	313	1,774	164								2,251	7.29	13.90
A		391	1,531	42	1						1,965	2.19	19.90
Baa			131	773	65	117				6	1,092	17.22	12.00
Ba			10	78	730	82	1	26		14	941	13.07	9.35
B				18	164	366	7	24		33	612	10.46	29.74
Caa						53	21			1	75	1.33	70.67
Ca					3	1	1	7		4	16	25.00	31.25
C											0		
Sum											10,493	8.40	11.08

Panel D. Financial issues

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C	Default	Sum	% Down	% Up
Aaa	303	56	7	28	1						395	23.29	
Aa	15	7,944	3,043	92	14	2		2		1	11,113	28.38	0.13
A	1	2,565	7,904	1,362	410	13		1	102	392	12,750	17.88	20.13
Baa	7	140	357	641	189	12	2	156	51	7	1,562	26.70	32.27
Ba		1	16	18	176	77	3	13	13	5	322	34.47	10.87
B			1	1	5	41	1	1		4	54	11.11	12.96
Caa						3	4				7	0.00	42.86
Ca						17		2			19	0.00	89.47
C									2		2	0.00	0.00
Sum											26,224	23.11	12.00

Panel E. Structured issues

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C	Default	Sum	% Down	% Up
Aaa	70,893	5,691	2,477	1,652	1,436	3,002	9,699	3,011	1,220	3,599	102,680	30.96	
Aa	2,452	14,798	2,500	1,136	599	490	617	387	1,199	5,885	30,063	42.62	8.16
A	667	1,739	8,980	1,391	1,093	547	616	309	819	5,521	21,682	47.49	11.10
Baa	248	304	821	6,782	1,191	1,155	997	464	742	6,874	19,578	58.35	7.01
Ba	24	55	98	235	2,280	354	656	221	505	2,585	7,013	61.61	5.87
B	2	38	12	21	86	1,065	213	81	313	798	2,629	53.44	6.05
Caa	9	45	19	2	3	4	245	6	13	315	661	50.53	12.41
Ca	3	38	20	1	1		2	137	13	193	408	50.49	15.93
C	8	71	28						415	104	626	16.61	17.09
Sum											185,340	39.22	3.81

Table 4
Cox proportional hazard regressions on credit rating adjustments
This table presents results from Cox proportional hazards regressions to estimate the relative downgrade and upgrade intensities of bonds by asset class. The coefficients represent the hazard rate of each asset class relative to the baseline hazard of the corporate asset class and the unit of observation is a rating change. We cluster standard errors at the issue level and they appear below coefficient estimates in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The data come from Moody's Default and Recovery Database, and Moody's Structured Finance Default Risk Service Database.

	Downgrades			Upgrades		
	Full sample	Ratings change initiates from investment grade	Ratings change initiates from speculative grade	Full sample	Ratings change initiates from investment grade	Ratings change initiates from speculative grade
	(1)	(2)	(3)	(4)	(5)	(6)
Corporate	1	1	1	1	1	1
Municipal	0.324***	0.272***	3.115***	1.570***	1.989***	1.057
	(0.010)	(0.009)	(0.231)	(0.033)	(0.044)	(0.157)
Sovereign	0.472***	0.341***	1.024	1.410***	1.609***	1.175***
	(0.008)	(0.008)	(0.030)	(0.023)	(0.032)	(0.037)
Financial	1.789***	1.660***	5.001***	1.691***	2.049***	1.981***
	(0.015)	(0.016)	(0.093)	(0.021)	(0.030)	(0.062)
ABS	1.265***	0.842***	3.783***	0.230***	0.277***	0.198***
	(0.010)	(0.008)	(0.054)	(0.004)	(0.005)	(0.008)
CDO	1.915***	1.494***	3.162***	0.592***	0.600***	0.579***
	(0.016)	(0.016)	(0.049)	(0.011)	(0.014)	(0.017)
CMBS	1.081***	0.752***	1.817***	0.961**	1.523***	0.208***
	(0.012)	(0.011)	(0.033)	(0.016)	(0.029)	(0.009)
PF	1.144***	1.150***	3.283***	0.918***	1.169***	0.345***
	(0.011)	(0.012)	(0.300)	(0.014)	(0.020)	(0.115)
RMBS	1.091***	0.692***	3.360***	0.191***	0.228***	0.160***
	(0.008)	(0.006)	(0.048)	(0.003)	(0.004)	(0.006)
N	483,520	369,405	114,115	483,520	369,405	114,115

Table 5
Cox proportional hazard regressions on first credit rating adjustments
This table presents results from Cox proportional hazards regressions to estimate the relative downgrade and upgrade intensities of bonds by asset class. The coefficients represent the hazard rate of each asset class relative to the baseline hazard of the corporate asset class and the unit of observation is the first rating change after issuance. We cluster standard errors at the issue level and they appear below coefficient estimates in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. -- indicates insufficient observations to estimate a coefficient. The data come from Moody's Default and Recovery Database, and Moody's Structured Finance Default Risk Service Database.

	Downgrades			Upgrades		
	Full sample	Ratings change initiates from investment grade	Ratings change initiates from speculative grade	Full sample	Ratings change initiates from investment grade	Ratings change initiates from speculative grade
	(1)	(2)	(3)	(4)	(5)	(6)
Corporate	1	1	1	1	1	1
Municipal	0.311***	0.294***	3.684***	1.816***	2.083***	1.104
	(0.013)	(0.012)	(0.646)	(0.054)	(0.065)	(0.321)
Sovereign	0.381***	0.295***	1.115*	1.499***	1.483***	1.308***
	(0.011)	(0.010)	(0.066)	(0.039)	(0.044)	(0.071)
Financial	1.290***	1.282***	1.912***	2.045***	2.353***	1.997***
	(0.019)	(0.020)	(0.291)	(0.042)	(0.053)	(0.276)
ABS	0.710***	0.666***	2.341***	0.182***	0.207***	0.098***
	(0.009)	(0.009)	(0.104)	(0.005)	(0.006)	(0.012)
CDO	1.399***	1.383***	1.553***	0.200***	0.232***	0.080***
	(0.020)	(0.020)	(0.073)	(0.008)	(0.010)	(0.010)
CMBS	0.639***	0.574***	0.972	0.985	1.094**	0.480***
	(0.019)	(0.020)	(0.065)	(0.037)	(0.047)	(0.040)
PF	0.846***	0.839***	--	0.828***	0.953	--
	(0.013)	(0.013)	(--)	(0.020)	(0.024)	(--)
RMBS	0.585***	0.571***	0.932	0.218***	0.227***	0.361***
	(0.007)	(0.007)	(0.046)	(0.005)	(0.006)	(0.023)
N	230,614	213,841	16,773	230,614	213,841	16,773

Table 6
Cox proportional hazard regressions on credit rating adjustments by time period
This table presents results from Cox proportional hazards regressions to estimate the relative downgrade and upgrade intensities of bonds by asset class over different time periods. The time periods represent the date of the rating change and exclude rating changes that do not lie in the specified interval. The coefficients represent the hazard rate of each asset class relative to the baseline hazard of the corporate asset class and the unit of observation is a rating change. We cluster standard errors at the issue level and they appear below coefficient estimates in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The data come from Moody's Default and Recovery Database, and Moody's Structured Finance Default Risk Service Database.

	Downgrades			Upgrades		
	1980 – 1999	2000 – 2006	2007 – 2010	1980 – 1999	2000 – 2006	2007 – 2010
	(1)	(2)	(3)	(4)	(5)	(6)
Corporate	1	1	1	1	1	1
Municipal	0.600***	0.102***	0.554***	0.915	2.267***	0.193***
	(0.030)	(0.007)	(0.026)	(0.053)	(0.055)	(0.025)
Sovereign	0.451***	0.638***	0.241***	1.104***	1.047*	2.772***
	(0.014)	(0.016)	(0.011)	(0.033)	(0.030)	(0.086)
Financial	0.837***	0.866***	3.073***	2.737***	1.196***	2.071***
	(0.019)	(0.013)	(0.046)	(0.059)	(0.025)	(0.055)
ABS	0.243***	0.298***	1.818***	0.246***	0.218***	0.301***
	(0.010)	(0.005)	(0.026)	(0.014)	(0.006)	(0.009)
CDO	1.190*	1.033	2.125***	0.737*	0.575***	0.775***
	(0.114)	(0.022)	(0.032)	(0.129)	(0.022)	(0.022)
CMBS	0.542***	0.287***	1.439***	1.329***	1.788***	0.751***
	(0.044)	(0.010)	(0.024)	(0.099)	(0.041)	(0.024)
PF	0.741***	0.236***	1.447***	2.158***	1.204***	1.068***
	(0.064)	(0.008)	(0.023)	(0.162)	(0.030)	(0.029)
RMBS	0.118***	0.014***	1.698***	0.443***	0.302***	0.076***
	(0.004)	(0.001)	(0.024)	(0.013)	(0.008)	(0.003)
N	57,305	138,103	288,112	57,305	138,103	288,112

Table 7
Rating change regressions

Panel A displays results from OLS regression of changes in credit ratings on asset class dummy variables and controls. We define the control variables in the legend of Table 1. The dependent variable is *Rating change*, the difference between the numerical translation of an issue's credit rating when the issue matures, defaults, or the sample ends and the initial rating. The highest credit rating, Aaa, equals 21 and the lowest credit rating, C, equals 1. Panel B displays results from Probit regression models where the dependent variable takes the value of one for downgrades that cross the investment grade threshold and zero otherwise. We cluster the standard errors at the issuer level. We cluster standard errors at the issuer level and they appear below coefficient estimates in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. OLS Regressions: Dependent variable is *Rating change*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Municipal	1.484***	1.525***	1.531***	1.531***	1.087***	1.449***	1.664***
	(0.280)	(0.294)	(0.282)	(0.282)	(0.142)	(0.165)	(0.273)
Sovereign	0.807***	0.798***	0.846***	0.856***	0.834***	1.019***	0.924***
	(0.189)	(0.199)	(0.177)	(0.179)	(0.123)	(0.159)	(0.202)
Financial	0.327	0.400	0.198	0.198	-0.502	-0.336	0.272
	(0.611)	(0.620)	(0.591)	(0.591)	(0.473)	(0.497)	(0.598)
Structured	-1.173***						
	(0.306)						
ABS		-1.061***	-0.088	-0.088	--	--	0.029
		(0.285)	(0.529)	(0.529)	(--)	(--)	(0.480)
CDO		-2.342***	-1.637***	-1.637**	--	--	-1.551***
		(0.409)	(0.573)	(0.573)	(--)	(--)	(0.532)
CMBS		1.316***	2.700***	2.700***	--	--	2.762***
		(0.465)	(0.911)	(0.911)	(--)	(--)	(0.868)
PF		1.261**	2.074***	2.074***	--	--	2.232***
		(0.491)	(0.654)	(0.654)	(--)	(--)	(0.558)
RMBS		-2.530***	-0.918**	-0.918**	--	--	-0.766
		(0.396)	(0.433)	(0.433)	(--)	(--)	(0.484)
Maturity			-0.085***	-0.085***	-0.029***	-0.027***	-0.086***
			(0.023)	(0.023)	(0.007)	(0.007)	(0.022)
Face				-0.187**	-0.087	-0.043	-0.186**
				(0.092)	(0.079)	(0.065)	(0.092)
Coupon					-0.010	-0.052***	
					(0.019)	(0.018)	
Initial rating						-0.075***	-0.027
						(0.015)	(0.029)
Constant	-1.337*	-1.360*	0.050	0.049	-0.501	1.184	0.490
(Corporate)	(0.722)	(0.724)	(0.820)	(0.820)	(0.821)	(0.829)	(0.803)
Yr.of.issue FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.28	0.33	0.36	0.36	0.06	0.07	0.36
N	260,031	260,031	257,963	257,963	56,353	56,353	257,963

Panel B. Probit regressions: Dependent variable equals one for downgrades across investment grade threshold

	(1)	(2)	(3)	(4)	(5)
Municipal	-2.644***	-2.677***	-2.158***	-1.418***	-2.169***
	(0.389)	(0.420)	(0.296)	(0.344)	(0.411)
Sovereign	-0.512	-0.471	-0.596**	-0.299	-0.308
	(0.342)	(0.336)	(0.261)	(0.260)	(0.343)
Financial	-0.178	-0.088	0.178	0.556*	0.165
	(0.430)	(0.427)	(0.288)	(0.303)	(0.407)
ABS	0.427***	0.067	--	--	0.508***
	(0.106)	(0.166)	(--)	(--)	(0.144)
CDO	0.680***	0.459***	--	--	0.857***
	(0.112)	(0.145)	(--)	(--)	(0.128)
CMBS	-0.114	-0.578**	--	--	-0.296
	(0.121)	(0.262)	(--)	(--)	(0.251)
PF	-1.427***	-1.720***	--	--	-1.039***
	(0.215)	(0.286)	(--)	(--)	(0.240)
RMBS	0.534***	0.006	--	--	0.713***
	(0.125)	(0.131)	(--)	(--)	(0.143)
Maturity		0.029***	0.008**	0.010***	0.028***
		(0.008)	(0.004)	(0.003)	(0.010)
Coupon			0.081***	0.036*	
			(0.028)	(0.022)	
Initial rating				-0.281***	-0.161***
				(0.038)	(0.025)
Constant	-1.061***	-1.405***	-1.991***	3.009***	1.241***
(Corporate)	(0.141)	(0.187)	(0.307)	(0.495)	(0.283)
Yr-of-issue FE?	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.29	0.32	0.10	0.22	0.38
N	242,437	241,013	48,567	48,567	241,013

Table 8
Offer yield regressions
This table displays results from bonds' yields at issuance regressed on asset class dummy variables and control variables. We measure offer yields in percentages. We cluster the standard errors at the issuer level. Standard errors appear below coefficient estimates in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The data come from Thomson Reuters' SDC Platinum.

	(1)	(2)	(3)	(4)
Public	0.10	0.14	0.09	-1.56***
	(0.16)	(0.16)	(0.16)	(0.32)
Financial	0.43***	0.45***	0.44***	0.14
	(0.08)	(0.07)	(0.07)	(0.32)
Structured	0.44***	0.42***	0.46***	2.63***
	(0.10)	(0.09)	(0.10)	(0.34)
Initial rating	-0.35***	-0.35***	-0.36***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.03)
Maturity		0.05***	0.05***	0.08***
		(0.00)	(0.00)	(0.01)
Face			0.01*	-0.00***
			(0.00)	(0.00)
Constant (Corporate)	11.66***	11.23***	11.25***	7.15***
	(0.09)	(0.10)	(0.11)	(0.47)
Year-of-issue FE?	Yes	Yes	Yes	No
Issuer FE?	No	No	No	Yes
Adjusted R^2	0.58	0.68	0.68	0.79
N	14,584	14,499	14,499	14,499