Institutional Rigidities and Bond Returns around Rating Changes

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Abstract

Corporate bonds face institutional rigidities from the division between investment grade and non-investment grade clientele. Examining how rigidities affect returns requires a methodology that takes the infrequent trading of bonds into account. Using a methodology that modifies the repeat sales method by incorporating bond characteristics, subsequent to a bond rating crossing the investment/non-investment boundary, we find the transaction price for the bond shows significant negative (or positive) abnormal returns over time, followed by a partial recovery. We further show that a structural shift occurred in these reactions after the financial crisis.

Many corporate bond portfolio managers' investment strategies depend critically on bond rating categories, in particular, the categorization between investment grade and non- investment grade (high-yield or junk) bonds. Because many bond portfolio strategies have a targeted benchmark index and specify limits on the proportion of each category in the portfolio, if a bond's rating approaches or crosses the boundary between investment and non-investment grade, the manager often has an imperative or an incentive to sell the position. At the same time, institutions on the other side of the divide should be ready to serve as the counterparty for the sell position, but are not always willing to do so. This institutional rigidity combined with the low levels of liquidity in the bond market can lead to disruptions when a bond's rating changes. In particular, if the rating change pushes a bond across the investment/non-investment grade boundary, the desire by one market segment to sell may not be met equally by a desire by the other market segment to buy, creating price pressure, a result similar to the mutual fund fire sales documented in the equity markets. Such fire sales result in negative abnormal returns on the affected stocks for a period of time, followed by a partial rebound.[1] In this paper we address the question of how institutional rigidities caused by bond ratings influence the bonds' returns and the extent to which they do so. We hypothesize that the rating changes can lead to long-lived price adjustments due to the institutional rigidities, which will then be partially if not completely reversed.

To test our hypotheses we use the Trade Reporting and Compliance Engine, more commonly known as TRACE, which since 2002 has provided publicly available bond transaction data.[2] However, important empirical challenges exist in analyzing corporate bond transactions. The first arises from the low liquidity levels in the markets given that we find most corporate bonds trade less than once a month, if at all. Our hypotheses are focused on short run serially correlated returns, which may be

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[1] Fire sales in the stock market, due to mutual fund flows have generated a great deal of interest. Papers by Coval and Stafford (2007), Ali, Wei and Zhou (2011), and Dyakov and Verbeek (2013) among others examine this issue. These papers identify equity fire sales by a pattern of serially correlated returns followed by a partial recovery. We suggest a similar pattern of returns can be induced by bond market institutional rigidities.

[2] See http://www.investopedia.com/terms/t/trace.asp for a brief history of TRACE's development.

difficult to measure with this lack of liquidity. A further empirical challenge is that the bond market illiquidity poses impediments to establishing a benchmark index with which abnormal returns can be measured. We provide a novel approach to the problem by developing an econometric model that combines two techniques from real estate research, a literature that faces similar data issues. The resulting returns are then used to determine whether the institutional rigidities, along with the limited liquidity, play a role in short-term bond returns and whether other aspects of bond portfolio manager trading strategies mitigate or exacerbate the institutional rigidities.

Our methodology is based on the repeat sales regression used in the real estate literature to deal with two characteristics common to the both the bond and the real estate markets, heterogeneous assets that trade infrequently (e.g., Goetzmann, 1992; Francke, 2010; and Peng, 2012). This technique calculates the returns between pairs of transactions on the same asset. Given the infrequency of sales, the resulting returns vary in length and cover different periods of time. To create an equally-weighted index, the returns are then regressed on a set of indicator variables representing the return per period.[3] However, the broad equally-weighted indices usually employed in the repeated real estate sales regressions would be insufficient for corporate bond return analyses because bond returns vary systematically with bond characteristics such as issue size, credit quality, industry, years to maturity and other factors. Although with stocks, such a problem is handled to some degree by estimating a factor model and then adjusting the benchmark returns accordingly, that approach would be impractical with securities that trade as infrequently as do bonds. Consequently, we create a custom index for each bond by estimating a "characteristic-weighted repeat sales index" in which we weight the repeat sales data by characteristic distance.[4] Consider a bond i with a vector of characteristics X_{it} as of date t. Another bond j

[3] For example if a model contains returns for dates 2 through 8 and a house sells on dates 3 and 5 it would have a dummy of one for returns 4 and 5 and zero elsewhere. Standard modifications account for heteroskedasticity in the data.
[4] This modification borrows from a separate strand of the real estate literature on hedonic models (Meese and Wallace (1991)).

in the data set has a characteristic vector X_{jt}. The model then calculates a Euclidean distance between the characteristic vectors and reweights the data accordingly. Thus, data from bonds with characteristics similar to the one in question are given larger weights in the regression model than those further away. Using this technique we generate a set of daily benchmark returns for each bond. These are then subtracted from the observed returns on the bond at issue to generate a set of abnormal returns (AR).

When analyzing stock data, calculated abnormal returns typically span a constant length of time, for example, a day or a month. However, for bonds the irregular time between observed trades means that the estimated index-adjusted ARs span various lengths of time. To account for this a second regression is run on the bond-by-bond ARs to estimate daily ARs for the set of bonds impacted by the event in question. The result is an estimated daily AR around the event date and we test the null hypothesis that the sum of the regression coefficients (CARs) equals zero.

The results from the estimated CARs over the sample period indicate that when a bond is downgraded from investment to non-investment grade, the ARs over the following days approximate −130 basis points (bps), a decrease in price that is both statistically and economically important. However, over the next few weeks the bonds gain back almost half their loss, about 60 bps. Downgrades to bonds that were already non-investment grade do not have as strong a price effect with a post announcement CAR of about −40 bps over the next week, which largely reverses by the end of the second week after the announcement. Bonds in the investment grade category that face downgrades but do not cross the investment/non-investment grade border have little market reaction either immediately or in the weeks that follow.

Thus, the institutional rigidity created by the investment/non-investment grade boundary has an important effect on bond returns, leading to returns that stray, for a time at least, from a random walk. One can rank the negative initial price reactions to a downgrade and subsequent recovery from smallest to largest: bonds starting and ending as investment grade, bonds starting and ending as non-investment grade and finally bonds that cross from investment to non-investment grade. This pattern is consistent with the hypothesis that the bonds' price pressure from investment grade funds takes some time to ameliorate when they are forced out of an issue and have to wait for non-investment grade demand to come in to take possession of it. However, there are clearly other forces at work as well since the post negative return and recovery reaction is also seen, if to a much smaller degree, for down-graded bonds that are already in the non-investment grade category.

Upgrades in which the bonds move across the investment/non-investment grade boundary have a more muted effect on bond returns than the border-crossing downgrades, but they still have significant returns. Specifically, bonds moving from the noninvestment to investment grade category experience small positive CARs in the first 2 weeks following the announcement and going out 8 weeks the returns are closer to 70 bps. In contrast, bonds that remain in their rating class after an upgrade see little if any change in value even after 8 weeks have passed. Again, the contrast in these patterns is consistent with institutional rigidities having an impact on bond returns. The fact that there is no significant difference in returns for upgrades in the same rating class, but that crossing the border from non-investment grade to investment grade provides significant increases in returns suggests that part of this return comes from the fact that the bonds have to transfer one set of potential investors, non-investment grade funds, to another, the investment grade funds. Since the latter has not had any reason to hold the bonds and thus research them prior to the rating change, it can take them some time to absorb the issue. This kind of friction can produce the return patterns seen in the border-crossing upgrades.

One aspect of the investment grade/non-investment grade rigidities in the financial markets allows us a unique identification when the market segmentation effects are likely to be most severe. Benchmark indices vary over types of bondholders. In particular, investment grade bond mutual funds tend to use Barclays indices as benchmarks, while non-investment grade bond mutual funds tend to use the Bank of America Merrill Lynch (BofAM) indices. The two indices do not score bonds equivalently or at the same time, which can result in a set of bonds, that for at least a period of time are dropped by one index provider but not included by the other. We dub these observations as “orphan” bonds, the bonds that experience a rating downgrade that drops the bonds out of the investment grade category using Barclays scoring rule, but not under the BofAML rule. As a consequence, these bonds lack a natural constituency since they are not in the benchmark index used by either investment or non-investment grade funds. That is, prior to the downgrade institutional investment grade funds would be the natural holders of these issues. Post announcement they no longer are. At the same time the non-investment grade funds do not have the bonds in their benchmark either. Thus, because of the difficulty in finding buyers, prices for these bonds keep falling as markets attempt to clear. This unique status provides a particularly appropriate test of whether institutional rigidities influence bond returns. We find the evidence supporting our hypotheses to be quite strong as the orphan bonds lose more than 500 bps of their value over the 8 weeks that follow the downgrade announcement.

Our hypotheses and results that rating changes have effects on bond returns run counter to some of the earlier literature on the impact of ratings changes. For example, Weinstein (1977) finds that rating changes follow bond price declines (with a 6-month lag), but that there was no impact after the ratings change, a pattern that has been replicated in numerous subsequent studies. The conclusion from this literature has been that bond rating changes reflect past market performance but correlate weakly, if at all, with future risk-adjusted returns. However, the earlier authors did not have access to bond transaction prices, which only became publicly available in 2002. Consequently, authors accounted for the missing trade data through techniques such as using data from pricing services (e.g., Wansley, Glascock and Clauretie, 1992) or trader quotes (e.g., Warga and Welch, 1993). The problem with such techniques is that market makers and pricing services may quote stale prices on bonds that have not traded for some time and that are unlikely to do so in the near future. Moreover, quotes are not price commitments and at most are only firm for a trivial volume. For a meaningful lot size, dealers may only feel compelled to produce accurate quotes after the arrival of a bona fide transaction query. This can easily result in what looks like return momentum following a rating change, even if there is none.

Several later studies (Hite and Warga, 1977; May 2010; Ellul, Jotikasthira, and Lundblad 2011) document some effects after a bond downgrade, but they have encountered other problems. First, benchmarking poses a problem for any study seeking to estimate bond returns. One solution has been to use commercial benchmarks as in Hite and Warga (1997). They find some price drift in the month before and after the announcement of a bond downgrade. The abnormal returns in their econometric model are net of a Lehman Brothers index that tracks bonds with a similar maturity and rating level. However, the firms calculating the benchmark returns have the same problem anyone else seeking to analyze bonds have – a lack of pricing data because bonds trade very infrequently.[5]

May (2010) uses the TRACE data to examine bond returns by value-weighting all bonds that traded on days t and $t-1$ with the same rating and broad maturity class, thus, avoiding the problem of using non-price estimates. He finds that both downgrades and upgrades impact bond returns in the two-day event window around the change with downgrades having the stronger economic impact. However, since most bonds do not trade even once a week, let alone daily, such a rule drops most issues from the database. Further, since those bonds that do trade frequently tend to be the larger, more liquid, and more recent issues, this obviously skews, and potentially biases, the indices created from them and potentially any empirical analysis based on these indices.

[5] Commercial firms work around this problem by calculating "matrix prices" to fill in for the missing data. However, Warga and Welch (1993) show that these prices often lag the market by a substantial length of time. Furthermore, when looking at rating changes across the investment-noninvestment boundary, the bond in question will be at the edge of any benchmark based on a particular rating class. This may make the benchmark a poor representative of how the bond would have done absent the event in question.

The study of insurance company transactions and prices around bond rating changes by Ellul, Jotikasthira, and Lundblad (2011) is the most similar to our paper. Our paper differs from theirs in a number of ways that add a unique contribution. First, and most importantly, we provide insights into the structural changes in the bond markets that occurred after the financial crisis. Moreover, our methodology of marking to a basket of similar securities rather than marking to model, allows for additional insights. In addition, we have a fuller sample of bonds and their trading because our data contains all bond transactions rather than just transactions with an insurance company on one side. As Bessembinder, Maxwell and Venkataraman (2006) point out, although insurance companies hold a large proportion of corporate bonds (estimated by Schultz (2001) to be about 40%), they only account for 12.5% of corporate bond trading. Thus, we have a much larger sample for examining abnormal returns since their analysis covers 384 bonds while ours covers over 8,000 bonds.[6] Finally, we examine crossing the investment/noninvestment grade boundary from both directions.

A further differentiation of our paper from previous research is that we consider how behavioral regularities in trading such as trend chasing, positive relationship between liquidity and return, and reaching for yield may extend or mitigate the effects from the ratings change. That is, in analyzing the effects of the institutional rigidities, one needs to also account for the effects from these trading behaviors.

The paper is structured as follows: in Section I we discuss the constraints faced by institutions that lead to rigidities in their willingness to hold certain issues. We next provide an overview of the data In Section II and discuss bond liquidity and document how infrequently most issues trade in Section III. In Section IV we contrast the scoring system used by Barclays and BofAML. In Section V we develop the

[6] Other articles have examined bonds around the investment grade/non-investment grade boundary in order to study other issues such as the effects on firms' investments (Chernenko and Sunderam, 2012), the purpose of credit ratings (Bongaerts, Cremers and Goetzmann, 2012), and how index labeling affects the bonds (Chen, Lookman, Schürhoff and Seppi, 2014).

econometric model used to estimate bond ARs and CARs and present the results in Section VI for various rating changes and various sample periods. We provide our conclusions in Section VIII.

I. Institutional Constraints

Corporate bond portfolio managers have a variety of investment goals. Some invest across all bonds, regardless of rating. Many, however, restrict their holdings to either investment grade or high yield issues, resulting in somewhat segmented markets. Whether a bond belongs in one category or another generally depends on the ratings assigned the bond by the rating agencies, the most prominent of which in the U.S. are S&P, Moody's and Fitch.[7] Examples of these restrictions can be found in the prospectuses of corporate bond mutual funds. The Calvert Long-Term Income Fund (ticker CLDAX) states within its "Principal Investment Strategies" section,

> The Fund typically invests at least 65% of its net assets in investment grade, U.S. dollar-denominated debt securities, as assessed at the time of purchase. A debt security is investment grade when assigned a credit quality rating of BBB- or higher by Standard & Poor's Ratings Services ("Standard & Poor's") or an equivalent rating by another nationally recognized statistical rating organization ("NRSRO"), including Moody's Investors Service or Fitch Ratings, or if unrated, considered to be of comparable credit quality by the Fund's Advisor.[8]

In theory, this means the fund can invest in any bond that one of the rating agencies has designated as investment grade and hold some non-investment grade issues as well. However, an added factor that could push bond portfolio managers to focus on investment grade bonds is that these managers are not oblivious to benchmark risk. Holding bonds outside the benchmark imposes significant performance risk. This incentive may be especially strong in the bond market where an individual bond's upside potential is quite limited, although its downside is not. Thus, the benchmark used to assess a bond's portfolio performance may also influence the manager's desire to hold or shun a particular issue. For example,

[7] For expositional clarity the investment, noninvestment and distressed classifications will be referred to as rating categories.
[8] Page 34.

the benchmark for CLDAX is Barclays Long U.S. Credit Index. (Our search through a number of investment grade fund prospectuses shows this is typical.)

The prospectuses of high yield funds also provide similar disclosure regarding the restrictions on their holdings. For example, Calvert's High Yield Bond Fund (ticker CYBAX, CHBCX and CYBYX depending on class) states

> Under normal circumstances, the Fund will invest at least 80% of its net assets (including borrowings for investment purposes) in high yield, high risk bonds, also known as "junk" bonds. The Fund will provide shareholders with at least 60 days' notice before changing this 80% policy. . . . When a corporation issues a bond, it generally submits the security to one or more nationally recognized statistical rating organizations ("NRSROs") such as Moody's Investors Service ("Moody's") or Standard & Poor's Ratings Services ("Standard & Poor's"). These services evaluate the creditworthiness of the issuer and assign a rating, based on their evaluation of the issuer's ability to repay the bond. Bonds with ratings below Baa3 (Moody's) or BBB- (Standard & Poor's) are considered below investment grade and are commonly referred to as junk bonds. Some bonds are not rated at all. The Advisor determines the comparable rating quality of bonds that are not rated. [9]

As with the earlier income fund examples, the prospectus states the fund's benchmark which in this case is the BofA Merrill Lynch High Yield Master II Index. (After reviewing a number of prospectuses this benchmark appears to be the industry standard for high yield funds.)

Barclays and BofA Merrill Lynch seem to run the industry standard benchmarks, making the list of bonds they either do or do not include of upmost importance to numerous fund managers. Since these are benchmarks, the firms publish rules governing when a bond is or is not included. For the Barclay investment grade indices the rule governing inclusion is:

> Securities must be rated investment grade (Baa3/BBB-/BBB- or higher) using the middle rating of Moody's, S&P and Fitch; when a rating from only two agencies is available, the lower is used; when only one agency rates a bond, that rating is used. In cases where explicit bond level ratings may not be available, other sources may be used to classify securities by credit quality:
>
> • Expected ratings at issuance may be used to ensure timely index inclusion or to properly classify split-rated issuers.

[9] Page 26.

• Unrated securities may use an issuer rating for index classification purposes if available. Unrated subordinated securities are included if a subordinated issuer rating is available.

The BofA Merrill Lynch (BofAML) index, however, uses a somewhat different rule based on an average score from S&P, Moody's and Fitch. Table 1 displays the numerical score assigned to each rating. After calculating a score BofAML then rounds out the result, rounding *up* numbers ending in 0.5.[10] For example, a bond has a rating from S&P of BBB2, from Moody's of Baa3 and none from Fitch. Then the score is (9+10)/2 = 9.5 and this is rounded up to 10. In a case like this, the result is identical to what the algorithm used by Barclays produces. However, there are cases where they are not. Consider a bond without a Fitch rating but with scores from S&P of BBB2 and Moody's of Ba1. In this case, the average score is 10 based on the BofAML rule. However, the Barclays algorithm yields an 11 since it takes the lower score when there are just two. While scoring discrepancies like this are not common, they do occur, from which we derive tests of orphan bonds in Section G.

A. Institutional rigidities and bond trades

A primary cause for institutional rigidities in the bond markets is the existence of a boundary based on bond ratings for portfolio managers' investment strategies. When a security drops from a portfolio's benchmark index because of a ratings change, managers have two reasons to sell the issue. First, as noted earlier, bond portfolios, particularly bond mutual funds, typically have clauses restricting the extent to which they can hold securities outside their primary strategic universe. As examples, consider the rules imposed on Oppenheimer's Corporate Bond Fund (OFIAX), T. Rowe Price's Corporate Income Fund (PRPIX) and Calvert's Income Fund (CFICX). These funds are investment grade corporate bond funds that include holding restrictions in their prospectuses. OFIAX limits its high yield holdings to 20% of its portfolio, PRPIX has a 15% limit and CFICX has a 35% limit. High yield funds have similar types of restrictions on their holdings of investment grade bonds. For example, both Oppenheimer's Global High

[10] We thank Preston Peacock from BofAML for providing us with the details regarding how they round scores ending in 0.5.

Yield Fund (OGYAX) and T. Rowe Price's High Yield Fund (PRHYX) limit their investment grade holdings to 20%.[11] Calvert's High Yield Bond Fund (CYBAX) does not have a strict limit, stating that investment grade bonds are "permitted but not a principal investment strategy." Thus, for either type of fund, a bond with a ratings change will move out of the fund's primary investment category, which then adds to the weight of the fund's portfolio that the prospectus limits, giving the fund manager a requirement or an incentive to sell the issue.

Beyond the prospectus limits, the potential benchmark tracking error created by the removal of the bond from the index also provides fund managers an incentive to sell the bond issues that move outside their mandate. For example, suppose a bond constitutes 5 bps of the index and 7 bps of a fund's portfolio, which means relative to the benchmark the fund is long the issue by 2 bps. If the bond is removed from the index, the fund is suddenly long the issue relative to the benchmark by 7 bps, a nontrivial swing that positions the fund from slightly bullish in the issue to very bullish. The fund manager can then achieve a position in line with the benchmark by selling the issue. Moreover, funds that took a relatively bearish position (under 5 bps) may have an even stronger incentive to sell. What was once a short position relative to the index is suddenly long.

B. Hypotheses on the Effects of Rating Changes

In this section we develop hypotheses regarding bond rating changes in two diverse circumstances, (1) the rating remains within the bond's category, that is, before and after the ratings change the bond is either an investment grade or non-investment grade bond; (2) the rating change moves the bond across the investment grade/non-investment grade boundary. Our primary focus revolves around the latter, that is, the effects of institutional rigidities on bond trading during the downgrades and upgrades due to the restrictions regarding the category of bonds a portfolio manager can hold, which should play a major

[11] Although Oppenheimer qualifies this restriction as only applying "under normal market conditions" the fund firm does not further define what this means.

role when a ratings change forces a bond across categories. The institutional rigidities should not affect bond returns when a rating change leaves a bond's broad ratings category unchanged.

Complications for testing the hypotheses arise because of systematic trading effects from microstructure models in which markets have limited liquidity due to an intermediary's inventory concerns.[12] In such models, large buys or sales are spit up over time and lead to serially correlated returns. Prices ultimately overshoot their long run equilibrium value and then partially reverse back. Further complicating the tests are several documented behavioral regularities in institutional investor trading that need to be considered as these regularities may extend or mitigate the trading effects from the ratings change: trend chasing, positive relationship between liquidity and return, and reaching for yield.

Trend Chasing: Evidence shows that when prices increase for a security, some investors engage in trend chasing by adding the security to their portfolio or increasing their current holdings. The opposite effect tends to occur after a price decline. Evidence that institutional investors behave this way is extensive (Grinblatt, Titman and Wermers (1995), Wermers (1999), Badith and Wahal (2002) and Alti, Kaniel and Yoeli (2012)).

With regard to bond funds, the trend-chasing hypothesis suggests prices should overshoot their equilibrium values after a ratings change; since they tend to follow price moves. On the way up trend-chasing funds will want to buy, but the trend chasing should restrict the supply of sellers. The opposite would hold when bonds lose value. The resulting pattern from the trend-chasing hypothesis is that returns should be serially correlated for some time and then partially reverse.

[12] A general discussion of these models can be found in Madhavan's (2000) survey article. A particularly relevant example to the current paper can be found in Keim and Madhavan (1996). In their model a block sale comes through that overwhelms the market's short term liquidity provision. When that happens returns exhibit positive serial correlation over time as the position is worked off. Once the block is exchanged, prices will have generally overshot their equilibrium value and then move in the opposite direction for a time.

Liquidity and Past Returns: A related phenomenon is that higher returns lead to higher future liquidity (Chordia, Roll and Subrahmanyam (2001) and Hameed, Kang and Viswanathan (2010)). If an institution wants to sell a security whose price has recently risen, there should be a smaller temporary price impact than if the same sized sale occurred following a price drop. Thus, for bond upgrades liquidity should increase, which would reduce the degree to which returns are serially correlated. This phenomenon should also reduce or eliminate any tendency for prices to overshoot their equilibrium value. For bond downgrades, the opposite should be true.

Reaching for Yield: Another related hypothesis with behavioral elements is based on the evidence that many institutional investors appear to chase yields. For example, if there are two AA bonds and one has a slightly higher yield, the investor would be more likely to hold the higher yielding one. Evidence in support of this tendency is provided in studies of the trading of insurance companies (Becker and Ivashina (2015) and Merrill, Nadauld and Strahan (2015)) that finds these investors appear to overweight relatively high yielding securities within the rating classes they hold. Thus, if institutional investors are reaching for yield, they would be natural buyers for bonds that move categories on downgrades. Similarly, they would be sellers for bonds that upgrade to a new category. This type of trading behavior should help offset the impact of trend chasers when an upgrade occurs.

The above discussion can be summarized as:

Hypothesis 1: (a) Following a ratings downgrade in which a bond remains in either the investment grade or non-investment grade category, i.e., its initial broad ratings category, trend chasing and liquidity provision suggests we should observe serially correlated returns on the bond and its prices should overshoot their equilibrium value. Reaching for yield will mitigate this. (b) For upgrades in which the bond remains in its ratings category, trend chasing should induce serially correlated returns and prices that overshoot their equilibrium values. Both liquidity provision and reaching for yield should mitigate this tendency. Overall, serial correlation and overshooting should be more pronounced for downgrades than upgrades. Institutional rigidities should have little effect for bonds that remain in their original ratings category after a change in rating.

When a bond switches from one ratings category to another, trend chasing and liquidity provision are likely to have the same influence on prices that they do when a bond remains within its original broad ratings category. However, this is not true for portfolio managers reaching for yield or those constrained by institutional rigidities. The combination may even exacerbate their individual influences.

When a bond rating switches from investment to non-investment grade, the bond goes from being among the highest yielding bonds in its ratings category to among the lowest. For investment grade funds reaching for yield, these bonds are initially attractive. However, after the downgrade they either have to sell out of the position or have strong incentives to do so because of the benchmark deviation they will face if they continue to hold a bond out of their benchmark. Moreover, among the bonds' potential buyers, the high yield portfolio managers reaching for yield will find these bonds to be particularly unattractive because the bonds will be the lower yielding in their new category. The combination of the investment grade bond portfolio managers wanting to sell and the high yield managers being less interested leads to net selling pressure and thus, may lead to serially correlated returns and prices that overshoot their equilibrium value. In contrast, upgrades that switch a bond's rating category cause it to go from being among the lowest yielding in its category to among the highest. While the bond was initially unattractive to high yield funds that are reaching for yield it is now particularly attractive to investment grade funds that wish to do so.

Hypothesis 2: (a) *When a rating downgrade causes a bond to switch into a new ratings category the institutional rigidity will work in the same direction with the three regularities, which suggests we should observe serially correlated returns and prices that overshoot their equilibrium values. (b) When a ratings* *upgrade causes a bond to switch into a new ratings category, reaching for yield should help reduce the degree to which returns are serially correlated and prices overshoot their equilibrium value. (c) Overall, the greatest degree of serial correlation and price overshooting should occur for downgrades that switch a bond's ratings category.*

II. Data

The tick-by-tick bond prices are obtained from the TRACE database for the period beginning July 1, 2002 and ending on June 30, 2015. The reported volume for each transaction is truncated, with non-investment grade bonds being reported as $1 million plus for transactions over $1 million (in par value). The truncation for investment grade bonds is higher; trades in excess of $5 million in par value are listed as 5 million plus.[13] We convert the prices and reported volumes into daily closing prices through the following algorithm. If a bond trades just once during the day we use that trade price as the closing price. If the bond trades multiple times during the day, we use the last trade as the closing price provided the trade volume is large enough to yield a truncated value (an institutional sized trade). Otherwise the closing price we use is derived by computing a size-weighted average of the last three trades in the day.[14]

Bond characteristics are drawn from the Mergent Corporate Bond Securities Database. This database reports a number of bond characteristics including the bond's ratings by the major rating agencies, call schedules, and coupon frequency among others. To be included in the final sample, a bond must be rated by S&P, Moody's or Fitch and also must conform to the following terms: (1) make semi-annual coupon payments, (2) accrue interest on a 360 day year, (3) have USA as the country of domicile,

[13] See the TRACE data guide offered by the Wharton Research Data Services at https://wrds-web.wharton.upenn.edu/wrds/query_forms/variable_documentation.cfm?vendorCode=TRACE&libraryCode=trace&fileCode=trace&id=ascii_rptd_vol_tx.

[14] If there are only two trades, then they are size weighted and averaged to produce a closing price. Trades dated on weekends and bond holidays are dropped from the database.

(4) list its denomination and payments in US dollars (this excludes "Yankee" bonds), (5) have a type of PSTK, PS, EMTN, MBS, TPCS or CCOV and (6) have an industry code below 40.[15]

III. Bond Liquidity

The limited trading in the corporate bond market means that market prices are unavailable to either estimate factor loadings or a bond's current market value. How problematic this is depends on how infrequently a trade takes place. In Table 2 we provide some indication of just how serious this issue is in the corporate bond market. The table displays, by percentile rank, what fraction of days per year a bond trades. (Throughout the paper, "days" refers to trading days, i.e., when the market is open.)

Table 2, summarizes a measure we term "fraction of days traded" (FDT). Because we only observe prices when a bond trades, we do not have precise information on the time at which the bond enters or leaves the market. Consequently, to assess trading frequency we use the following algorithm. A bond *B* is included in year *Y*'s data if it trades in any day during or prior to year *Y* and during or after year *Y*. The FDT in year *Y* for bond *B* then has as its numerator, the number of days bond *B* traded in year *Y*. The denominator contains the number of trading days in year *Y* on or after the first trading day and on or before the last trading day observed for *B* in the entire dataset. Some examples:

- Example 1: A bond trades in 2005 and 2007 but not 2006. FDT(2006) = 0/total trade days in 2006 = 0.
- Example 2: A bond trades on July 11, 2006 and July 12, 2006 but never before or after. FDT(2006) = 2/2 = 1, since total trade days during 2006 between the first and last trade date in the bond is 2.

[15] This excludes bonds issued by foreign agencies, foreign governments, supranationals, the U.S. Treasury, a U.S. Agency, a taxable municipal entity or is in the miscellaneous or unassigned group.

This measure is designed to overstate just how frequently a bond trades during the year. The number of days built into the denominator assumes that once a bond's final trading date is observed the bond leaves the market and can never trade again. Similarly, it assumes a bond is unavailable for trade prior to the first date it appears in TRACE. This is clearly untrue. Unless the bond has been called or matured trading can take place, even if trades do not occur. The point is to provide some intuition regarding how infrequently bonds trade and this measure provides an upper bound on that concept.

Within each year the bonds that are part of that year's sample are ranked by their FDT. Table 2 displays the percentile break points, in percentage terms. Rows represent years for which a full year of data is available. Many of the lower percentile cells contain zeros due to bonds that trade prior to and after the year in that row, but not in that year. The early and late years have entries in all columns due to how end point problems impact the FDT calculation. If a bond trades in 2001 and 2004, it is not included in the 2003 row since the earlier 2001 trade occurred prior to the initial date for the Trace database. Similarly, a bond that trades in 2013 and again in 2016 will not be included in the 2014 data as a 0, since the 2016 observation occurs after the end period for the sample. However, the important point to note is that even with this very conservative measure of trading frequency the median bond trades about 12 or 13 days during the average 254 trading days in a year, which amounts to only about 5% of the available trading days.

Panel B in Table 2 reports the FDT in a different way by measuring time by the number of years since a bond first trades (t_0). The year 1 label is applied to all trades from t_0 to its first anniversary. For example, if a bond first trades on July 11, 2006 all trades in that issue up to July 10, 2007 are aggregated into year 1. The denominator equals all trading days between July 11, 2006 and July 10, 2007. The figures in Panel B across all years shows just how infrequently most issues trade both initially and over time. The median value is just 8.59% during year 1 and falls off to 3.12% by year 4. Even bonds with an FDT score at the 75 percentile, trade on just under 20% of the available trading days in their first year and by year 4 are down to just under 10%. It is only at the 95% level that the drop off in FDT becomes somewhat less severe over the years. However, even at this level it goes from 37.5% down to 23.5% from years 1 to 4. If the criteria for calling an issue liquid is that it averages close to 1 trade a week, then only bonds in the top 1% of all issues can be said to be liquid past the 5th anniversary of their first trade.

IV. Rating Changes

The hypotheses developed earlier are based on the idea that crossing the boundary between investment and non-investment grade leads to different market reactions than when ratings change within each classification. The drop in a bond's liquidity over time, as indicated in Table 2, suggests rating changes that occur farther from the initial issue date will be accompanied by relatively thin transactions data. We next examine whether this holds in our data by collecting any rating changes that lead a bond to move across the investment/non-investment grade boundary. Panel A of Table 3 reports these numbers by calendar year and Panel B reports them by the number of years since the bond was first rated. Panel A shows a clear variation across years. Prior to 2011, downgrades occur more frequently than upgrades. Clearly, the financial crisis led to a large number of downgrades in 2008 and 2009. From 2011 to 2013 upgrades became more common, with a particular jump in their occurrence in 2013, although in 2014 there were a few more downgrades than upgrades. Panel B of the table shows that many of the rating changes leading to a change in classification to or from investment and non-investment grade occur years after a bond has been issued. Combined with the evidence in Table 2, this occurs after trading in the bond has likely dropped significantly. Thus, estimates of how rating changes impact bond returns will necessitate making up for the lack of daily pricing data.

Given the increased motivation for trading in bonds that cross between investment and non-investment grade, the question arises as to whether the additional trading is sufficient to employ the return estimates commonly used on stock data to the bond data at hand. To check this we tabulate the

FDT over the months and days following a rating change that pushes a bond across categories and report the results in Table 4. In the months prior to a rating change, consistent with previous evidence showing that information precedes bond rating changes, the bonds initially in the investment grade group trade more often than their peers; on about 20% of all days. Those initially in the non-investment grade group trade only about 6% or 7% of the time until the month prior to being upgraded. In the prior month trade nearly doubles in frequency to around 12% or 13%. In the months following a downgrade from investment to non-investment grade a typical bond's FDT score drops significantly. After about 6 months these bonds seem to trade about as often as the non-investment grade bonds that were ultimately upgraded. The reverse is also true of those bonds upgraded from investment to investment grade. Their FDT scores jump. Six months prior to the rating change they have a FDT score of about 6% and after the rating change it goes to about 15% and remains there for at least 6 months. These patterns are consistent with the general observation the bond market liquidity declines with the rating (Han and Zhou (2007) and Chen, Lesmond, and Wei (2007) and Kalimipalli and Nyak (2012)).

V. Estimating Bond Returns

As Section III shows, most bonds trade too infrequently to create factor loading estimates as could be done for stocks. Even creating a benchmark to use as a factor poses a challenge. Real estate is an area in which academics need to deal with heterogeneous assets that trade infrequently. A popular solution has been to employ a repeat sales regression. We create what can be called a distance-weighted bond index by combining the repeat sales algorithm with a kernel estimation model used by Meese and Wallace (1991).[16]

In a traditional repeat sales model, the price *p* of asset *i* at dates *b* (buy) and *s* (sale) is assumed to follow

[16] Meese and Wallace (1991) used their statistical model to estimate San Francisco housing returns.

$$p_{is} = p_{ib} \prod_{t=b+1}^{s} (1 + r_{mt}) \varepsilon_{it} \quad (1)$$

where r_{mt} is the return on the benchmark portfolio *m* and ε_{it} is a log normal error term. The model assumes no intervening cash flows exist between the two transaction dates. Taking logs, letting *R* = log(1+*r*) and $e = \log(\varepsilon)$ yields

$$\log(p_{is}/p_{ib}) = \sum_{t=b+1}^{s} R_{it} + e_{it}. \quad (2)$$

The model in equation (2) can then be estimated by using dummies equal to 1 if the time period *t* is between the buy and sale dates and zero otherwise. The variance of each observation equals $(s-b)\sigma_e^2$ where σ_e^2 is the variance of *e*. Equation (2) can be estimated via weighted least squares to account for the heteroscedasticity across observations.

Equation (2) is based on the assumption that there are no intervening cash flows between sales.[17] The vast majority of corporate bonds pay coupons semi-annually. (This study drops the few that do not.) Because coupons arrive so infrequently most transactions pairs lack an intervening cash flow and thus satisfy equation (2). The few trading pairs where this is not true have been dropped from the data used to estimate returns in this paper.

The standard repeat sales model works well when the goal is to measure the average return across a broad array of illiquid assets. However, the model may not do as well when dealing with assets that have particular characteristics within the group. In our setting the focus is on bonds that recently transitioned between investment and non-investment grade, which are not representative of the whole

[17] Geltner and Goetzmann (2000) propose a variant of the repeat sales model that can handle transaction pairs with intervening cash flows. As a practical matter, to estimate the model with any reliability there need to be sufficient time 0 data points. The TRACE data lacks that requirement and when we attempted to implement the Geltner and Goetzmann model the design matrix was not numerically invertable.

bond market. In particular, their returns may vary from the general corporate bond market due to characteristics such as maturity, current yield and industry. The repeat sales model can be adapted to this problem by using a variant of the technique suggested by Meese and Wallace (1991), in their case for estimating a hedonic model. Conceptually, we adapt the model to distance weight the rows in (2) to account for how far in characteristic space the observation is from the bond whose return one wants to benchmark.

Define the distance between two observations *i* and *j* with characteristics vectors $X = (x_1 \ldots x_n)$, with *n* characteristics by $D\left[X_{it}, X_{jt}\right]$. In the current application, *D* is a ratio in which the numerator is the Euclidean distance between the two sets of characteristics, where the characteristics *x* are normalized to have unit standard deviations. The denominator is a value that sets *D*<1 for X% of the data. The characteristics we employ are a bond's current yield, days to worst call date and a measure derived from the issuer's 4-digit SIC code, defined as a dummy equal to 1 if two firms are in different 4-digit SIC codes, and 0 if they are in the same one.[18] All characteristics are measured as of the date of the first trade in each repeat sales pair.

Following Meese and Wallace (1991) once distances are calculated the observations are then weighted with the tri-cube function

$$\begin{aligned} W_j &= \left(1 - D_{ij}^3\right)^3, \text{ if } D_{ij} < 1 \\ &= 0 \text{ otherwise.} \end{aligned} \tag{3}$$

After weighting the rows in (2), the return parameters are then estimated via least squares. The resulting estimates are used as the benchmark returns for asset *i*. A bond's abnormal return between dates *b* and *s* is then estimated as

[18] The days to worst call date is the same as days to maturity if the bond is either non-callable or if the yield to worst call date is the maturity date.

$$AR_{i,b,s} = \log\left(p_{bi}/p_{si}\right) - \sum_{t=b+1}^{s} \hat{R}_t \tag{4}$$

where $\hat{R}_t$ is the distance weighted repeat sales estimate of R_t.

In principle, the repeat sales index in equation (2) can be estimated using the entire TRACE database from 2002 to date. However, current computing power makes this approach technologically challenging. The solution used in the analysis that follows is to estimate equation (2) year-by-year using 3 year rolling windows. For example, the benchmark index for 2006 rating changes is created from trade data spanning January 1, 2005 to December 31, 2007. Similarly, the 2007 benchmarks are estimated using data from January 1, 2006 to December 31, 2008.

B. Commercial Benchmarks as an Alternative

Institutional investors typically have their returns compared to the benchmark indices by BofAML and Barclays. While these benchmarks are readily available, using them to estimate the abnormal return to a bond that transitions between investment and non-investment grade seems likely to produce biased results. Relative to an investment grade index, these bonds are rated at the lowest edge of the comparison group and at the upper edge in terms of risk. Relative to a non-investment grade index the opposite is true. It seems unlikely that either index will yield an appropriate return adjustment. Furthermore, default rates are not linear in the ratings. Rather they are convex in their numerical scores, as documented by Emery, et al. (2008) for corporate bonds and Altman and Suggitt (2000) for syndicated loans.

Another option is to use an overall bond index. However, the overall bond market is not equally distributed across rating classes. According to the Securities Industry and Financial Markets Association, high-yield bonds have comprised between 6% and 25% of the overall new issues market. An overall bond index will therefore skew towards less risk and a higher rating than a bond transitioning between investment and non-investment grade. Finally, there is the issue of index measurement. The index providers also have to deal with the lack of transactions on which to base prices. Their solution is to estimate a bond's value using a spread to Treasuries. For example, the Barclays US Corporate Index Factsheet states, "Most securities in the US Corporate Index are priced using a spread to Treasuries. . . " While this technique is simple, if ratings are sticky estimated price changes will lag the market.[19]

VI. Estimating and Testing Cumulative Abnormal Bond Returns

Estimating equation (4) across bonds produces a list of abnormal bond returns (AR).[20] However, due to the infrequency with which bonds trade these returns cover various spans of time. One option is to assume the ARs are spread evenly between trade dates. For example, if the AR is 100 bps from date 2 to 12 one can assign an AR of 10 to each day. However, this can lead to problems when the time span crosses a date boundary where the suspicion is that ARs before and after differ.

A variation of the repeat sales model can help deal with the fact that the AR calculations cover varying lengths of time. The hypothesis is that the AR on date *t* relative to some event data is R_t. Thus, one can estimate

$$AR_{i,b,s} = \sum_{t=b+1}^{s} R_t + e_t \tag{5}$$

and then calculate the CAR from date t_0 to t_1 as $\sum_{\tau=t_0}^{t_1} \hat{R}_t$, where $\hat{R}_t$ is the estimated value of R_t. A standard significance test can then be conducted as to whether the CAR (sum of the regression coefficients) does or does not equal 0. As in a standard repeat sales regression, return data on the left

[19]Again, see Warga and Welch (1993) and Hite and Warga (1997) for detailed discussions of this issue.
[20] Here, as in the prior discussions returns should be interpreted as log(1+*r*); the estimated value produced by the repeat sales regression.

hand side of (5) will exhibit heteroscedasticity in proportion to the time between sales. A simple weighted regression will correct this and is what this paper uses to estimate the reported $\hat{R}_t$.

As Webb (1988 and 1991) shows estimates from a repeat sales model, like those in equations (2) and (5) suffer from measurement errors that follow an AR(1) process. While this issue disappears in large samples it can be problematic when the data is thin, as it is in some of the tests conducted here. A simple solution is to bootstrap the estimates. The mean return estimates based on the random sampling eliminates the AR(1) measurement error and produce robust standard errors.[21] In what follows, all of the abnormal return estimates using equation (5) and estimates derived from them are based on bootstrapped values. We do not bootstrap the repeats sales estimates from the first stage regression (equation (2)). These negatively serial correlated measurement errors should not qualitatively impact the final estimates from (5), which are the ones of interest.[22]

Once the first stage regression is completed the ARs from it are stacked and estimated against a second repeat sales model. To the degree that the negative serial correlation in the parameter estimates then feeds into the estimated ARs, these should either be completely or close to independent across much of the sample. For example, ARs for a bond in 2005 are calculated with a dataset that is independent of the one used to calculate the ARs for a bond in 2010. Thus, in the second stage regression where the first stage ARs become the dependent variable, the result is just additional noise.

[21] We thank William Goetzmann for this insight and suggestion.

[22] It is also true, that attempting to bootstrap the first stage regression would take current computers months to perform the calculations. Without bootstrapping calculating the custom index and the resulting ARs for each bond in a category (e.g. downgrades within the non-investment grade category) takes about a day.

C. CARs in the Days around a Category Crossing

The first set of tests look at the daily CARs around a rating change that either leaves a bond in the same ratings category or moves it between investment and noninvestment. Day 0 is the date on which the rating change is recorded in the Mergent database. The results are in Table 6.

Table 6 Columns 1 and 2 tabulate the results for rating changes that drop a bond from investment to non-investment grade. The estimated post announcement returns are in the −180 bps range. The results are both economically and statistically significant. There is some evidence of continued negative returns for another day or two after which the price appears to level off with a net loss of approximately 250 bps.

The next set of columns examine the returns to a bond that is downgraded but still remains inside its original ratings category. For downgrades within both the investment and non-investment grade categories returns are relatively small and not persistently significant. Nevertheless, they are uniformly negative indicating that investors in these issues may well suffer losses after a rating downgrade. Within the non-investment grade category it appears that losses within a week of the downgrade come to somewhere between 50 and 70 bps, with some evidence of the start of a recovery by day 10.

On the right side of Table 6 are the returns around upgrades. Upgrades for bonds that cross from noninvestment to investment grade show evidence of positive returns that take a week or two to materialize post announcement. By the end of the second trading week post announcement (day +10) returns are about 50 bps and statistically significant using either the BofAML or Barclays rule. Upgrades for bonds beginning and ending in the non-investment grade category are smaller. There is some evidence using the Barclays rule that the returns are positive for about a week and then mean revert to some degree. A similar pattern appears under the BofAML rule, but there the significance levels are quite a bit lower. For bonds that are upgraded within the investment grade category the estimated returns are small, of inconsistent sign and lack statistical significance. It is very hard to reject the idea that the announcements have no impact on the market.

The results from Table 6 support the hypothesis that institutional rigidities play an important role in the market reaction when a bond downgrades from the investment to the noninvestment category. For other downgrades that do not move a bond across the investment/noninvestment border, there is little return reaction possibly due to trend chasing affecting the market's overall liquidity and the influence of reaching for yield apparently offset it. With respect to upgrades into the investment grade category, institutional rigidities seem to play a role as well, but to a lesser degree. (Of course, it may be that the rigidities play just as strong a role but are offset by other factors. For example, liquidity, reaching for yield and trend chasing may all combine to produce a reduced overall price impact.) In the other upgrade tests, it may be that the additional liquidity in the investment grade market (see Table 4) is sufficient to offset the impact of a ratings upgrade, while the same may not be true for non-investment grade bonds.

D. CARs Prior to a Rating Change

As noted earlier, numerous studies have found that bond rating changes follow changes in the bonds' market prices. Thus, the ratings change may be expected. We examine this possibility in Table 7 by repeating the analysis in Table 6 for the weeks prior to the rating change. The results are generally consistent with previous studies. Almost across the board, downgrades follow negative returns in excess of 100 bps. For bonds that cross from investment to non-investment grade the negative returns start at least five weeks prior to the downgrade and ultimately total over 150 bps. For downgrades among non-investment grade bonds that remain non-investment grade (i.e. do not transition to distressed) negative returns only precede rating changes by between 1 and 3 weeks and the statistical significance depends on the scoring rule used. For changes among investment grade bonds that then remain in the investment grade category the negative returns are close to 120 bps but seem to start as much as 6 weeks earlier. [23]

For upgrades the picture is again somewhat mixed. Bonds upgraded from noninvestment to investment and those that start and end in the noninvestment category yield statistically significant positive abnormal returns prior to the rating change. About 70 bps in the former case and 100 in the latter. But, for upgrades that involve bonds that start and end in the investment category there is no economically or statistically significant indication that rating changes follow a string of positive returns.

E. CARs Following a Ratings Change

As demonstrated in the earlier tables the corporate bond market is an illiquid market. As pointed out earlier, microstructure models suggest that this illiquidity can lead prices to overshoot their equilibrium values and then bounce back to some degree in the weeks following the initial price change (Keim and Madhavan (1996)). In Table 8 we address this issue by examining reported CARs that begin at the end of the 10^{th} day following a ratings change, which is the day on which the results reported in Table 6 end.

Table 6 shows that up to day 10 bonds downgraded from investment to non-investment grade experience post announcement returns in the range of −233 bps. Table 8 shows that these same bonds have a partial rebound of 130 or 78 bps depending on the scoring rule used, which is consistent with the Keim and Madhavan model in which price pressure from block sellers and limited liquidity produce serially correlated returns and prices that overshoot their equilibrium value. A similar rebound is observed for downgrades that cause a bond to start and end as non-investment grade. Again, this occurs

[23] We conjecture that the rating agencies are reluctant to downgrade investment grade bonds and require a relatively long negative run of news before doing so. For non-investment grade bonds, the rating agencies may worry about missing an event that leads to default. They therefore require a shorter negative news run prior to downgrading such bonds. Of course, these are just conjectures at this point and we do not pursue them any further in this paper.

in the part of the market where liquidity is likely to be thinnest. In contrast, the bonds that start and end in the investment grade category after a downgrade that showed at most a modest post announcement negative return in Table 6, have little evidence of a price rebound in Table 8.

For upgrades in which a bond crosses from the noninvestment to investment grade category, reports an approximate 50 bps post announcement price reaction in the days following the rating change. Table 8 indicates a continued upward drift for an additional 4 weeks. By trading day +26 returns have increased by another 61 to 78 bps. In contrast, the other rating upgrade groupings show little consistent evidence of systematic price changes. At most, for bonds that are upgraded but start and end in the noninvestment category there may be a small positive post announcement price increase of between 13 and 22 bps after 3 weeks, a gain which then reverses itself by week 5. However, the evidence for this is pretty thin and it would be reasonable to conclude that one cannot dismiss the null hypothesis that the post announcement benchmark adjusted returns are random noise around zero.

F. CARs for Border Bonds that then Cross the Border

Following a ratings change, Table 6 through Table 8 compare bonds that move from an investment or non-investment grade category to another against those that remain in their initial category. However, the potential size of the rating change for bonds that switch categories is quite a bit larger than for bonds that do not. Consider a bond with an initial rating of 1 (AAA). For this bond to continue to be included in the no change investment grade category, it cannot fall below a rating of 10, thus, a change of at most 9 points. For the AAA bond to move from the investment to non-investment grade category, its rating has to change by at least 10 points. In fact, it can change up to 15 points (to 16 points) and still be included in the investment to non-investment grade group. Large rating changes such as this are likely perceived very differently by market participants than a typical downgrade that simply moves a bond by a single rating point. As noted earlier, another problem with a potential large rating change is that rather than being rated, a ratings agency may simply drop coverage, resulting in measurement error being introduced into the ratings history. That is, rating agencies are not obligated to rate a bond for its entire life. A firm that undergoes a large negative or positive corporate event may induce a rating agency to drop coverage, in which case such a decision will not be included in the database. All one has is the last rating; a rating that is no longer valid. It seems likely that the market is fully aware of this and that the firms creating bond benchmarks adjust their scoring rules accordingly. This measurement error can lead to situations where bond rating changes are underestimated based on the available ratings data.

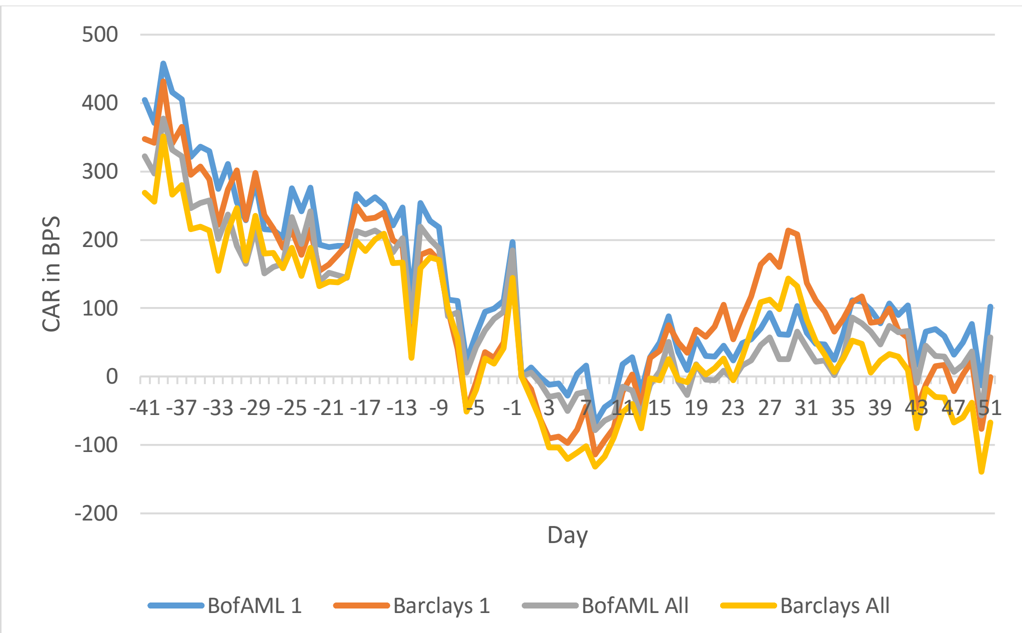

Figure 1: Downgrades that Change a Bond's Classification from Investment to Noninvestment.

Figure 1 and Figure 2 address the issue of whether large rating jumps are driving the prior results. The two graphs compare the CARs for bonds that start near the border of their rating class and then cross versus bonds that simply move from one rating class to another. The legend shows both the scoring system used and the filter used to select bonds. The prefix “BofAML” or “Barclays” indicates the classification scoring system. A suffix of “all” indicates that the CARs include any bond that begins in one class (investment or noninvestment) and then crosses to the other class. A suffix of “1” indicates that the CARs only include bonds that begin within one point of the border prior to crossing it.

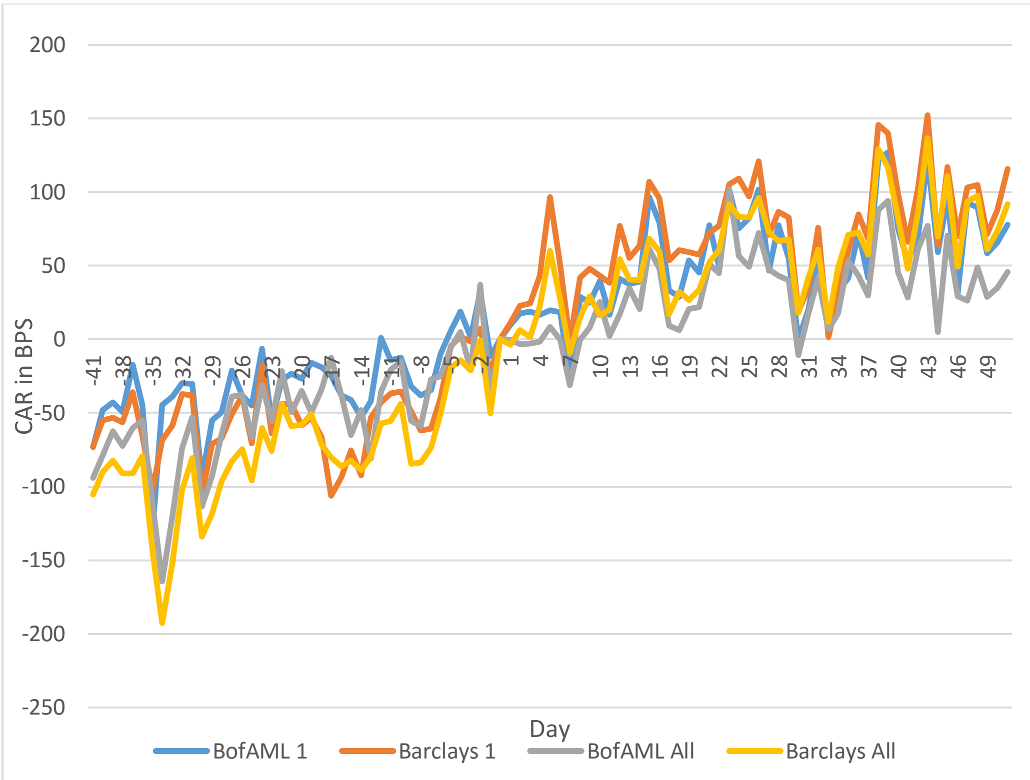

Figure 2: Upgrades that Change a Bond's Classification from Noninvestment to Investment.

While including either all bonds or just those that are near the border prior to crossing makes some difference in the CARs, these do not seem to be material. It is true that including all bonds results in a slightly lower CAR overall. For downgrades, the average CAR differs by 63 bps and 85 bps based on the BofAML and Barclays scoring rules respectively. For upgrades, the average differences are 25 and 22 bps respectively. However, more importantly, in terms of the overall return pattern there seems to be little difference. For both upgrades and downgrades bonds tend to see a price reaction over a number of days following the rating change after which there is some evidence of a recovery (stronger for downgrades than upgrades).

G. Orphan Bonds

As pointed out earlier, because BofAML and Barclays use slightly different classification rules, they do not always lead to the same groupings. In principle, some bonds may be rated investment grade by one and non-investment grade by the other. Recall, that investment grade funds tend to use the Barclays classification rule and investment grade funds the BofAML rule. The result is that some bonds are orphans in that they are non-investment grade via Barclays rule and investment grade via the BofAML rule.[24,25] While orphans are not created very often, they do provide another way to test the hypothesis that institutional frictions lead to liquidity problems. If the frictions arising from a change in rating category impact bond returns, then orphan bonds should be particularly vulnerable. These are bonds that are not part of the benchmarks used by either income or high yield funds. If institutional rigidities are important, this is the group that should be most affected. The current investment grade holders need to sell the issue, but non-investment grade funds have no reason to buy it as it is not in their benchmark either.

Table 5 lists the number of bonds that become orphaned in each year. For these bonds institutional rigidities should play a particularly dramatic role. There is, however, no reason to believe the other three factors listed in Section I.B will impact any differently in this case than in the more general case of a ratings downgrade.

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[24] While cases where a rating change leads Barclays to rate the issue investment and BofAML non-investment grade are theoretically possible, the data do not contain any examples where it occurred.

[25] For the orphan bond tables, cases where the BofAML and Barclays rules produce scores that differ by 3 or more are dropped. Occasionally, a bond goes from the higher end of the investment grade scale into either the low end of the non-investment grade scale or even into default. Whether this will be reflected in the Mergent database depends on if all of the agencies issue new ratings in response to the change in the company's fortunes. For example, following a default Moody's may reduce the rating to a D while S&P and Fitch may just stop following the issue. In this case, the database shows the change to the Moody's rating but does not indicate that any change occurred in the S&P or Fitch rating. Whatever the cause, one suspects that such bonds are not really "orphans" and are recognized by all as being either non-investment grade or distressed and are thus dropped from the orphan analysis.

Hypothesis 3: *Orphan bonds should see the greatest degree of negative serial correlation in returns and the greatest degree of price overshooting.*

For fund managers orphan bonds present a unique problem. These bonds leave the investment grade category under the Barclays scoring rule but not that of the BofAML rule. Since investment grade managers use the former and non-investment grade managers the latter, it is not clear what funds will find these issues conformable with their mandate. An advantage of these cases is that they present a unique test of whether institutional rigidities affect bond returns. For these bonds, investment grade funds have an incentive to sell, while their natural counterparties (non-investment grade funds) have little incentive to buy.

Figure 3 displays the CARs for 120 trading days before and after bonds that are orphaned, defined as date 0. The CARs are relative to the announcement date. Blue dots represent CARs that are not significantly different from zero at the 10% level and orange dots CARs that are. In the 60 days prior to a bond being orphaned it loses nearly 500 bps. This is substantially more than the pre rating change losses seen for any of the other downgrades in Table 7. After the downgrade, these bonds lose approximately another 750 bps until about day 45. After that there appears to be an approximately 250 bps recovery until about day 60 after which returns appear to stabilize.

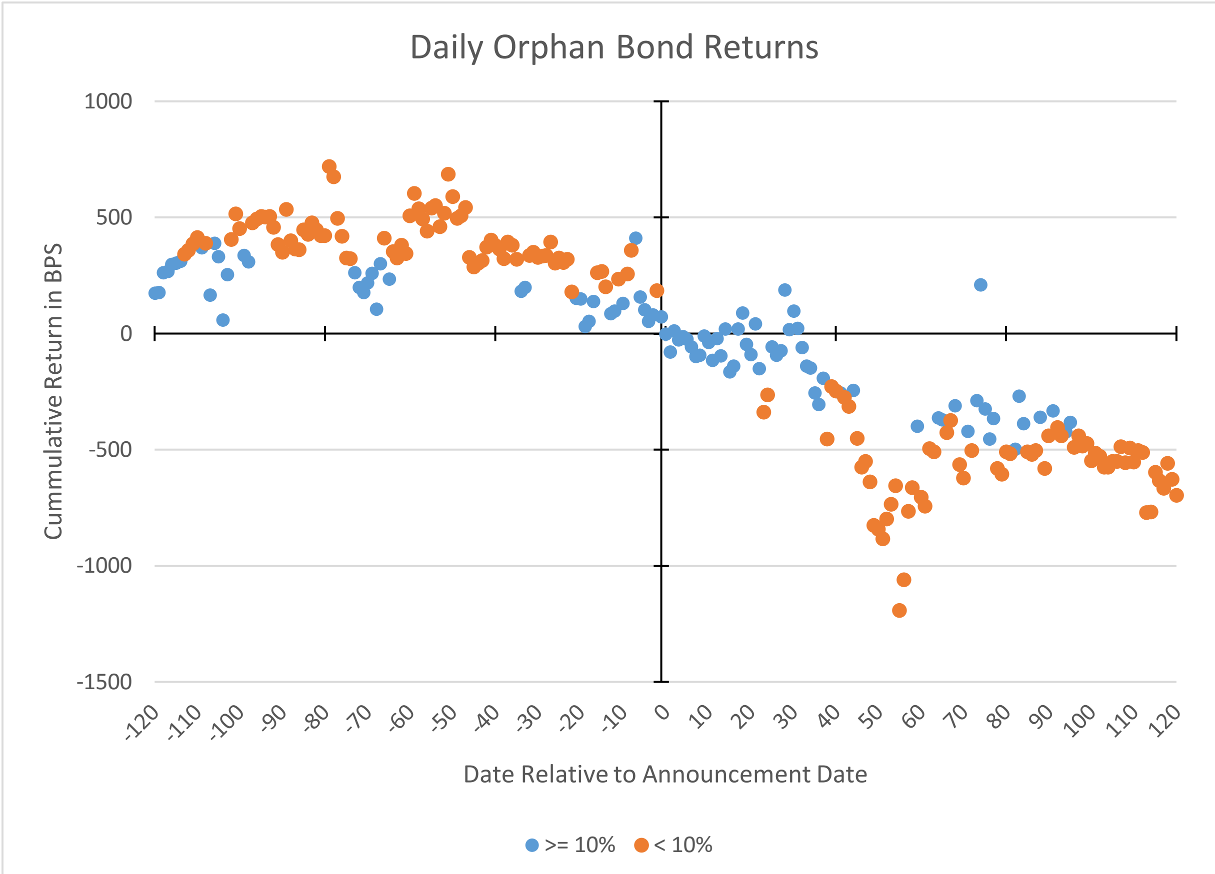

Figure 3: Orphan Bond CARs. Colors represent significance at the 10% level relative to 0.

The post announcement return pattern in Figure 3 is consistent with the institutional rigidity argument. These bonds see a substantial drop in their value while in Barclays investment grade categorization. Once the downgrade goes through the investment grade funds holding the issue are incented to sell it. However, these bonds are still rated investment grade under the BofAML scoring system. That reduces the incentive non-investment grade funds would have to buy the issue. While the investment grade funds may want to eventually sell out of their position, their prospectuses do not typically require that they do so immediately. In a case like this, they may find it optimal to try and hold out as long as they can. Of course, once the price drops far enough it becomes sufficiently attractive that fund managers become willing owners despite the restrictions imposed upon them by their prospectuses. In a microstructure model like Keim and Madhavan (1996) the result would be long term selling pressure with a recovery. This would result in a pattern like the one in Figure 3.

VII. Changes over Time

In this section we examine how the reaction to bond downgrades around the investment grade/non-investment grade boundary has changed over time given the institutional changes in the bonds markets after the financial crisis of 2007-2008. One aspect of that change has been the change in bond market ratings agencies optimism. Cornaggia, Cornaggia and Hund (2015) argue and present evidence that corporate bonds have optimism in their ratings. Skreta and Veldkamp (2009) argue that this optimism is a result of the pay-by-issuer model.

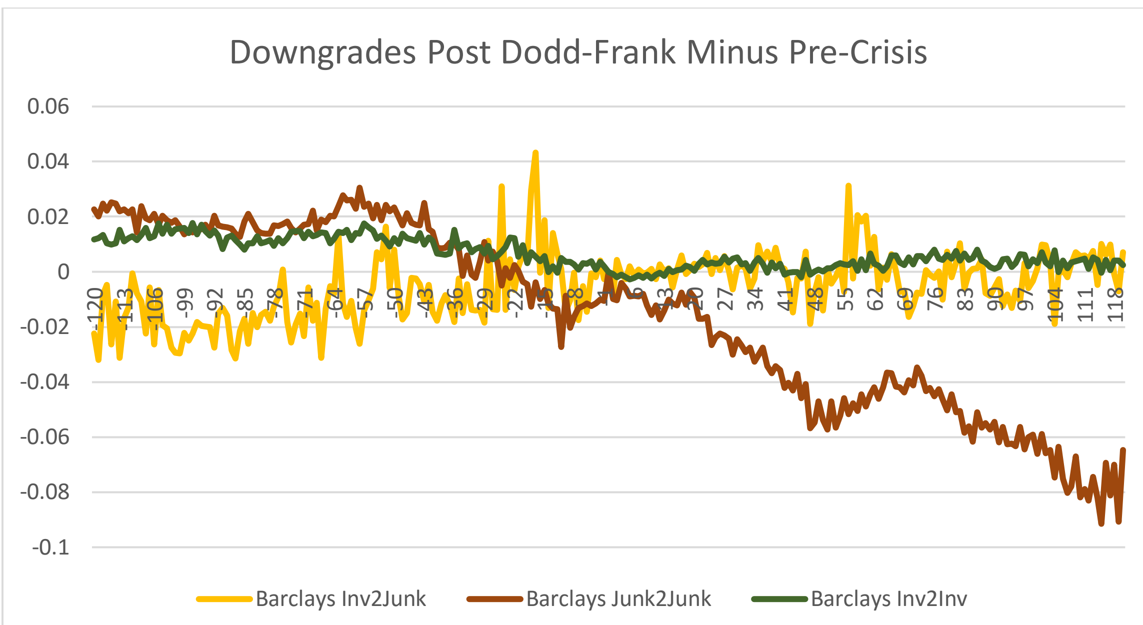

Figure 4: Downgrades post Dodd-Frank minus Pre-crisis

Figure 4, which shows the differences in abnormal returns to downgrades before and after the financial crisis and the passage of the Dodd-Frank law, is consistent with the conjecture that the optimism shown by ratings agencies has changed since the financial crisis. The figure also suggests that the changes have primarily occurred for the downgrades to high-yield bonds that were already in the high-yield market segment. The downgrades in which a bond still remains an investment grade bond or in which a bond moves from investment grade to non-investment grade have not materially changed. Panel A of Table 3 in our paper also shows that the pattern of downgrades to upgrades changes significantly after the financial crisis. That is, a striking difference exists in the ratio of downgrades relative to upgrades, suggesting again that the rating agencies have changed their issuance of the most optimistic forecasts.

VIII. Conclusion

Many bond funds restrict their holdings to either investment or non-investment grade. When a bond crosses from one category to another, this self-imposed institutional rigidity induces current investors to sell the issue. At the same time, the bond moves into the investment opportunity set for other funds which find that if they so choose, they can now add the bond to their portfolio because it has the moved into their restricted category. Market microstructure models indicate that in an illiquid market with relatively anxious sellers or buyers, security returns will exhibit serial correlation (while the positions are worked off or acquired) followed by a period when prices partially revert. This is the hypothesis tested in this paper.

Given the illiquidity in the corporate bond market, to test this hypothesis we adapt the repeat sales models from the real estate literature in order to estimate abnormal bond returns that arise from institutional rigidities in the market. That model creates a general index about which housing returns vary. Implicitly, this gives each house a factor loading of 1. For bonds, that may be a problematic assumption. To accommodate the factors that may impact benchmark loadings this paper employs a modified repeat sales index. The modification weighs each observation's by the inverse of its distance from the target bond. For each bond this forms a unique distance weighted repeat sales index to use at its benchmark. Once the vector of abnormal returns are generated around an event, CARs can be estimated and tested for significance using standard regression techniques.

Overall, the empirical results support the institutional rigidity hypothesis in that rating changes that push a bond from one rating category to another lead to return patterns consistent with microstructure theory. Downgrades that cross a bond from investment to noninvestment lead to negative CARs from the announcement day and for a few days afterward. This period is then followed by a partial price rebound. For bonds that see rating changes that leave them in their overall investment or non-investment grade category there is some indication that the bond market's general lack of liquidity leads to prices that overshoot their long run equilibrium value in the non-investment grade market. But it is far more muted than the case where the change drops the security from the investment to noninvestment category. Upgrades show similar patterns to downgrades, but to lesser degree and with returns in the opposite direction.

A unique test of the how institutional rigidities impact bond returns can be seen via an examination of orphan bonds. These bonds undergo rating changes that drop them from investment grade under Barclays scoring rule but not under the BofAML rule. Since investment grade portfolios are typically benchmarked against a Barclays index and non-investment grade portfolios against the BofAML index, there is no natural investment pool for these issues. The results are seen clearly in the data. When a bond becomes an orphan its value drops in the weeks following the rating change and then recovers somewhat. Overall, the loss appears to total close to 5%.

The somewhat artificial designation of a bond as investment or non-investment grade is used by many institutional investors to restrict their holdings. This is obviously done for the convenience of investors and their regulators. But, it also creates an institutional rigidity. When a bond crosses the investment-noninvestment barrier it must also transition from one set of bond funds to another. The evidence in this paper indicates that this transfer does not take place smoothly. Instead, bond returns exhibit persistent returns for days after the ratings change that are then partially reversed in the weeks that follow. Obviously, this would not happen if the bond market was sufficiently liquid. But it is not. Most bonds trade less than once a month, which makes these transfers potentially very difficult to pull off.

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Table 1: Ratings scale for calculating composite

Scoring system used by BofA Merrill Lynch to determine the index a bond belongs to. Original source: BofA Merrill Lynch Bond Indices; Bloomberg

Numeric	Composite	Moody's	S&P	Fitch
1	AAA	Aaa	AAA	AAA
2	AA1	Aa1	AA+	AA+
3	AA2	Aa2	AA	AA
4	AA3	Aa3	AA-	AA-
5	A1	A1	A+	A+
6	A2	A2	A	A
7	A3	A3	A-	A-
8	BBB1	Baa1	BBB+	BBB+
9	BBB2	Baa2	BBB	BBB
10	BBB3	Baa3	BBB-	BBB-
11	BB1	Ba1	BB+	BB+
12	BB2	Ba2	BB	BB
13	BB3	Ba3	BB-	BB-
14	B1	B1	B+	B+
15	B2	B2	B	B
16	B3	B3	B-	B-
17	CCC1	Caa1	CCC+	CCC+
18	CCC2	Caa2	CCC	CCC
19	CCC3	Caa3	CCC-	CCC-
20	CC	Ca	CC	CC
21	C	C	C	C
22	D	D	DDD-D	

Table 2: Fraction of Days Traded by Year by Bond

Fraction of days traded (FDT) during a one year time period over which a bond trade is observed. The numerator in FDT equals the number of trades in bond *B* during year *Y*. The denominator is the number of trading days in year *Y* between the first and last trade date across all years in bond *B*. Panel A includes a bond in year *Y* if: (1) there is at least one trade in year *Y* or prior to it and (2) at least one trade in year *Y* or after it. Note, a single trade in year *Y* will lead to a bond's inclusion in year *Y*. Also bonds with trade on dates prior to and after but not in year *Y* are included in the year *Y* data. Example: A bond trades in 2005 and 2007 but not 2006. Fraction equals 0/total trade days in 2006 = 0. A bond trades on July 11, 2006 and July 12, 2006 but never before or after. FDT equals 2/2 = 1, since total trade days during 2006 between the first and last trade date in the bond is 2. In Panel B, the same exercise is carried out. But this time Year refers to the number of years since the bond is first observed to trade t_0. Time from t_0 to its first anniversary is labeled 1. The denominator follows the rule for Panel A, with the reference year being the number of years from t_0, again with the first year being from t_0 to its anniversary. Example: A bond first trades on July 11, 2006. It trades again on August 8, 2007 and September 16, 2008. FDT equals 1/trading days between July 12, 2007 and July 11, 2008. If the bond traded on August 8, 2007 but never again traded then FDT equals 1/trading days between July 12, 2007 and August 8, 2007. Row 11+, averages across all years greater than or equal to 11. Displayed is the FDT on a percentage basis (i.e. 100×FDT).

	Percentile						
Year	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**
Panel A: FDT by Bond by Calendar Year							
2003	0.85	1.47	3.44	8.52	21.53	38.08	53.59
2004	0.79	1.61	3.92	10.26	22.97	40.50	51.56
2005	0.49	1.19	2.78	7.82	19.05	36.51	47.60
2006	0.40	0.80	2.39	7.94	19.56	36.59	48.21
2007	0.00	0.40	1.98	6.35	17.86	34.61	46.41
2008	0.00	0.40	1.19	4.35	13.44	31.38	45.57
2009	0.00	0.40	1.59	5.16	15.74	32.54	44.34
2010	0.00	0.40	1.19	4.74	15.42	32.00	42.99
2011	0.00	0.40	1.59	5.16	14.68	29.69	40.48
2012	0.00	0.00	1.18	3.70	12.09	27.06	39.92
2013	0.00	0.38	1.52	4.94	14.07	29.28	42.86
2014	0.38	0.77	1.92	5.75	15.33	31.03	42.91
Panel B: FDT by Bond by Year's Since Initial Trade Date							
1	0.40	1.14	3.16	8.59	19.92	37.50	49.80
2	0.38	0.75	1.95	5.40	14.68	30.62	42.44
3	0.00	0.40	1.20	4.11	12.26	26.63	38.94
4	0.00	0.39	1.13	3.12	9.84	23.51	36.11
5	0.00	0.39	0.79	2.77	8.56	20.43	30.56
6	0.00	0.00	0.76	1.92	5.84	16.03	25.18
7	0.00	0.00	0.40	1.53	4.37	12.99	20.76
8	0.00	0.00	0.39	1.18	3.77	11.40	19.32
9	0.00	0.00	0.39	1.18	3.82	9.58	19.63
10	0.00	0.38	0.39	1.52	3.61	9.38	17.29
11+	0.00	0.38	0.55	1.16	3.05	8.78	16.98

Table 3: Changes between Investment and Non-investment grade over Time

Panel A of this table reports for each year the total number of bonds crossing the investment grade and investment grade category using the Bank of America Merrill Lynch (BofAML) or Barclays rule for their indices. Panel B reports the total number of bonds in years since initial rating is defined so that year 1 includes any transition from investment to investment or the reverse occurring within 1 year of the initial rating date.

	Downgrades		Upgrades		Ratio of Downgrades to Upgrades	
Year	BofAML	Barclays	BofAML	Barclays	BofAML	Barclays
Panel A: Calendar Year						
2003	292	312	76	80	3.84	3.90
2004	209	215	135	138	1.55	1.56
2005	1700	2245	216	233	7.87	9.64
2006	688	285	179	155	3.84	1.84
2007	361	433	161	144	2.24	3.01
2008	1604	1572	264	263	6.08	5.98
2009	2361	2467	111	102	21.27	24.19
2010	253	264	137	127	1.85	2.08
2011	152	183	180	176	0.84	1.04
2012	160	157	199	201	0.80	0.78
2013	145	124	352	341	0.41	0.36
2014	125	127	127	101	0.98	1.26

Panel B: Years Since Initial Rating

	Downgrades		Upgrades	
Year	BofAML	Barclays	BofAML	Barclays
1	1237	1465	266	231
2	1618	1583	312	307
3	1236	1206	257	247
4	864	863	228	225
5	812	874	167	151
6	836	844	136	138
7	371	392	145	139
8	202	233	92	90
9	242	260	101	86
10	221	223	84	94
11+	411	441	349	353

Table 4: Fraction of Days with Trading Around Classification Rating Changes

This table shows the fraction of days in the months or days a bond trades around a rating change to or from investment and investment grade. For months, other than 0, it is the average across bonds of the number of trading days on which the bond traded divided by the number of trading days. For month 0 it is just the day of the rating change. For days it is the fraction of bonds with a trade on that day. Bonds are excluded from a period if there are no trades recorded for them both before and after the period in question. Values are in percentage terms. Standard errors are in square brackets.

Time	Investment Grade to Non-investment grade				Non-investment grade to Investment Grade			
Units	Months		Days		Months		Days	
	BofAML	Barclays	BofAML	Barclays	BofAML	Barclays	BofAML	Barclays
-6	20.87	20.58	11.34	9.33	6.59	6.23	15.80	15.07
	[2.02]	[2.02]	[2.09]	[2.08]	[2.48]	[2.50]	[2.43]	[2.45]
-5	21.34	20.59	10.47	9.67	7.31	6.88	15.09	15.31
	[2.02]	[2.02]	[2.09]	[2.08]	[2.46]	[2.48]	[2.43]	[2.45]
-4	20.44	19.99	10.12	8.81	7.45	6.86	14.39	14.83
	[2.02]	[2.01]	[2.09]	[2.08]	[2.48]	[2.50]	[2.43]	[2.45]
-3	20.48	19.91	11.52	11.57	7.96	7.89	16.27	14.59
	[2.00]	[1.99]	[2.09]	[2.08]	[2.47]	[2.48]	[2.43]	[2.45]
-2	21.89	21.10	13.96	12.44	8.63	8.63	13.92	13.16
	[2.06]	[2.04]	[2.09]	[2.08]	[2.45]	[2.47]	[2.43]	[2.45]
-1	24.34	25.01	14.14	12.78	13.12	12.62	13.21	12.68
	[2.05]	[2.03]	[2.09]	[2.08]	[2.40]	[2.44]	[2.43]	[2.45]
0	21.82	19.00	21.82	19.00	24.53	22.25	24.53	22.25
	[2.09]	[2.08]	[2.09]	[2.08]	[2.43]	[2.45]	[2.43]	[2.45]
1	11.62	10.48	32.29	30.40	15.10	14.87	20.28	20.81
	[2.07]	[2.06]	[2.09]	[2.08]	[2.38]	[2.40]	[2.43]	[2.45]
2	9.66	8.99	27.57	26.60	14.41	13.82	15.33	14.35
	[2.08]	[2.07]	[2.09]	[2.08]	[2.39]	[2.41]	[2.43]	[2.45]
3	7.89	7.55	24.61	24.87	15.80	15.65	15.09	14.11
	[2.10]	[2.09]	[2.09]	[2.08]	[2.39]	[2.41]	[2.43]	[2.45]
4	8.26	8.35	25.13	26.08	15.21	15.15	9.91	8.13
	[2.12]	[2.10]	[2.09]	[2.08]	[2.39]	[2.41]	[2.43]	[2.45]
5	7.79	7.35	21.29	21.07	16.49	16.44	11.56	11.24
	[2.12]	[2.10]	[2.09]	[2.08]	[2.40]	[2.42]	[2.43]	[2.45]
6	8.21	7.80	22.51	24.87	16.54	16.50	8.96	9.33
	[2.11]	[2.10]	[2.09]	[2.08]	[2.42]	[2.45]	[2.43]	[2.45]

Table 5: Orphans by Year

This table shows the number of orphan bonds in the sample each year. An orphan bond is defined as one with a BofAML score of less than or equal to 10 and a Barclays score of greater than or equal to 11. Bonds are only included if the absolute difference between the two scores is less than or equal to the value in Abs(Diff). The upgrades are bonds that having a rating change that causes them to go from BofAML investment grade group to its investment grade group, while remaining in the Barclays investment grade group. Downgrades are bonds that have a rating change that moves them from the Barclays investment grade category to Barclays investment grade category while remaining in the BofAML investment grade category.

	Upgrades		Downgrades	
Abs(Diff)	1	2	1	2
2003	8	16	37	47
2004	14	25	68	71
2005	24	38	155	769
2006	42	52	36	51
2007	31	35	52	60
2008	32	38	103	124
2009	13	17	366	456
2010	30	33	72	81
2011	37	41	28	37
2012	17	24	35	39
2013	32	41	8	10
2014	31	33	36	36

Table 6: Day 0 to +10 Cumulative Abnormal Returns for Bonds Experiencing a Rating Change

This table shows daily bond returns following a rating change. Investment grade (“Inv.”) (defined as having a score between 1 and 10) and noninvestment grade (“Junk”) (a score of 11 to 16) are based on the rating aggregation method used by either BofAML or Barclays (“Barc”). Bonds with a rating of 17+ are defined as distressed. Column headers indicate downgrades or upgrades for bonds from one rating group to another. Columns “Inv. To Inv.” Indicate a rating change for an investment grade bond that remains investment grade after the rating change. Columns “Junk to Junk” indicate the same for bonds initially rated non-investment grade. Finally, “Inv to Junk” and “Junk to Inv.” Indicate bonds that switch class after a rating change. Displayed returns by day are the benchmark adjusted cumulative abnormal returns (CAR) from the end of day 0 to the end of day 10 in basis points. Return estimates are based on the mean bootstrapped values repeated 500 times. Day 0 is the date on which a bond’s numerical rating score changes. Days are measured in trading, not calendar, days. In the row *X* to *Y* the numbers represent borders. It should be read as pre rating change score greater than or equal to *X* and post rating score less than or equal to *Y*. Bootstrapped *p*-values against a null of 0 is below in square brackets. Key: ***=1%, **=5% and *=10%.

	Downgrades						Upgrades					
	Inv. to Junk		Junk to Junk		Inv. to Inv.		Junk to Inv,		Junk to Junk		Inv. to Inv.	
Day	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**
0	-194.938	-157.632	-15.616	-35.410	-12.379	-12.505	13.635	19.435	13.749	10.321	15.418	12.500
	[0.00]***	[0.00]***	[24.60]	[7.20]*	[11.60]	[13.60]	[29.00]	[22.20]	[7.20]*	[11.20]	[26.40]	[32.40]
1	-184.572	-175.765	-29.816	-40.633	-11.806	-15.474	23.375	30.903	21.719	23.613	-3.319	-6.350
	[0.00]***	[0.00]***	[15.60]	[4.80]**	[16.60]	[12.80]	[24.40]	[16.60]	[1.80]**	[2.20]**	[45.40]	[44.80]
2	-197.277	-218.186	-40.715	-47.246	-17.060	-22.713	29.976	43.337	17.801	25.808	10.087	7.015
	[0.00]***	[0.00]***	[10.20]	[2.60]**	[12.00]	[7.20]*	[20.00]	[8.00]*	[9.40]*	[4.00]**	[31.40]	[36.40]
3	-209.022	-252.310	-55.861	-46.606	-23.158	-26.848	30.626	44.680	18.373	21.743	23.016	22.286
	[0.20]***	[0.00]***	[4.40]**	[4.20]**	[5.00]**	[5.80]*	[16.20]	[7.60]*	[8.00]*	[6.80]*	[15.40]	[23.00]
4	-207.288	-246.507	-66.675	-45.971	-28.594	-16.974	28.715	64.707	8.509	27.182	3.649	-12.017
	[0.00]***	[0.00]***	[3.20]**	[4.60]**	[2.40]**	[16.00]	[20.00]	[5.40]*	[25.20]	[2.80]**	[43.20]	[38.60]
5	-227.234	-256.209	-60.003	-39.044	-34.688	-33.761	31.607	114.154	10.238	25.764	-15.235	-19.551
	[0.20]***	[0.00]***	[7.60]*	[9.40]*	[2.00]**	[2.20]**	[20.60]	[16.20]	[17.00]	[1.60]**	[28.80]	[28.40]
6	-192.621	-235.745	-74.061	-57.773	-33.781	-34.023	32.410	71.889	4.271	24.746	14.018	11.550
	[0.60]***	[0.00]***	[2.60]**	[5.00]**	[2.40]**	[2.00]**	[16.80]	[3.00]**	[34.40]	[2.40]**	[28.60]	[34.00]
7	-182.391	-203.713	-73.559	-51.926	-31.870	-29.754	-12.395	19.601	17.687	41.681	3.567	-6.695
	[0.40]***	[0.00]***	[3.40]**	[7.00]*	[3.80]**	[4.60]**	[38.40]	[34.00]	[9.20]*	[0.00]***	[43.80]	[45.40]
8	-263.868	-273.247	-52.757	-39.172	-30.965	-29.555	43.390	62.157	22.706	34.847	-4.617	-12.207
	[0.00]***	[0.00]***	[12.00]	[14.40]	[5.20]*	[5.80]*	[14.80]	[7.80]*	[6.00]*	[1.20]**	[44.20]	[38.40]
9	-241.856	-252.054	-58.927	-40.121	-33.884	-30.324	35.633	67.880	11.264	20.671	-14.880	-30.196
	[0.00]***	[0.00]***	[8.60]*	[15.00]	[6.20]*	[10.00]*	[13.80]	[2.00]**	[20.80]	[9.40]*	[32.80]	[24.00]
10	-234.680	-233.550	-50.261	-9.872	-18.867	-16.836	53.064	62.461	15.408	23.480	4.215	-0.184
	[0.00]***	[0.00]***	[12.80]	[40.00]	[15.20]	[18.40]	[6.60]*	[4.80]**	[13.00]	[6.00]*	[43.00]	[50.60]

Table 7: Weekly Abnormal Returns prior to a Rating Change

This table shows weekly bond returns preceding a rating change. Investment grade ("Inv.") (defined as having a score between 1 and 10) and noninvestment grade ("Junk") (a score of 11 to 16) are based on the rating aggregation method used by either BofAML or Barclays ("Barc"). Bonds with a rating of 17+ are defined as distressed. Column headers indicate downgrades or upgrades for bonds from one rating group to another. Columns "Inv. To Inv." Indicate a rating change for an investment grade bond that remains investment grade after the rating change. Columns "Junk to Junk" indicate the same for bonds initially rated non-investment grade. Finally, "Inv to Junk" and "Junk to Inv." Indicate bonds that switch class after a rating change. Displayed returns by day are the benchmark adjusted cumulative abnormal returns (CAR) from the end of day −42 to the end of day −1 in basis points. Return estimates are based on the mean bootstrapped value repeated 500 times. Day 0 is the date on which a bond's numerical rating score changes. Days are measured in trading, not calendar, days. In the row *X* to *Y* the numbers represent borders. It should be read as pre rating change score greater than or equal to *X* and post rating score less than or equal to *Y*. Bootstrapped *p*-values against a null of 0 is below in square brackets. Key: ***=1%, **=5% and *=10%.

	Downgrades						**Upgrades**					
	Inv. to Junk		**Junk to Junk**		**Inv. to Inv.**		**Junk to Inv,**		**Junk to Junk**		**Inv. to Inv.**	
Day	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**
-41	38.067	41.387	-15.095	-11.543	2.923	7.749	9.990	6.000	23.433	23.361	1.951	-5.590
	[21.00]	[10.20]	[18.40]	[25.00]	[43.00]	[28.80]	[29.80]	[35.60]	[0.00]***	[0.20]***	[46.20]	[39.80]
-36	-45.125	-13.052	1.620	-4.642	1.518	-13.058	42.290	12.392	40.361	44.360	-4.217	-10.094
	[14.00]	[39.00]	[45.00]	[41.80]	[47.20]	[28.40]	[5.00]**	[34.00]	[0.20]***	[0.00]***	[44.20]	[38.20]
-31	-113.882	-2.892	-39.855	-78.027	-40.525	-64.014	57.983	42.151	31.631	51.038	24.269	24.432
	[6.20]*	[47.80]	[20.40]	[4.80]**	[3.40]**	[0.40]***	[3.00]**	[9.60]*	[2.60]**	[0.20]***	[15.80]	[19.60]
-26	-160.872	-115.271	-1.163	-6.020	-78.660	-82.646	49.378	42.054	44.186	67.468	32.157	21.517
	[3.00]**	[4.00]**	[48.20]	[42.60]	[0.00]***	[0.00]***	[4.20]**	[4.80]**	[1.20]**	[0.00]***	[12.40]	[26.00]
-21	-174.456	-143.735	-48.537	-34.210	-66.138	-67.399	65.019	38.481	82.121	86.395	20.581	23.414
	[0.60]***	[2.00]**	[13.80]	[23.60]	[0.20]***	[0.60]***	[3.40]**	[13.00]	[0.00]***	[0.00]***	[22.80]	[22.60]
-16	-103.037	-75.971	-70.308	-6.622	-99.753	-106.587	44.957	-12.862	83.488	87.734	43.294	41.156
	[9.20]*	[17.80]	[8.80]*	[44.20]	[0.00]***	[0.00]***	[10.20]	[37.80]	[0.00]***	[0.00]***	[5.80]*	[8.40]*
-11	-105.845	-136.582	-126.372	-26.323	-91.627	-104.333	72.646	43.581	86.458	80.015	0.790	-1.742
	[11.60]	[6.60]*	[0.80]***	[31.80]	[0.00]***	[0.00]***	[0.80]***	[6.00]*	[0.00]***	[0.20]***	[48.80]	[46.00]
-6	-338.419	-366.826	-130.892	-39.717	-91.634	-104.603	77.580	40.072	126.386	130.624	-5.862	-6.342
	[0.00]***	[0.00]***	[0.80]***	[22.20]	[0.00]***	[0.00]***	[0.60]***	[9.00]*	[0.00]***	[0.00]***	[40.00]	[39.40]
-1	-168.812	-158.603	-179.588	-69.953	-120.926	-121.672	77.107	61.394	116.214	112.005	17.036	19.316
	[5.60]*	[4.40]**	[0.00]***	[12.60]	[0.00]***	[0.00]***	[2.60]**	[5.20]*	[0.00]***	[0.00]***	[34.00]	[38.40]

Table 8: Weekly Cumulative Abnormal Returns following a Rating Change

This table shows weekly bond returns following a rating change. Investment grade ("Inv.") (a score between 1 and 10) and noninvestment grade ("Junk") (a score of 11 to 16) are based on the rating aggregation method used by either BofAML or Barclays ("Barc"). Bonds with a rating of 17+ are defined as distressed. Column headers indicate downgrades or upgrades for bonds from one rating group to another. Columns "Inv. To Inv." Indicate a rating change for an investment grade bond that remains investment grade after the rating change. Columns "Junk to Junk" indicate the same for bonds initially rated non-investment grade. Finally, "Inv to Junk" and "Junk to Inv." Indicate bonds that switch class post rating change. Displayed returns are the benchmark adjusted cumulative abnormal returns (CAR) from the end of day 10 to the end of day 51 in basis points. Return estimates are based on the mean bootstrapped value repeated 500 times. Day 0 is the date on which a bond's numerical rating score changes. Days are measured in trading, not calendar, days. In the row *X* to *Y* the numbers represent borders. It should be read as pre rating change score greater than or equal to *X* and post rating score less than or equal to *Y*. Bootstrapped *p*-values against a null of 0 is below in square brackets. Key: ***=1%, **=5% and *=10%.

	Downgrades						**Upgrades**					
	Inv. to Junk		**Junk to Junk**		**Inv. to Inv.**		**Junk to Inv,**		**Junk to Junk**		**Inv. to Inv.**	
Day	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**	**BofAML**	**Barc**
11	52.521	54.073	-40.873	-16.187	-11.624	-16.490	-24.123	-2.610	-2.347	-7.305	9.069	15.499
	[1.00]***	[0.60]***	[0.40]***	[24.40]	[12.20]	[2.80]**	[16.00]	[46.60]	[39.00]	[24.20]	[34.60]	[22.20]
16	118.016	152.258	-43.811	-47.570	-1.567	-7.267	39.926	52.912	19.759	19.370	23.805	34.790
	[1.60]**	[0.00]***	[5.60]*	[16.00]	[46.20]	[30.20]	[6.80]*	[2.60]**	[5.40]*	[5.20]*	[29.20]	[23.80]
21	58.562	149.228	-39.756	-84.984	-11.059	-11.283	36.116	29.944	16.209	10.861	1.779	-3.287
	[17.20]	[1.20]**	[11.20]	[4.80]**	[22.20]	[22.40]	[15.80]	[14.20]	[14.20]	[24.40]	[45.80]	[45.00]
26	99.791	241.368	-15.553	-99.237	-7.807	-15.778	61.086	78.571	24.868	10.758	-2.114	-18.408
	[11.00]	[0.20]***	[35.60]	[8.80]*	[27.20]	[16.40]	[7.00]*	[2.40]**	[8.00]*	[26.40]	[44.60]	[22.80]
31	90.579	213.793	15.051	-32.809	8.938	-7.848	-20.389	-6.412	18.899	9.458	-18.820	-29.257
	[14.00]	[0.00]***	[38.00]	[38.40]	[31.20]	[34.40]	[30.20]	[42.60]	[16.00]	[34.80]	[19.60]	[12.80]
36	145.725	188.416	21.810	-36.189	-8.377	-20.374	31.377	45.082	-0.184	-19.016	-16.215	-11.854
	[7.00]*	[2.20]**	[32.00]	[34.00]	[34.20]	[17.60]	[30.80]	[21.00]	[47.60]	[18.20]	[24.40]	[31.20]
41	118.666	142.396	48.547	-8.893	-2.508	-25.743	11.146	25.435	-17.491	-25.199	1.467	-13.270
	[10.40]	[7.40]*	[16.80]	[49.60]	[44.80]	[14.40]	[42.00]	[30.00]	[22.60]	[17.20]	[46.40]	[35.40]
46	87.101	94.085	94.394	44.718	-19.431	-36.708	-7.093	29.980	-12.081	-19.108	-37.520	-56.980
	[18.40]	[18.20]	[5.20]*	[29.60]	[18.40]	[6.60]*	[46.40]	[31.40]	[31.60]	[22.60]	[13.40]	[6.60]*
51	130.523	78.511	143.570	52.294	-2.255	-12.872	37.780	75.669	-0.755	-10.317	7.367	12.231
	[17.60]	[28.00]	[1.40]**	[26.20]	[47.00]	[30.60]	[18.80]	[6.40]*	[50.60]	[34.20]	[39.20]	[34.40]