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Explaining and Benchmarking Corporate Bond Returns

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Abstract

We evaluate how different betas and characteristics related to default, term, and liquidity risk fare against one another in explaining the cross-section of corporate bond returns. We find that characteristics–credit rating, duration, and Amihud illiquidity measure–fare better. Yields add incremental explanatory power. Consistent with yields providing a timelier assessment of default risk than ratings, bonds with higher yields but similar credit ratings, durations and Amihud measures experience more subsequent ratings downgrades, fewer upgrades, and a higher frequency of defaults. Based on our findings, we present characteristic portfolios that can be used to benchmark individual bond and portfolio returns.

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Explaining and Benchmarking Corporate Bond Returns:

Considerable evidence now exists that default, term, and liquidity risk all play significant roles in explaining the cross-section of corporate bond returns. In this paper, we evaluate how various betas and characteristics fare against one another in measuring corporate bond sensitivities to these systematic risks.

The first issue we study is whether betas or characteristics fare better. Although betas directly link to underlying priced factor risks, they are estimated with noise using historical data. Characteristics, on the other hand, lack the direct link, but are more up-to-date and potentially capture qualitative information beyond what is reflected in historical data. The best approach to use is open to debate. For stocks, considerable attention has been given to the issue of whether betas or characteristics are more relevant in describing the cross-section of expected returns (see, for example, Daniel and Titman (1997) and Davis, et al. (2000)). For bonds, less work has been done, in large part because of a comparative lack of data. A notable exception is Gebhardt, Hvidkjaer, and Swaminathan (2005) (hereafter GHS), who find that default betas, and to a lesser degree term betas, are related to the return cross-section after controlling for the corresponding rating and duration characteristics. In contrast, ratings and duration add no explanatory power after controlling for default and term betas.

A second related issue we study is which specific betas or characteristics fare best. GHS's foundational study considered only default and term risk. More recent research examines whether liquidity risk is also priced. Specifically, this research shows that numerous betas and characteristics proxying for liquidity risk are related to corporate bond yield spreads and returns (see, for example, Longstaff, et al. (2005), Chen, et al. (2007), De Jong and Dreiessen (2007), Bao, et al. (2011), Lin, et al. (2011), Dick-Nielsen, et al. (2012), and Friewald, et al. (2012)). The betas studied include those obtained by regressing individual bond returns on a Pastor-Stambaugh bond market liquidity factor or Amihud bond market liquidity factor. The characteristics include those that capture liquidity in an indirect way (e.g., a bond's issued amount or age), trading activity (e.g., bid-ask spreads or volume), or estimated transaction costs or market impact (e.g., the Roll measure or Amihud measure).[1] These liquidity proxies are found to have varying economic and statistical importance. None of the prior studies, however, directly compares the various liquidity betas to characteristics in a comprehensive way.

A third related issue we study is whether yield adds explanatory power after controlling for default, term, and liquidity risk sensitivities using betas and characteristics studied in prior research. Yield serves as a catchall for a bond's all priced risks. If proxies do not fully capture sensitivities to default, term, and liquidity risks, then yield may add information. We examine whether yields add incremental information about the return cross-section, and if so, we explore why.

We begin our empirical investigation by revisiting GHS's question of how betas and characteristics fare against one another. Importantly, we expand the scope of the analysis to include not only default and term proxies but also multiple liquidity proxies and yield. Equally important is that the quality and availability of corporate bond data has changed markedly since GHS's study. Their 1973–1996 sample excludes HY bonds, has limited coverage, and includes returns calculated from matrix prices.[2] Our 1994–2015 sample remedies all three shortcomings by merging market-based prices from four databases: Mergent FISD, Bloomberg, FactSet Trade-based data, and Trade Reporting and Compliance Engine (TRACE) Enhanced.

Our comprehensive dataset also addresses important data shortcomings of the later liquidity studies referenced above. Prior studies of corporate bond liquidity that examine a period prior to the July 2002 implementation of TRACE typically use either a source that includes matrix prices or the NAIC database only.[3] Our use of multiple databases significantly increases the number of bonds in the pre-July 2002 part of our sample period and increases the number of quotes per bond, which allows us to more accurately estimate returns.

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[1] Schestag, Schuster, and Uhrig-Homburg (2016) show that most liquidity measures constructed with intraday data perform well when measuring transaction costs. As shown in their study, not all measures perform well, however, when data are measured with daily frequency. We take this into consideration when we construct our own liquidity proxies.

[2] Matrix or evaluated prices are derived using data vendor proprietary algorithms that incorporate various bond characteristics to extrapolate bond prices.

[3] Closer investigation of bond data sources revealed that matrix pricing is used by FT Interactive (used in FactSet Bond data but with Matrix/Trade-based flag) and Datastream which are frequently used in prior studies.

Prior studies that examine corporate bond liquidity after July 2002 typically use TRACE Standard (a notable exception is Schestag, Schuster, and Uhrig-Homburg (2016)). We obtain data from the TRACE Enhanced database, available to academics only recently. TRACE Enhanced includes a sizeable increase in the number of bonds covered during the July 2002–February 2005 rollout of TRACE. Especially important for our study, TRACE Enhanced removes filters placed on the reported trade volume. The volume figures reported in TRACE Standard are truncated at $5 million for investment-grade (IG) bonds and $1 million for HY bonds. As we later detail, these truncated trades generally account for more than half of the monthly dollar volume for IG bonds and more than 80% for high-yield (HY) bonds. Employing unfiltered volume data available in TRACE Enhanced is critical to our understanding of the role liquidity plays in explaining the cross-section of corporate bond returns.

One methodology we use to evaluate how betas and characteristics fare is the portfolio approach of Daniel and Titman (1997). Cross sectional variation in bond returns is crucial to analyze the asset pricing implications of liquidity and other characteristics. We group bonds with similar betas into portfolios and then divide each beta-sorted portfolio based on characteristics. This allows us to analyze the cross-sectional variation in bond returns related to characteristics but independent of betas. We then group bonds in the opposite way, first by forming groups of bonds that share similar characteristics and then dividing each characteristic-sorted portfolio on betas. This allows us to analyze the cross-sectional variation in bond returns related to loadings but independent of characteristics.

Another methodology we use examines the dispersion of individual bond returns within subsets of bonds that share similar betas or characteristics. The idea is that bonds with similar exposures to factor risks ought to exhibit returns that move together through time. A subset of bonds with similar risk sensitivities ought to exhibit less return dispersion on average over time than a subset of randomly selected bonds. We measure dispersion using the average mean absolute deviation (MAD) of returns for subsets of bonds. The better a set of betas or characteristics do in capturing sensitivities to factor risks, the lower is the average MAD of returns for bond subsets sorted on that set of betas or characteristics.

To illustrate insights that the MAD measure provides, suppose a model exists that accurately describes sensitivities to factor risks. Risk factors will experience negative outcomes from time to time. Periods (particularly shorter ones) that include negative outcomes may show average returns for high-sensitivity bonds that are equal to or less than low-sensitivity bonds. Tests based on average returns from sample periods that include such instances may reject the model, even though the model is correct,[4] while tests based on the MAD measure are less likely to reject the model (i.e., more likely to avoid Type II errors) given the return co-movement of bonds with like sensitivities regardless of negative or positive risk outcomes.

We find that credit ratings and duration do as well, or better, than default and term betas in describing the cross-section of corporate bond returns. Our results contrast sharply with the GHS finding that betas do better than characteristics. Moreover, liquidity risk is best modeled by a characteristic, a bond's own Amihud measure. Recognize that the Amihud measure captures price impact through the ratio of absolute return to trading volume. Thus, accurate volume data is critical.

We also find that bonds' yields play a role in explaining the return cross-section after controlling for credit rating, duration, and Amihud measure. Digging deeper into the reasons why, we present evidence consistent with yield reflecting an efficient market's assessment of default risk that is not captured by credit ratings. We find that within a group of bonds that share similar credit ratings, durations, and Amihud measures, those with higher yields experience more subsequent ratings downgrades, fewer ratings upgrades, and more defaults. We interpret the evidence as consistent with rating agencies' reluctance (or inability) to frequently alter ratings in response to the flow of new information. Informed investors, on the other hand, will quickly trade and drive prices, and hence yields, to reflect their ever-changing assessment of default risk.

Finally, we present a way to construct characteristic-based benchmark portfolios for corporate bonds in the spirit of the Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) method for stocks. In their approach, 125 benchmark portfolios for stocks are formed based on quintile sorts on size, book-to-market, and momentum. In our approach,

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[4] For example, our 1995–2015 sample period includes severe outcomes such as the 1999–2001 collapse due to the burst of the dot-com bubble and the 2007–08 financial crisis.

135 benchmark portfolios for corporate bonds are formed based on a five-way sort on ratings, and tercile sorts on the Amihud measure, yield, and duration. Given that our sample is the most comprehensive to date–consisting of 17,900 distinct corporate bonds between 1994 and 2015–this approach provides a comprehensive way to benchmark the returns of individual corporate bonds or portfolios with known weights in individual corporate bonds.

The remainder of the paper is organized as follows: Section 1 describes the data we use and details how data shortcomings of prior studies are addressed; it also describes how we calculate returns and construct our sample. Section 2 evaluates how betas fare against characteristics in the GHS setting of only default and term risk. Section 3 runs "horse races" among various liquidity betas and characteristics. Section 4 examines whether yields add explanatory power once we control for default, term, and liquidity risk using characteristic-based measures. Finding that it does, we dig into the reasons why. Section 5 offers a benchmarking model based on our study's insights. Section 6 concludes.

1. Data Sources, Return Computation, and Sample Statistics

In this section, we first describe the databases used in our study. We then delineate the steps we use to calculate returns, paying particular attention to how we estimate returns when bonds default. Finally, we describe our sample filtering criteria and provide summary statistics.

1.1. Data Sources

We limit our sample to fixed-coupon, non-convertible corporate bonds. Monthly returns are constructed using prices from four databases: (1) National Association of Insurance Commissioners (NAIC) Transactions, (2) Factset, (3) Bloomberg, and (4) TRACE Enhanced. We also explored the pricing data available from Datastream. However, Dick-Nielsen, Feldhütter, and Lando (2012) and Bushman, Le, and Vasvari (2010) make the case that Datastream bond prices are contaminated by matrix pricing.

Our analysis confirms their finding, and thus we exclude Datastream bond prices.[5] Trade volume is drawn from all but the Bloomberg database. A description of each source we use follows.

From the *NAIC Transaction* database, we obtain the price and volume of all market transactions of corporate bonds by insurance companies. The NAIC pricing and volume data we use runs from January 1994 to June 2002.

From *FactSet*, we obtain "exchange" prices and volume data. FactSet flags its prices as being either "exchange," meaning they were derived from a trade or dealer quote, or "matrix," meaning they were derived from matrix pricing algorithms.[6] We exclude any prices flagged as matrix prices. Volume data was missing for some exchange prices, presumably those derived from dealer quotes. The FactSet pricing and volume data we use runs from January 1994 to June 2002.

From *Bloomberg*, we obtain month-end composite bid and ask quotes that combine prices from multiple bond dealers. Occasionally Bloomberg will set the bid and ask quotes equal to each other when it is unable to obtain bid and ask quotes but is able to obtain a price from a trade that occurred that day. The Bloomberg pricing data we use runs from January 1997 to June 2002.

From *TRACE Enhanced*, we obtain the price and volume of over-the-counter secondary market transactions by all market participants. We clean prices by eliminating any corrected, reversed, or cancelled trades using the procedures outlined in Bessembinder, Maxwell, and Venkataraman (2006) and Bessembinder, Kahle, Maxwell, and Xu (2009). TRACE Enhanced pricing data starts in July 2002 and ends in December 2014. It represents a considerable improvement over the TRACE Standard data package

[5] Factset flags prices as either exchange or trade based or matrix/evaluated based. We use only Factset prices flagged as exchange or trade based. Datastream, in contrast, does not flag prices. When we compare Factset prices flagged as matrix based against Datastream prices for the same bond on the same date, more than 90% of prices matched. The implication is that a large portion of Datastream prices appears to be matrix based.

[6] FactSet's price data contributors are Interactive Data Corporation (IDC, the data feed is known as FT Interactive), Telekurs, Mergent FISD, and TRACE. IDC and Telekurs, two of the largest and most widely utilized commercial data sources, provide evaluated prices that are based on proprietary matrix pricing algorithms. The matrix prices used in FT Interactive Bond data which are incorporated in other feeds (such as Datastream) have been under investigation by regulators on multiple occasions for valuation accuracy and pricing problems: http://www.wsj.com/articles/SB107144176847294500

because it has more coverage.[7] Specifically, all TRACE eligible securities (except Rule 144A) had their trades reported since July 2002 in Trace Enhanced, while the coverage of TRACE eligible securities in TRACE Standard was partial during the phased TRACE dissemination period from July of 2002 till September of 2004. Another attractive feature of TRACE Enhanced is that its trade volumes are reported as is and are not truncated like TRACE Standard, which reports trade volumes capped at $5 million for IG bonds and $1 million for HY bonds. However, one limitation of the TRACE Enhanced package is that it is offered only at an 18 months' delay. This necessitates that we use TRACE Standard to supplement the TRACE Enhanced feed and extend the end of the sample period till December 2015. Given TRACE data errors documented by previous research, we follow data cleaning procedures that are detailed in Asquith, Covert and Pathak (2013) and Dick-Nielsen (2009, 2014).[8]

Finally, from *Mergent FISD*, we obtain bond characteristics such as credit ratings, coupon rates, maturity dates, and issue sizes. The Mergent FISD data we use run over our entire sample period from January 1994 to December 2015.

1.2. Return Calculation

We follow a multi-step procedure for collecting and processing bond pricing information from the above sources. We describe the steps below in sequential order. If the data required to estimate the price of a particular bond for a given month-end date is unavailable in step (1), we proceed to step (2). If the data required is unavailable in step (2), we proceed to step (3), et cetera. For the period before the implementation of TRACE in July 2002:

(1) We search NAIC for all instances of a bond trading at least once in a given month. For every bond each trading day of a given month, we follow Bessimbinder, Kahle, Maxwell and Xu (2009) and weight each trade price by the dollar value of the trade. They argue that the size weighting of trades more accurately reflects true prices since more weight is placed on the institutional trades that incur lower executions costs.

[7] TRACE Standard data package is also referred to as TRACE MarketData in selected FINRA publications.

[8] Some of the data issues in TRACE Enhanced arise due to trade cancellations, corrections, reversals, and double counting of trade records. Some more minor errors are in the form of missing prices, missing volume, missing date ranges, etc.

This procedure produces a price for each day of the month. We include prices from the last trading day within the month. If the bond did not trade during the month, then we code the NAIC price as missing for that particular month.

(2) We search Factset for all instances of a bond having at least one exchange price during the month. As with NAIC, we compute a trade-size-weighted price for each bond on each day, generating daily prices within each given month. Exchange prices without volume, which are presumably derived from dealer quotes rather than a trade, are given a zero weight in this calculation unless they are the only prices for that particular day, in which case they are given a weight of one. Again, as with NAIC, we include prices from the last trading day within the month. If the bond did not trade during the month, then we code the FactSet price as missing for that particular month.

(3) We search Bloomberg for all instances of a bond having valid month-end bid and ask quotes. When a bond has valid bid and ask quotes, its month-end price is computed by averaging the quotes.

To obtain month-end prices for the period after the implementation of TRACE in July 2002, we again follow Bessimbinder, Kahle, Maxwell and Xu (2009) but we use only TRACE Enhanced prices.

To calculate monthly returns, we combine month-end prices with coupon information obtained from Mergent FISD. The return is calculated for a particular bond in a given month only if it has a valid beginning-of-month price, end-of-month price, and coupon information for that month. We compute monthly returns as follows:

$$Return_t = \frac{\left(Price_t + Accrued\ Interest_t\right) - \left(Price_{t-1} + Accrued\ Interest_{t-1}\right) + Coupon_t}{\left(Price_{t-1} + Accrued\ Interest_{t-1}\right)},$$

where t is aligned at month end, and *Accrued Interest* is the coupon payment divided by the ratio of number of days since the last payment date to the number days between last and next payment.

In our final step, we address potential default-induced bias that might arise if default months are treated as missing observations.[9] We build on the Cici and Gibson (2012) methodology used to compute composite corporate bond default returns for all defaulted bonds. Before calculating monthly bond returns, we generate post-default prices for any bonds that defaulted. We search for any price information after the default event. For bonds that default in a given month, we run an additional step if valid post-default price information is unavailable between the default date and the end of the month. We search over the subsequent month for the first available price. If a price is available, we use it as the month-end price to compute the default-month return for that particular bond. We were able to find pricing information on 492 defaulted issues out of the 1,098 issues that defaulted after July 2002. Then, we compute the median return on these defaulted issues in the ± 1 month window around the default date and we find that it is equal to -45.639% for defaulting IG issues and -15.783% for defaulting HY issues.

For IG and HY issues that defaulted without post-default prices, we use the corresponding IG and HY default return averages as proxies for default-month returns. Using this in-sample composite default-month returns for defaulting bonds without valid post-default pricing information enables us to avoid default-induced bias which is similar to the delisting bias that has been documented in previous research on equity returns (Shumway (1997)).

Figure 1 shows the number of unique bonds sourced each month from each of the four sources we use. Prior studies of corporate bond liquidity that examine a period before to the July 2002 implementation of TRACE typically use either a source that includes matrix prices or the NAIC database. The Factset and Bloomberg databases add a considerable number of bonds incrementally to the NAIC database; the number more than doubles after January 1997 when Bloomberg data becomes available. Moreover, our use of multiple sources increases the frequency of price quotes and trade volume figures for a given bond, which allows us to more accurately estimate returns and liquidity measures.

[9] By treating default returns as missing observations, return estimates can be overstated, particularly for HY bonds.

[Insert Figure 1 about here.]

Prior studies that examine corporate bond liquidity after the July 2002 typically use TRACE Standard (a notable exception is Schestag, Schuster, and Uhrig-Homburg (2016)). We use TRACE Enhanced, available to academics only recently. Figure 2 shows the number of bonds covered by TRACE Enhanced increases considerably during the July 2002–February 2005 rollout of TRACE.

[Insert Figure 2 about here.]

Especially important for our study is that while TRACE Standard reports volume figures that are truncated at $5 million for IG bonds and $1 million for HY bonds, TRACE Enhanced removes these filters. Figure 3 shows the fraction of trades and dollar volume that meet the filter criteria for IG and HY bonds. For IG bonds, generally a bit more than half of dollar volume involves trades exceeding $5 million. For HY bonds, typically more than 80% of dollar volume involves trades exceeding $1 million. Given that several of the liquidity proxies are based on dollar volume, the unfiltered volume data available in TRACE Enhanced are critical to our understanding of the role liquidity plays in explaining the cross-sectional pattern of corporate bond returns.

[Insert Figures 3 about here.]

1.3. Our Sample

Without any filters placed on our data, our sample consists of 3,503,773 monthly return observations. Removing post-default observations, our sample drops by 47,650 observations to 3,456,123. We limit our sample to bonds having at least one year to maturity. As GHS point out, short time-to-maturity bonds may be less liquid and thus more prone to pricing errors. This restriction drops our sample size by 435,714 observations to 3,020,409. We also remove non-rated bonds, which drops our sample size by an additional 472,463 observations to 2,547,946. Next, we remove observations with missing or negative size or duration fields, which drops our sample size by an additional 1,183,942 observations to 1,364,004. Finally, in order to estimate betas, we exclude a bond in a given month if it has fewer than 15 monthly return observations over the past five years, which drops our sample size by an additional 561,226 observations to 802,778 for 17,900 different bonds. To mitigate possible data errors, we winsorize the returns in the bottom and top 1% of the distribution every month. Given the look back and our pricing data start date of January 1994, our empirical tests run from May 1995 to December 2015.[10]

Summary statistics for the final sample of 17,900 bonds are reported in Table 1. Bond characteristics by year are shown for the whole sample and separately for IG bonds and HY bonds. The number of bonds in our final sample is lowest at 516 in 1995 and highest at 4,836 in 2015. The average rating and duration remains fairly stable. Yield spreads varied considerably throughout the sample period, reflecting cycles in the interest rate environment. Investors who held an equally weighted portfolio of all bonds over the entire sample period earned 48bp per month compared to one-year Treasury Bills. Average excess returns were 44bp and 62bp for IG and HY bonds, respectively. The standard deviation of excess returns shows considerable variability, particularly around the 2007-08 financial crisis.

2. Default and Term Risk

The GHS foundational study of whether betas or characteristics are more relevant in describing the cross-section of corporate bond returns considered only default risk, which arises from unexpected changes in economic conditions that change the likelihood of default, and term risk, which arises from unexpected shifts in long-term interest rates relative to short-term interest rates. To allow for a more direct comparison of our results to theirs, we too start by considering only default and term risk.

In this section, we first describe how we construct test portfolios based on default and term betas and rating and duration characteristics. We then examine how betas and characteristics fare in explaining the cross-sectional pattern of corporate bond returns by

[10] All our characteristics and betas are computed with a one-month lag. Our pricing data sample starts in January 1994, and our computed monthly return series begins in February 1994. The 15-month return record lower bound to compute beta loadings makes the sample effective start data in May 1995.

using the portfolio approach of Daniel and Titman (1997), and by using the MAD methodology to examine the dispersion of individual bond returns within subsets of bonds that share similar betas or characteristics.

2.1. Default and Term Betas and Characteristics

Following Fama and French (1993) and GHS, we construct the default factor, *DEF*, as the difference between the monthly returns of a value-weighted portfolio of IG corporate bonds with at least ten years to maturity and a portfolio of long-term Treasury bonds. We construct the term factor, *TERM*, as the difference between the returns of a portfolio of long-term Treasury bonds and a portfolio of one-month Treasury bills.

The two-factor model involving default risk and term risk is:

$$r - r_f = \alpha + \beta_d DEF + \beta_t TERM + \varepsilon$$

where $r - r_f$ is the excess return on corporate bonds, α is the intercept, β_d is the loading on the default factor, β_t is the loading on the term factor, and ε is the error term. For each bond each month, we estimate the two-factor model using the past five years of monthly returns.

For the measurement of the two characteristics that correspond to β_d and β_t, we proceed as follows. We use Standard & Poor's credit ratings to proxy for bonds' sensitivity to default risk. If a Standard & Poor's credit rating is unavailable for a bond in a given month, we use its Moody's credit rating. If Moody's is unavailable, we use its Fitch credit rating. To measure the second characteristic, we use the modified duration, calculated as the Macaulay duration divided by one plus the yield to maturity.

2.2. Construction of Portfolios

We rank bonds by their default loadings and form five portfolios using quintile breakpoints. Within each default-loading portfolio, we form five portfolios using quintile breakpoints based on the term-beta rankings. This results in 25 portfolios sorted on default and term betas.

To form characteristic-sorted portfolios, we first rank bonds by credit ratings at the end of the prior month. There are 10 IG ratings (AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, and BBB-) and 11 HY ratings (BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, and C). Each month, we determine breakpoints that most evenly distribute IG bonds into three portfolios and HY bonds into two portfolios. We then rank bonds using their modified duration at the end of the prior month. Within each of the five credit-rating portfolios, we form five portfolios using quintile breakpoints based on the duration rankings. The result is 25 portfolios sorted on credit ratings and duration.

2.3. Excess Returns

We compute average monthly excess returns for portfolios by equal or value weighting individual bond returns and subtracting the one-year Treasury Bill return. Table 2 reports the average monthly excess returns for the portfolios sorted on betas in Panel A and characteristics in Panel B. Individual bond returns are equal-weighted in Panels A.1 and B.1 and value weighted in Panels A.2 and B.2. All 25 beta-sorted portfolios and 25 characteristic-sorted portfolios show positive average excess returns. Turning to the pattern of returns across portfolios, we should observe default risk manifest itself in higher returns as we move down the columns and term risk in higher returns as we move left to right within each row. We find these general patterns as we move down the low-term beta and duration columns and across the high-quality beta and rating rows. However, the pattern does not hold in both panels as we move to the lower right, which represents lower-quality, longer-term bonds. Such bonds are closest to having credit and term risk profiles of equities, which, during our sample period, experienced the first ten-year period in which average returns were negative since at least 1871. Thus, the breakdown in the patterns as we move to the lower right may be specific to our sample period.[11]

[11] Since results in Table 2 and the rest of the tables are similar when we use equal or value weighted returns, in the interest of brevity we report only equal-weighted returns in the rest of the Tables.

[Insert Table 2 about here.]

We next examine whether betas or characteristics perform better relative to each other in explaining the cross-section of corporate bond returns. To do so, we follow the portfolio approach of Daniel and Titman (1997). We first sort each of the 25 portfolios formed using ratings and duration into five portfolios based on default-beta quintile breakpoints. The average excess returns of each of the 25 high default-beta portfolios are equally weighted and each of the 25 low default-beta portfolios are equally weighted. The process is repeated for term betas. This allows us to analyze the cross-sectional variation in bond returns related to betas but independent of characteristics. Panel A of Table 3 presents results. If default betas reflect sensitivities to priced default risk that is independent of characteristics, the high default-beta portfolio should outperform the low. Indeed, the high default beta portfolios outperform the low by 14bp, but with weak statistical significance. The high term loading portfolios also outperform the low, but the 3bp difference is insignificant.

[Insert Table 3 about here.]

In Panel B of Table 3, we reverse the portfolio formation process. We first sort each of the 25 portfolios formed using default and term loadings into five portfolios based on the credit rating breakpoints described earlier. The average excess returns of each of the 25 high credit rating portfolios are equally weighted and each of the 25 low credit rating portfolios are equally weighted. The process is repeated for duration. This allows us to analyze the cross-sectional variation in bond returns related to characteristics but independent of loadings. Results, shown in Panel B of Table 3, indicate that high-rating portfolios outperform the low by 9bp and the long-duration portfolios outperform the short by 6bp, but the differences are insignificant.

In sum, the evidence from Tables 2 and 3 show weak evidence that default and term betas or characteristics capture sensitivities to priced factor risks. In addition, we do not find compelling evidence that betas provide information about the cross-section of average excess bond returns that is independent of characteristics, or vice versa. It is important to remember though that risk factors will experience negative outcomes from time to time, and that our sample period includes the particularly turbulent period around the 2007-08 financial crisis. Default and term risks may in actuality be priced and betas or characteristics may describe sensitivities well, but tests based on average excess returns from our volatile sample period may fail to detect such evidence. We address this limitation with our alternative MAD methodology.

2.4. Mean Absolute Deviations

The MAD methodology examines the dispersion of individual bond returns within subsets of bonds that share similar betas or characteristics. Tests are based on the premise that the returns of bonds with like sensitivities to priced factor risks will tend to move together regardless of whether negative or positive risk outcomes occur during the sample period. The MAD for a subset of bonds *J*, MAD_J, is computed as the average dispersion of the individual bond returns around the mean of the bonds in that subset:

$$MAD_J = \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{j=1}^{N_{Jt}}\left|r_{jt} - \overline{r_{Jt}}\right|}{N_{Jt}}$$

where r_{jt} is the return of the *j*th bond in subset *J* in month *t*, $\overline{r_{Jt}}$ is the mean return of all bonds in subset *J* in month *t*, N_{Jt} is the number of bonds in subset *J* in month *t*, and *T* is the number of months in the sample period. The tighter the comovement of bonds within a portfolio, the lower is the MAD.

Every month of the sample period, we compute the average MAD weighted equally across the 25 portfolios sorted on ratings and duration or across the 25 portfolios sorted on default and term betas. The monthly MADs are then averaged to come up with an overall MAD measure. To evaluate statistical significance of the resulting average MAD, we examine whether it is significantly lower than the average MAD resulting from randomly constructed 25 bond subsets. Every month we randomly place each bond in our sample into one of 25 equally sized portfolios. We compute the MAD for each of the 25 portfolios over the sample period, and then compute an equally weighted average MAD for the 25 portfolios, which is then aggregated across all the sample months. We repeat this process 1,000 times, saving the average MAD from each run. The results of the bootstrap simulation are pictured in Figure 4 as a histogram. Tests are consistent with the average MAD of the randomly sorted portfolios being normally distributed, with a mean of 281.56bp and standard deviation of 0.038bp.

[Insert Figure 4 about here.]

Table 4 reports the MAD results. The average MAD for the beta-sorted portfolios is 265.69bp, 15.87bp less than the mean MAD of 281.56bp from the bootstrap distribution. The bootstrapped *p*-value indicates that the difference is significant at the 0.000 level. The lower average MAD is consistent with default and term betas capturing sensitivities to priced factor risks. The average MAD for the characteristic-sorted portfolios is 255.88bp, a statistically significant 25.68bp less than the bootstrap average. Ratings and duration also appear to serve as proxies for priced factor risks. Comparing the average MADs of the two approaches, we find that the 9.81bp differential between the characteristic-sorted portfolios and the beta-sorted portfolios is significant at the 0.000 level. This suggests that characteristics do a better job than betas in proxying for default and term risk.

[Insert Table 4 about here.]

We next run a horse race between the characteristic and loadings using the MAD methodology. We divide each of the 25 portfolios sorted on ratings and duration into 5 portfolios based on the default betas. We then compute the average MAD of the resulting 125 portfolios. We repeat the process, sorting on term betas instead of ratings. To evaluate significance, we again run a bootstrap. This time every month we take bonds from each of the 25 portfolios sorted on ratings and duration and randomly place them into 5 different equally sized portfolios. We compute the MAD for each of the resulting 125 portfolios over the sample period, and then compute an equally weighted average MAD for the 125 portfolios. We repeat this process 1,000 times, saving the average

MAD from each run.

The results of the simulation are pictured in Panel A of Figure 5 as a histogram. Notice that the average MAD of the 125 randomly sorted portfolios is 255.88bp, same as for the 25 portfolios sorted on ratings and duration; simply increasing the number of portfolios from 25 to 125 using random sorts does not change the average MAD. A reduction in the MAD will only occur if the additional sort is based on a risk proxy that captures bond comovement. We repeat the above process, sorting the 25 default-beta/term- beta portfolios 5 ways on rating breakpoints described earlier, then separately on duration. Panel B of Figure 5 shows that the 265.69bp average MAD of the 125 randomly sorted portfolios equals that of the 25 rating-duration portfolios, reinforcing that a reduction in the MAD requires an informed sort.

[Insert Figure 5 about here.]

In Panel A of Table 5, we see that sorting the rating-duration portfolios on default and term betas results in significant reductions in average MADs of 4.18bp and 4.09bp, respectively, suggesting that betas add information to the characteristics about the comovement of bonds. The reverse also proves true. As shown in Panel B, sorting the beta portfolios on ratings and duration results in significant reductions. However, these reductions are of larger magnitudes than in those of Panel A, with average MAD decreases of 7.54bp and 10.36bp, respectively. Characteristics add information to the betas about the comovement of bonds.

[Insert Table 5 about here.]

In sum, both betas and characteristics provide information about bond comovements. Our results contrast with the GHS finding find that default and term betas fair better than ratings and duration in explaining the return cross-section. We find that characteristics do as well, if not better. So far, though, the analysis has considered only default and term risk. We now expand the analysis to consider liquidity risk.

3. Adding Liquidity to the Mix

Amihud and Mendleson (1986) argue that investors demand a liquidity premium for holding illiquid securities. Pastor and Stambaugh (2003) add that liquidity risk arises from unexpected fluctuations in market conditions that change the compensation demanded by investors for holding illiquid securities. Prior research that examines corporate bond yields or returns (see, for example, Longstaff, et al. (2005), Chen, et al. (2007), De Jong and Dreiessen (2007), Bao, et al. (2011), Lin, et al. (2011), Dick-Nielsen, et al. (2012), and Friewald, et al. (2012)) finds varying economic and statistical importance for various liquidity proxies. None of the prior studies, however, directly compares the various liquidity betas to characteristics in a comprehensive way, or uses as extensive a sample with uncapped volume data.

In this section, we describe the various liquidity proxy candidates and then run “horseraces” among them, using both the average excess returns and the mean absolute deviation methodologies. The goal is to determine whether liquidity is indeed priced and, if so, which proxies better describe the cross-section of returns.

3.1. Liquidity Proxy Candidates

We consider 18 different liquidity proxies in total. Eight of them are characteristics:

1) *Size* is the book value of the bond at the time of its issue.
2) *Volume* is the average monthly dollar trading volume of the bond over the prior three months.
3) *Zero Frequency* is the number of days in the last year that the bond did not trade.
4) *Spread* is the bond’s proportional spread. Prior to July 2002, it is computed as the Bloomberg bid-ask spread divided by its price. Afterwards, we construct a trade-based spread measure using the difference between the average buy-initiated trade price and the sell-initiated trade price during the day from TRACE data.
5) *CS Spread* is constructed following Corwin and Schultz (2012) as a bond’s modified bid-ask spread, which is a function of the high-to-low price ratio over two consecutive trading days.

6) *High-Low Daily Range* is the bond's difference between the high and low prices normalized by the mid-price, calculated every day and then averaged within a month.
7) *Amihud Liquidity* is constructed as the prior month average daily Amihud (2002) liquidity measure, calculated using individual intraday trades as:

$$Amihud_{it} = \frac{1}{Days_{it}} \sum_{d=1}^{Days_{it}} \frac{1}{Number\ of\ Trades\ \tau} \sum_{\tau} \frac{|r_{idt\tau}|}{Vol_{idt\tau}}$$

where r_{idt} is the return for a trade τ of a bond *i* on day *d* of month *t* and $Days_{it}$ is the number of days in month *t* that bond *i* traded, and $Vol_{idt\tau}$ is the dollar volume of trade τ.

8) *Roll's Daily Measure* is constructed following Roll (1984) as two multiplied by the square root of the negative one multiplied by the serial covariance of each bond's daily returns within each month.

The first characteristic—*size*—proxies for liquidity risk in an indirect way. The next five—*Volume, Zero Frequency, Spread, CS Spread, and the High-Low Daily Range*—are based on trading activity. The next measure—*Amihud Liquidity*—estimates market impact. The last one—*Roll's Daily Measure*—reflects negative serial dependence in returns caused by trading costs. Although most of these measures have been used in various studies to different extents, we thought it important to especially include the *CS* and *Roll measures,* since Schestag, Schuster, and Uhrig-Homburg (2016) single them out as the best measures of trading costs when data of daily frequency are used for estimation.

A priori it is unclear which characteristic should best describe the return cross-section. As Bao, Pan, and Wang (2011) point out, certain characteristics that we can straightforwardly observe, for example the spread, do not fully capture important aspects of liquidity such as market depth and resilience. Other characteristics that directly estimate illiquidity's influence on prices, such as the Amihud measure, take market depth and resilience into account, but they cannot be straightforwardly observed and their estimates may suffer from potential misspecification.

The next seven liquidity proxies we consider are betas estimated using the Fama and French methodology. We expand the two-factor model used earlier to include a third factor for liquidity:

$$r - r_f = \alpha + \beta_d DEF + \beta_t TERM + \beta_l LIQ + \varepsilon$$

where $r - r_f$ is the excess return on corporate bonds, α is the intercept, β_d is the loading on the default factor, β_t is the loading on the term factor, β_l is the loading on the liquidity factor, and ε is the error term. We run the three-factor model separately for each of the following eight liquidity factors formed by differencing returns of portfolios sorted on the characteristics described above:

9) *FF Size* is a factor constructed as the return differential of small issue bonds and large issue bonds.
10) *FF Volume* is a factor constructed as the return differential of low volume bonds and high volume bonds.
11) *FF Zero Frequency* is a factor constructed as the return differential of less frequently traded bonds and more frequently traded bonds.
12) *FF Spread* is a factor constructed as the return differential of bonds with large spreads and small spreads.
13) *FF CS Spread* is a factor constructed as the return differential of bonds with high and low CS measure.
14) *FF High-Low Range* is a factor constructed as the return differential of bonds with high and low High-low daily range.
15) *FF Amihud* is a factor constructed as the return differential of the least liquid and most liquid bonds according to the Amihud measure.
16) *FF Roll* is a factor constructed as the return differential of bonds with high and low Roll's daily measure.

The high and low portfolios used to create the *FF Size*, *FF Volume*, and *FF Zero frequency* factors are formed by sorting each of the 25 rating-duration portfolios each month on the corresponding liquidity characteristic using quintile breakpoints. Each month the resulting 25 high portfolios are equally weighted and the 25 low portfolios are equally weighted. To create the *FF Spread*, *FF CS Spread*, *FF Amihud*, and *FF Roll* factors, we adjust the process to account for missing observations, which are assigned to the low portfolio under the presumption that the most illiquid bonds are those without a dealer bid-ask quote or trading activity during the month. We estimate the three-factor model for each bond each month using the past five years of monthly returns.

The last two liquidity proxies are betas estimated using liquidity factors constructed following a methodology proposed in Lin, Wang, and Wu (2011) (hereafter LWW):

17) *LWW Amihud* is a factor based on market wide innovations in liquidity estimated using the Amihud measure. Steps include calculating the Amihud measure for each bond each month, then taking an average of all bonds in a given month, and lastly obtaining innovations of the market wide averages from a time series regression. Details of the multistep process we replicate can be found in LWW.
18) *LWW Pastor-Stambaugh* is a factor based on market wide innovations in liquidity estimated using the Pastor-Stambaugh measure, which captures temporary price changes associated with order flow. We again follow the multistep process detailed in LWW.

As before, beta estimates are computed for each bond each month using five years of monthly returns.

3.2. Excess Returns

To illustrate the excess returns methodology used for each liquidity proxy, we describe the steps using size. We first sort each of the 25 portfolios formed using ratings and duration into five portfolios based on size quintile breakpoints. The average excess returns of each of the 25 largest size portfolios are equally weighted and each of the 25 smallest size portfolios are equally weighted. We then test whether the average returns of low liquidity (i.e., smallest size) portfolios differ significantly from those of the high liquidity (i.e., largest size) portfolios.

Table 6 presents results for portfolios sorted on characteristics (Panel A) and betas (Panel B). Given the importance of accurate volume data for our liquidity proxies, we not only report results for the entire 5/1995–12/2015 sample period, but also the 7/2002–12/2015 TRACE period when more complete volume data available is available. For all five characteristics over both periods, the average excess return of the low liquidity portfolios exceeds those of the high liquidity portfolios. The largest differences in terms of magnitude and statistical significance are for the Amihud measure, which shows a 30bp differential over the entire sample period and 35bp differential over the TRACE period.

[Insert Table 6 about here.]

Turning to the beta candidates, the evidence across the average excess return differentials is mixed as some are positive and some are negative, with none of them being statistically significant at conventional levels.

In sum, the excess return evidence suggests that liquidity risk is priced and best modeled by a bond's own Amihud measure.

3.3. Mean Absolute Deviations

We illustrate the methodology using size. We divide each of the 25 portfolios sorted on ratings and duration into 5 portfolios based on size using quintile breakpoints. We then compute the average MAD of the resulting 125 portfolios. To evaluate statistical significance, we again compare to the average MADs generated by random sorts as in the bootstrap simulation discussed in Section 2.4 and illustrated in Figure 5 and Table 5.

Table 7 presents the MAD results for the characteristics (Panel A) and betas (Panel B). For all five sorts based on the liquidity characteristics, the average MAD is lower than when portfolios are randomly sorted. The Amihud measure shows the largest difference, a significant 11.17bp for the entire sample period and 8.26bp for the Trace sample period. Turning to the beta liquidity proxies, the average MAD of each is also lower than when portfolios are randomly sorted. Sorting on the FF Amihud beta results in the largest difference at a significant 7.17bp for the entire sample period and 6.54bp for the Trace period, which is roughly two thirds of the magnitude of the difference when we sort on the Amihud measure.

[Insert Table 7 about here.]

In sum, evidence from the MAD approach is consistent with the excess return evidence in that it suggests that liquidity risk is priced and best captured by a bond’s own Amihud measure. Furthermore, the bigger drop in MAD when the Amihud measure rather than the FF Amihud beta is added to the sort is consistent with evidence from Section 2, which shows that characteristics do a better job in explaining the return cross-section of corporate bond returns. Our evidence suggests that betas’ direct link to underlying priced factor risks is trumped by characteristics’ use of more up-to-date information and their potential to capture qualitative information beyond what is reflected in historical data.

4. Adding Yield to the Mix

Yield serves as a catchall for a bond’s all priced risks. If ratings, duration, and the Amihud measure do not fully capture sensitivities to default, term, and liquidity risks, then yield may add information. In this section, we examine whether yield helps explain the return cross-section beyond what is explained by ratings, duration, and the Amihud measure. And if so, we explore why.

4.1. Excess Returns and Mean Absolute Deviations

Building on our previous results suggesting that characteristics perform better than betas, our first step for both the excess return and MAD approaches is to form portfolios based on ratings, duration, and the Amihud measure. We sort our sample each month into the five ratings portfolios as before, then we sort each ratings portfolio on duration using tercile breakpoints, and then finally we sort each of the 15 ratings-duration portfolios on the Amihud measure using tercile breakpoints. The result is 45 portfolios each month sorted on ratings, duration, and the Amihud measure.

Given that yield is directly affected by pricing noise induced by market microstructure issues, we lag yield by one month. We sort each of the 45 portfolios on yield using tercile breakpoints. We compute the average excess returns for the 45 highest yielding portfolios each month and then average across the sample period. We repeat the process for the lowest yielding portfolios. We also compute the MADs for each of the 135 portfolios that result from our sorting approach described above each month and then average them across each month of the sample period. To evaluate statistical significance of the average MADs, we again run a bootstrap simulation.

Table 8 presents excess return results for the entire sample period (Panel A) and TRACE sample period (Panel B). Higher yielding IG bonds exhibit significantly higher excess returns of 0.17% and 0.20% per month compared to lower yielding IG bonds over the entire sample period and TRACE period, respectively. The economic magnitude of the return difference for higher versus lower yielding HY bonds is greater, but statistically insignificant at conventional levels.

[Insert Table 8 about here.]

Table 9 presents MAD results for the entire sample period (Panel A) and TRACE sample period (Panel B). MAD results suggest yields provide significant incremental explanatory power for both IG and HY bonds. The average MAD for the yield-sorted portfolios relative to that of the randomly-sorted portfolios is a significant 6.09bp and 19.89bp lower per month for IG and HY bonds, respectively, over the entire sample period and 8.26bp and 21.69bp lower, respectively, over the TRACE period.

[Insert Table 9 about here.]

Our evidence that yields add information is consistent with ratings, duration, and the Amihud measure not fully capturing sensitivities to default, term, and liquidity risks. The advantage of characteristics over betas in capturing sensitivities to priced risks stems from their use of more up-to-date information and their potential to capture qualitative information beyond what is reflected in historical data. We posit that duration is an up-to-date measure of a bond's exposure to term risk. Likewise, the market impact from recent trading captured by the Amihud measure is an up-to-date measure of a bond's exposure to liquidity risk. However, ratings are known to be "sticky," that is slow to adjust to changes in default risk. We hypothesize that yield's incremental explanatory power reflects an efficient market's more timely assessment of default risk that is not captured by sticky ratings.

4.2. Digging Deeper

Prior research (see, for example, Altman and Rijken (2004) and Loffler (2005)) finds that credit ratings tend be sticky. This is because rating agencies are deliberate when making changes, employing a "through-the-cycle" methodology that measures default risk over long horizons. Ratings are adjusted only when rating agencies expect default risk changes to be long-lasting. Investors who engage in corporate credit analysis, on the other hand, trade continuously based on the information flow that alters their perception of default risk, impounding that information quickly into bond prices. Therefore, yield, as a function of price, should react quickly to changes in a bond's ever changing sensitivity to default risk. The implication is that yields should reflect an efficient market's more timely assessment of default risk that is not captured by ratings.

Two testable predictions emerge. First, if investors react more quickly than rating agencies to new information that impacts a bond's sensitivity to default risk, then yields should foreshadow ratings upgrades and downgrades. Second, yields should contain information about future defaults that is not contained in ratings.

We test these predictions by forming portfolios each month as before by sorting five ways on ratings, three on duration, three on the Amihud measure, and finally three on yield. For each of the resulting 135 portfolios, we track the frequency of downgrades and upgrades over the subsequent month and the frequency of defaults over the subsequent year.

Table 10 presents results for subsequent downgrades (Panel A), upgrades (Panel B), and defaults (Panel C) broken out by each of the five ratings categories. In Panel A, we see that for both sample periods for all five ratings categories, higher yielding bonds were downgraded in the subsequent month more often than lower yielding bonds with similar ratings, durations, and Amihud measures. Focusing on the TRACE period, we see that higher yielding bonds for all three IG ratings categories were downgraded more than twice as often. Higher yielding bonds for both HY ratings categories were downgraded about four times as often.

[Insert Table 10 about here.]

In Panel B, upgrades tell the same story. In both periods, higher yielding bonds for all five ratings categories were upgraded in the subsequent month less frequently than their lower yielding bond counterparts.

In Panel C, default frequencies also suggest yields contain information about default risk that is not captured by ratings. In both sample periods for all five ratings categories, higher yielding bonds default more often in the subsequent year than their lower yielding counterparts. The differences are dramatic. For example, in the TRACE period, higher yielding category 5 bonds default on average 9.58% of the time versus 0.44% for lower yielding category 5 bonds. Strikingly, lower yielding bonds in each of the credit ranking portfolios 2 through 4 default less often than higher yielding bonds in the credit ranking portfolio immediately above. For example, higher yielding credit ranking portfolio 3 bonds, which are the lowest rated IG bonds, default on average 0.27% of the time versus only 0.03% for lower yielding credit ranking portfolio 4 bonds, which are the highest rated HY bonds. In other words, after controlling for term and liquidity risk with duration and the Amihud measure, lower rated bonds with low yields default less often than higher rated bonds with HYs.

Our evidence suggests that the extra return realized by higher yielding bonds, documented in Table 8, was compensation for default risk not captured by sticky ratings. Thus, any benchmarking model based on ratings, duration, and the Amihud measure would be incomplete without the addition of yield.

5. Characteristic-Based Benchmarks for Corporate Bonds

The insights of our study can be used to construct characteristic-based benchmark portfolios for corporate bonds using an approach in the spirit of the one used by Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) for stocks. DGTW form 125 benchmark characteristic portfolios for stocks by triple sorting on market capitalization, book-to-market, and momentum. Specifically, each month all stocks are first sorted into quintiles based on market capitalization, then the resulting five market-capitalization portfolios are sorted into quintiles based on book-to-market, and then finally each of the 25 market-capitalization/book-to-market portfolios are sorted into quintiles based on momentum. This results in 125 market capitalization, book-to-market, and momentum sorted portfolios that can be used to benchmark the returns of individual stocks or portfolios with known position weights.

We form 135 benchmark characteristic-based benchmark portfolios by quadruple sorting five ways on a bond's rating and three ways each on duration, the Amihud measure, and yield. We first sort all bonds each month into five ratings portfolios using the ratings breakpoints that most evenly distribute IG bonds into three portfolios and HY bonds into two portfolios. For each ratings portfolio, we then tercile sort on each of duration, Amihud measure, and yield. To determine the best sort order, we compute average MADs for each of the possible ordering sequences. As before, we run a bootstrap simulation to evaluate the statistical significance of the resulting average MADs.

Table 11 presents results. Panel A shows that the average MAD for all six informed sort orderings is significantly lower than when bonds are randomly sorted into 135 portfolios over the entire sample period and the TRACE period. The lowest average MAD is obtained in both periods by sorting the ratings portfolios first on the Amihud measure, then yield, and finally duration. The MAD of the rating/Amihud/yield/duration sort is 45.84bp lower than the average MAD of the random sort for the entire sample period and 48.25bp lower for the TRACE period.

[Insert Table 11 about here.]

Given that yield serves as a catchall for all a bond's priced risks, one may question whether sorting bonds into 135 portfolios every month based solely on yield would do as well, or perhaps better, than sorting into 135 portfolios every month based on rating/Amihud/yield/duration, as we do above. As a final robustness check, we carry out the empirical exercise and report the results in Panel C. We find that sorting solely on yields results in significantly lower average MADs compared to those of the random sorts, but significantly higher compared to those of the rating/Amihud/yield/duration sort, 18.52bp higher for the entire sample period and 16.22bp higher for the TRACE period.

In summary, our study suggests 135 ratings, duration, Amihud measure, and yield sorted portfolios that can be used to benchmark an individual corporate bond's return against the matching-characteristic portfolio's return. Our benchmark portfolios can also be used to evaluate the performance of portfolios when the holdings in individual bonds are known, with each bond matched and benchmarked directly based on its characteristics.

Our benchmarking approach offers advantages when measuring portfolio performance relative to the alternative approach that regresses portfolio returns on the returns of factor portfolios in a traditional multifactor regression model. As DGTW point out, by matching the characteristics of individual securities, a portfolio manager's performance relative to a passive index can be easily decomposed into characteristic selectivity, characteristic timing, and average style.[12]

6. Conclusion

In this paper, we use the most comprehensive database of corporate bond returns studied to date–to our knowledge–and insights from recent research on priced liquidity risk to study how factor loadings and characteristics fare in explaining the cross-section of corporate bond returns.

Our results indicate that characteristics–credit rating, duration, and Amihud illiquidity measure–fare better than betas in describing the cross-section. Moreover, a bond's yield explains the cross-section after controlling for the set of characteristics. For

[12] Characteristic selectivity is the return contribution from identifying bonds that will outperform other bonds with similar characteristics. Characteristic timing is the return contribution from the ability to tilt holdings towards bonds with characteristics that will outperform, for example, by anticipating yield spread shifts that differ across ratings categories. Average style is the return generated by a tendency to hold bonds with characteristics that differ from the index.

bonds with similar credit ratings, durations and Amihud measures, higher yields are associated with more subsequent rating downgrades, fewer upgrades, and a higher frequency of defaults. Strikingly, after controlling for term and liquidity risk with duration and the Amihud measure, lower rated bonds with low yields default less often than higher rated bonds with HYs. This evidence suggests that a significant part of yield's incremental explanatory power reflects an efficient market's timely assessment of default risk that is not captured by sticky ratings.

Based on our findings, we present a way to construct 135 portfolios sorted on ratings, duration, the Amihud measure, and yield that can be used to benchmark the returns of individual bonds or the performance of portfolios with known position weights. Our benchmarking approach offers the advantage to future researchers of easily decomposing a portfolio manager's performance relative to a passive index into characteristic selectivity, characteristic timing, and average style.

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Table 1
Sample Descriptive Statistics
Panel A: All Bonds

		Averages				
Year	N	Credit Rating	Duration	Yield Spread	Excess Return	Std Dev of Excess Returns
1995	516	8	6.3	2.56%	0.86%	2.55%
1996	574	8	6.0	2.41%	0.19%	2.23%
1997	775	7	5.7	2.04%	0.43%	1.74%
1998	1,165	7	6.0	2.13%	0.30%	2.43%
1999	1,273	7	6.0	2.58%	-0.32%	2.58%
2000	1,569	7	5.5	2.93%	0.19%	3.28%
2001	1,913	7	5.3	4.43%	0.61%	3.64%
2002	2,149	8	5.3	5.67%	0.70%	4.87%
2003	3,214	9	5.5	5.05%	1.06%	3.76%
2004	4,001	9	5.7	3.73%	0.49%	2.24%
2005	4,171	9	5.8	2.30%	-0.01%	2.14%
2006	4,358	9	5.7	1.67%	0.18%	1.87%
2007	4,340	9	5.8	1.97%	-0.04%	2.22%
2008	4,437	9	5.6	6.39%	-0.78%	6.03%
2009	4,500	9	5.6	8.43%	2.43%	7.10%
2010	4,718	9	6.1	4.95%	0.85%	2.74%
2011	4,740	8	6.2	4.47%	0.69%	2.57%
2012	4,293	9	6.3	3.99%	0.83%	2.23%
2013	4,381	9	6.3	3.80%	0.14%	1.89%
2014	4,649	9	6.5	3.67%	0.54%	1.62%
2015	4,836	9	6.7	3.70%	0.81%	2.48%
1995-2015	17,900	8	5.9	3.76%	0.48%	2.96%

Panel B: IG Bonds

		Averages				
Year	N	Credit Rating	Duration	Yield Spread	Excess Return	Std Dev of Excess Returns
1995	406	6	6.7	2.12%	0.86%	2.54%
1996	435	6	6.4	1.91%	0.09%	2.23%
1997	632	6	6.0	1.68%	0.40%	1.70%
1998	991	6	6.3	1.78%	0.33%	2.26%
1999	1,088	6	6.3	2.11%	-0.38%	2.32%
2000	1,303	6	5.8	2.17%	0.28%	2.69%
2001	1,612	6	5.6	3.51%	0.59%	2.65%
2002	1,746	7	5.5	4.32%	0.75%	3.67%
2003	2,448	7	5.8	3.64%	0.69%	3.02%
2004	3,058	7	5.9	2.91%	0.39%	1.93%
2005	3,159	7	6.1	1.57%	-0.01%	1.88%
2006	3,271	7	6.0	1.00%	0.06%	1.65%
2007	3,269	7	6.1	1.30%	0.01%	1.99%
2008	3,351	7	6.0	4.77%	-0.21%	5.17%
2009	3,389	7	6.1	5.95%	1.68%	5.49%
2010	3,711	7	6.5	4.00%	0.75%	2.48%
2011	3,916	7	6.5	3.78%	0.74%	2.36%
2012	3,478	7	6.7	3.16%	0.75%	2.05%
2013	3,572	7	6.7	3.14%	0.01%	1.78%
2014	3,806	7	6.9	3.09%	0.60%	1.45%
2015	3,941	7	7.1	2.90%	0.78%	2.10%
1995-2015	14,052	7	6.2	2.89%	0.44%	2.54%

Panel C: HY Bonds

Year	N	Averages: Credit Rating	Duration	Yield Spread	Excess Return	Std Dev of Excess Returns
1995	110	13	4.9	4.19%	0.86%	2.57%
1996	139	13	4.6	4.01%	0.50%	2.17%
1997	143	14	4.3	3.60%	0.51%	1.85%
1998	174	13	4.3	4.19%	0.13%	3.03%
1999	185	13	4.2	5.36%	-0.02%	3.64%
2000	265	14	4.0	6.67%	-0.31%	5.17%
2001	301	14	4.0	9.32%	0.70%	6.54%
2002	403	14	4.0	11.42%	0.42%	7.83%
2003	766	14	4.5	9.65%	2.25%	5.17%
2004	943	14	4.7	6.40%	0.82%	2.90%
2005	1012	14	4.9	4.58%	-0.01%	2.68%
2006	1086	14	4.8	3.71%	0.53%	2.29%
2007	1071	14	4.8	4.02%	-0.22%	2.59%
2008	1086	14	4.4	11.44%	-2.58%	7.55%
2009	1111	14	3.9	16.12%	4.73%	10.12%
2010	1006	14	4.4	8.42%	1.26%	3.22%
2011	824	14	4.6	7.74%	0.46%	3.15%
2012	815	14	4.5	7.55%	1.16%	2.74%
2013	809	14	4.7	6.72%	0.68%	2.13%
2014	843	14	4.7	6.29%	0.27%	2.11%
2015	895	14	4.6	7.25%	0.90%	3.22%
1995–2015	5,442	14	4.5	7.08%	0.62%	3.94%

This table reports descriptive statistics for our sample of corporate bonds by year for the 1995 to 2015 sample period. Credit ratings are expressed as an ordinal ranking of Standard & Poor's credit ratings: (1) AAA, (2) AA+, (3) AA, (4) AA-, (5) A+, (6) A, (7) A-, (8) BBB+, (9) BBB, (10) BBB-, (11) BB+, (12) BB, (13) BB-, (14) B+, (15) B, (16) B-, (17) CCC+, (18) CCC, (19) CCC-, (20) CC, and (21) C. Duration is the bond's modified duration, calculated as the Macaulay duration divided by one plus the yield to maturity. Yield spread is computed as the yield implied by the bond's month-end price less the yield on one-year Treasury Bills. Excess return is the bond's monthly return less the monthly return on one-year Treasury Bills.

Table 2
Average Excess Returns

Panel A: Default and Term Loadings Sort, 1995 - 2015

Panel A.1: Equal-weighted Returns

	Term Loading					Difference
Default Loading	1 (Short)	2	3	4	5 (Long)	(5 - 1)
1 (High Quality)	0.39%	0.34%	0.41%	0.51%	0.68%	0.29%
	5.40	*5.37*	*4.98*	*4.61*	*4.18*	*2.43*
2	0.36%	0.27%	0.34%	0.39%	0.49%	0.13%
	5.73	*5.74*	*5.38*	*4.29*	*3.67*	*1.26*
3	0.40%	0.37%	0.35%	0.43%	0.50%	0.10%
	5.01	*6.08*	*5.11*	*5.27*	*4.10*	*1.05*
4	0.55%	0.43%	0.42%	0.43%	0.47%	-0.07%
	4.71	*4.94*	*5.35*	*4.96*	*4.11*	*-0.75*
5 (Low Quality)	0.73%	0.52%	0.51%	0.47%	0.54%	-0.18%
	4.20	*3.82*	*4.05*	*4.05*	*4.14*	*-1.38*
Difference (5 - 1)	0.32%	0.18%	0.10%	-0.05%	-0.14%	
	2.65	*1.74*	*1.09*	*-0.54*	*-1.39*	

Panel A.2: Value-weighted Returns

Default Loading	1 (Short)	2	3	4	5 (Long)	(5 - 1)
1 (High Quality)	0.32%	0.30%	0.40%	0.52%	0.49%	0.17%
	4.42	*4.65*	*4.53*	*4.35*	*2.74*	*1.21*
2	0.32%	0.25%	0.32%	0.37%	0.46%	0.15%
	4.66	*5.42*	*4.69*	*3.91*	*3.21*	*1.29*
3	0.41%	0.34%	0.33%	0.38%	0.45%	0.04%
	5.05	*5.46*	*4.63*	*4.36*	*3.45*	*0.43*
4	0.59%	0.39%	0.42%	0.44%	0.48%	-0.12%
	4.49	*4.23*	*5.10*	*4.58*	*3.86*	*-1.01*
5 (Low Quality)	0.66%	0.57%	0.53%	0.50%	0.55%	-0.09%
	3.34	*3.96*	*3.95*	*4.09*	*4.06*	*-0.59*
Difference (5 - 1)	0.33%	0.27%	0.13%	-0.02%	0.05%	
	2.16	*2.49*	*1.28*	*-0.17*	*0.44*	

Panel B: Credit Rating and Duration Sorts, 1995 – 2015

Panel B.1: Equal-weighted Returns

	Duration					Difference
Credit Rating	1 (Short)	2	3	4	5 (Long)	(5 - 1)
1 (IG. High)	0.18%	0.29%	0.38%	0.50%	0.38%	0.20%
	4.76	*5.00*	*4.68*	*4.94*	*2.89*	*1.76*
2	0.26%	0.38%	0.44%	0.56%	0.41%	0.15%
	6.81	*6.76*	*5.27*	*5.46*	*3.05*	*1.31*
3	0.31%	0.40%	0.44%	0.55%	0.31%	0.01%
	6.59	*6.17*	*5.05*	*5.02*	*2.29*	*0.04*
4	0.49%	0.51%	0.46%	0.52%	0.57%	0.07%
	5.23	*4.77*	*4.03*	*3.92*	*4.04*	*0.82*
5 (HY. Low)	0.75%	0.47%	0.52%	0.43%	0.48%	-0.27%
	3.92	*2.19*	*2.93*	*2.32*	*2.38*	*-2.02*
Difference (5 - 1)	0.57%	0.18%	0.15%	-0.07%	0.10%	
	3.17	*0.89*	*0.84*	*-0.38*	*0.49*	

Panel B.2: Value-weighted Returns

Credit Rating	1 (Short)	2	3	4	5 (Long)	(5 - 1)
1 (IG. High)	0.19%	0.28%	0.38%	0.46%	0.42%	0.23%
	4.69	*4.06*	*4.11*	*4.29*	*2.74*	*1.70*
2	0.24%	0.35%	0.45%	0.56%	0.47%	0.22%
	5.65	*5.45*	*4.59*	*4.71*	*3.02*	*1.71*
3	0.27%	0.36%	0.46%	0.60%	0.40%	0.13%
	5.66	*5.08*	*4.72*	*4.94*	*2.58*	*0.97*
4	0.43%	0.49%	0.47%	0.50%	0.61%	0.18%
	4.55	*4.49*	*3.78*	*3.63*	*4.05*	*1.96*
5 (HY. Low)	0.72%	0.52%	0.57%	0.47%	0.47%	-0.25%
	3.79	*2.54*	*3.02*	*2.51*	*2.18*	*-1.60*
Difference (5 - 1)	0.53%	0.24%	0.19%	0.01%	0.05%	
	2.95	*1.19*	*1.02*	*0.04*	*0.24*	

This table shows average monthly excess returns for each of the 25 portfolios constructed using a 5 by 5 sort on loadings (Panel A) and characteristics (Panel B). To form loadings-sorted portfolios, we first rank bonds by their default loadings and form five portfolios using quintile breakpoints. Next, within each default-loading portfolio, we form five portfolios using quintile breakpoints based on the term-beta rankings. The result is 25 portfolios sorted on default and term betas. To form characteristic-sorted portfolios, we first rank bonds by their credit rating at the end of the prior month. There are 10 IG ratings (AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, and BBB-) and 11 HY ratings (BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, and C). Each month, we determine breakpoints that most evenly distribute IG bonds into three portfolios and HY bonds into two portfolios. We then rank bonds using their modified duration at the end of the prior month. Within each of the five credit-rating portfolios, we form five portfolios using quintile breakpoints based on the duration rankings. The result is 25 portfolios sorted on credit ratings and duration. Monthly bond returns are averaged by equal weighting individual excess bond returns in Panels A.1 and B.1 and by value weighting individual excess bond returns in Panels A.2 and B2. t-statistics associated with the average excess returns for each portfolio are reported in italics.

Table 3

Average Excess Returns Using Portfolio Approach of Grinblatt and Titman (1997)

Panel A: Characteristic Portfolios Sorted on Loadings, 1995-2015

	Low	High	Difference (High - Low)
Add Default Loading	0.45%	0.58%	0.14%
	4.32	*4.56*	*1.90*
Add Term Loading	0.50%	0.53%	0.03%
	4.29	*4.63*	*0.51*

Panel B: Loading Portfolios Sorted on Characteristics, 1995-2015

	Low	High	Difference (High - Low)
Add Credit Rating	0.40%	0.49%	0.09%
	4.52	*4.04*	*0.83*
Add Duration	0.39%	0.45%	0.06%
	5.23	*3.62*	*0.67*

This table reports average excess returns for bond portfolios constructed using the portfolio approach of Daniel and Titman (1997). We first sort each of the 25 portfolios formed using ratings and duration into five portfolios based on default-beta quintile breakpoints. The process is repeated for term betas. Equal-weighted average excess returns for the resulting 25 high and low default-beta and term-beta portfolios are reported in Panel A. In Panel B, we reverse the portfolio formation process. Each of the 25 portfolios formed using default and term loadings are sorted into five portfolios based on the credit rating breakpoints described in Table 2. The process is repeated for duration. Equal-weighted average excess returns of each of the 25 high and low credit rating and duration portfolios are reported in Panel B. t-statistics associated with the average excess returns for each portfolio are reported in italics.

Table 4

Average MADs for 5x5 Portfolios Sorted on Characteristics and Factor Loadings

Sample Period: 1995–2015

Sorting Method:	Random Sort	Informed Sort	Difference (Informed - Random)
Characteristics	2.8156%	2.5588%	0.2568%
			(0.000)
Loading	2.8156%	2.6569%	0.1587%
			(0.000)
Difference		0.0981%	
		(0.000)	

This table shows the average mean absolute deviations (MADs) for portfolios constructed using 5x5 sorts on characteristics (credit ratings and duration) and factor loadings (default and term). Also shown is the average MAD for 1,000 runs of portfolios constructed by randomly sorting bonds into 25 equal-sized portfolios each month. Reported *p*-values in parentheses are based on the percentage of the 1,000 random-sort runs with average MADs less than the informed sort average MAD.

Table 5

Average MADs Using Portfolio Approach in the Spirit of Grinblatt and Titman (1997)

Panel A: Characteristic Portfolios Sorted on Factor Loadings, 1995–2015

	5 x 5 Characteristic Portfolios		
Sorting Method:	Random Sort	Informed Sort	Difference
Add Default Loading	2.5588%	2.5169%	0.0418%
			(0.000)
Add Term Loading	2.5588%	2.5179%	0.0409%
			(0.000)

Panel B: Factor Loading Portfolios Sorted on Characteristics, 1995–2015

	5 x 5 Factor Loading Portfolios		
Sorting Method:	Random Sort	Informed Sort	Difference
Add Credit Ratings	2.6569%	2.5815%	0.0754%
			(0.000)
Add Duration	2.6569%	2.5533%	0.1036%
			(0.000)

The first column of this table shows the average mean absolute deviations (MADs) for 125 portfolios constructed by sorting each of the 25 ratings-duration portfolios into 5 different equally sized random portfolios (Panel A) and by sorting each of the 25 default-beta/term-beta portfolios into 5 different equally sized random portfolios (Panel B). The second column shows the average MADs for portfolios constructed as in Table 3. Specifically, In Panel A we first sort each of the 25 portfolios formed using ratings and duration into five portfolios based on default-beta quintile breakpoints. The process is repeated for term betas. In Panel B, we reverse the portfolio formation process. Each of the 25 portfolios formed using default and term loadings are sorted into five portfolios based on the credit rating breakpoints described in Table 2. The process is repeated for duration. Reported p-values in parentheses are based on the percentage of the 1,000 random-sort runs with average MADs less than the informed sort average MAD.

Table 6
Average Excess Returns for Liquidity Sorts

Panel A : Portfolios Sorted on Characteristics

Panel A.1 : Sample Period 1995-2015

	All Bonds			*IG Bonds*			*HY Bonds*		
	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)
Size	0.46%	0.41%	0.05%	0.38%	0.36%	0.01%	0.51%	0.47%	0.04%
	6.27	*4.01*	*1.00*	*5.58*	*3.85*	*0.21*	*4.38*	*2.80*	*0.35*
Volume	0.48%	0.40%	0.08%	0.41%	0.36%	0.05%	0.56%	0.46%	0.10%
	5.70	*4.09*	*1.52*	*5.60*	*3.79*	*0.92*	*3.80*	*2.61*	*0.90*
Zero Frequency	0.48%	0.38%	0.11%	0.42%	0.35%	0.06%	0.55%	0.41%	0.15%
	6.71	*3.63*	*1.67*	*5.94*	*3.65*	*0.99*	*4.95*	*2.19*	*1.11*
Spread	0.54%	0.43%	0.12%	0.44%	0.39%	0.05%	0.68%	0.44%	0.24%
	4.39	*5.31*	*1.74*	*3.96*	*4.47*	*0.86*	*2.87*	*3.71*	*1.36*
CS Spread	0.54%	0.55%	-0.02%	0.47%	0.44%	0.03%	0.64%	0.63%	0.00%
	3.32	*4.66*	*-0.23*	*3.56*	*4.88*	*0.33*	*2.05*	*3.44*	*0.01*
High-Low Daily Range	0.49%	0.35%	0.12%	0.40%	0.32%	0.09%	0.50%	0.46%	0.04%
	3.39	*3.91*	*1.24*	*3.13*	*3.46*	*0.93*	*1.41*	*3.33*	*0.14*
Amihud Liquidity	0.53%	0.26%	0.30%	0.48%	0.23%	0.25%	0.62%	0.55%	0.07%
	4.29	*2.95*	*3.59*	*4.47*	*2.45*	*3.23*	*2.05*	*3.37*	*0.34*
Roll's Daily Measure	0.55%	0.47%	0.09%	0.47%	0.42%	0.05%	0.81%	0.57%	0.24%
	3.43	*3.88*	*1.09*	*3.00*	*3.58*	*0.46*	*2.71*	*2.54*	*1.74*

Panel A.2: Sample Period 2004-2015									
	All Bonds			*IG Bonds*			*HY Bonds*		
	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)
Size	0.47%	0.40%	0.07%	0.39%	0.36%	0.03%	0.51%	0.45%	0.07%
	4.25	*2.61*	*0.90*	*3.95*	*2.52*	*0.33*	*2.88*	*1.82*	*0.47*
Volume	0.56%	0.39%	0.17%	0.47%	0.36%	0.11%	0.61%	0.42%	0.19%
	4.43	*2.63*	*2.19*	*4.47*	*2.53*	*1.31*	*2.80*	*1.69*	*1.24*
Zero Frequency	0.50%	0.37%	0.14%	0.41%	0.35%	0.06%	0.59%	0.38%	0.22%
	4.69	*2.32*	*1.38*	*4.04*	*2.40*	*0.61*	*3.78*	*1.42*	*1.14*
Spread	0.58%	0.44%	0.14%	0.45%	0.38%	0.07%	0.73%	0.43%	0.30%
	3.19	*3.79*	*1.40*	*2.74*	*3.13*	*0.80*	*2.38*	*2.53*	*1.42*
CS Spread	0.41%	0.49%	-0.08%	0.40%	0.41%	-0.01%	0.38%	0.50%	-0.12%
	2.45	*3.87*	*-1.00*	*2.89*	*4.37*	*-0.12*	*1.18*	*2.57*	*-0.52*
High-Low Daily Range	0.55%	0.38%	0.17%	0.43%	0.34%	0.09%	0.48%	0.40%	0.08%
	2.89	*3.51*	*1.44*	*2.66*	*3.00*	*0.92*	*1.41*	*2.64*	*0.31*
Amihud Liquidity	0.71%	0.36%	0.35%	0.61%	0.32%	0.29%	0.63%	0.41%	0.22%
	4.22	*3.12*	*4.15*	*4.40*	*2.65*	*4.67*	*2.07*	*2.31*	*1.32*
Roll's Daily Measure	0.49%	0.38%	0.10%	0.42%	0.36%	0.06%	0.54%	0.34%	0.20%
	2.74	*2.86*	*1.60*	*2.74*	*2.73*	*1.08*	*1.74*	*1.45*	*1.41*

Panel B: Portfolios Sorted on Loadings									
Panel B.1: Sample Period 1995-2015									
	All Bonds			*IG Bonds*			*HY Bonds*		
	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)
FF Size	0.49%	0.48%	0.02%	0.41%	0.42%	-0.01%	0.49%	0.50%	-0.01%
	5.26	*4.50*	*0.26*	*4.45*	*3.81*	*-0.11*	*3.24*	*2.94*	*-0.10*
FF Volume	0.48%	0.50%	-0.02%	0.43%	0.41%	0.02%	0.51%	0.50%	0.01%
	5.08	*4.80*	*-0.40*	*4.55*	*3.84*	*0.26*	*3.36*	*3.00*	*0.07*
FF Zero Frequency	0.45%	0.49%	-0.05%	0.38%	0.41%	-0.03%	0.48%	0.43%	0.05%
	4.79	*4.33*	*-0.69*	*4.05*	*3.59*	*-0.37*	*3.27*	*2.35*	*0.50*
FF Spread	0.51%	0.43%	0.08%	0.45%	0.38%	0.07%	0.49%	0.53%	-0.04%
	4.06	*4.36*	*1.07*	*3.53*	*3.71*	*0.79*	*2.39*	*3.13*	*-0.28*
FF CS Spread	0.52%	0.46%	0.06%	0.44%	0.41%	0.03%	0.46%	0.55%	-0.09%
	3.06	*3.45*	*0.61*	*2.54*	*3.03*	*0.24*	*1.76*	*2.64*	*-0.55*
FF High-Low Range	0.51%	0.43%	0.09%	0.42%	0.36%	0.06%	0.50%	0.50%	0.00%
	4.50	*4.77*	*1.29*	*3.63*	*3.96*	*0.79*	*2.72*	*3.35*	*-0.04*
FF Amihud	0.53%	0.43%	0.10%	0.47%	0.38%	0.09%	0.43%	0.59%	-0.16%
	4.67	*4.91*	*1.59*	*4.09*	*4.18*	*1.17*	*2.27*	*4.16*	*-1.33*
FF Roll	0.50%	0.45%	0.06%	0.43%	0.42%	0.02%	0.49%	0.47%	0.02%
	4.75	*4.51*	*1.11*	*4.27*	*3.93*	*0.28*	*2.77*	*2.98*	*0.20*
LWW Amihud	0.52%	0.48%	0.04%	0.47%	0.40%	0.07%	0.53%	0.48%	0.04%
	5.43	*4.64*	*0.66*	*4.79*	*3.74*	*0.92*	*3.26*	*3.07*	*0.44*
LWW PS	0.52%	0.44%	0.08%	0.44%	0.38%	0.06%	0.54%	0.45%	0.09%
	5.30	*4.58*	*1.74*	*4.33*	*3.97*	*0.95*	*3.24*	*2.91*	*1.03*

Panel B.2: Sample Period 2004-2015

	All Bonds			*IG Bonds*			*HY Bonds*		
	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)	Low	High	Difference (High - Low)
FF Size	0.47%	0.50%	-0.02%	0.41%	0.44%	-0.03%	0.44%	0.48%	-0.04%
	3.33	*3.06*	*-0.24*	*2.96*	*2.68*	*-0.31*	*1.96*	*1.93*	*-0.25*
FF Volume	0.48%	0.48%	0.00%	0.43%	0.42%	0.01%	0.56%	0.49%	0.07%
	3.40	*3.02*	*-0.03*	*2.97*	*2.56*	*0.13*	*2.60*	*2.02*	*0.54*
FF Zero Frequency	0.45%	0.52%	-0.07%	0.41%	0.43%	-0.02%	0.49%	0.46%	0.04%
	3.31	*3.02*	*-0.67*	*2.93*	*2.49*	*-0.16*	*2.37*	*1.76*	*0.24*
FF Spread	0.54%	0.41%	0.12%	0.48%	0.36%	0.12%	0.45%	0.52%	-0.06%
	3.09	*3.12*	*1.16*	*2.73*	*2.61*	*0.97*	*1.66*	*2.51*	*-0.34*
FF CS Spread	0.51%	0.45%	0.06%	0.43%	0.40%	0.03%	0.44%	0.53%	-0.09%
	2.97	*3.35*	*0.58*	*2.46*	*2.95*	*0.23*	*1.67*	*2.54*	*-0.56*
FF High-Low Range	0.52%	0.42%	0.10%	0.44%	0.37%	0.06%	0.46%	0.53%	-0.07%
	2.97	*3.14*	*0.96*	*2.46*	*2.76*	*0.50*	*1.70*	*2.54*	*-0.40*
FF Amihud	0.52%	0.41%	0.11%	0.44%	0.40%	0.04%	0.35%	0.52%	-0.18%
	3.05	*3.16*	*1.14*	*2.58*	*2.87*	*0.40*	*1.24*	*2.57*	*-1.09*
FF Roll	0.50%	0.46%	0.04%	0.44%	0.44%	-0.01%	0.46%	0.52%	-0.06%
	3.23	*3.20*	*0.53*	*2.97*	*2.85*	*-0.06*	*1.93*	*2.35*	*-0.53*
LWW Amihud	0.50%	0.52%	-0.01%	0.46%	0.42%	0.04%	0.60%	0.50%	0.10%
	3.59	*3.25*	*-0.17*	*3.24*	*2.55*	*0.35*	*2.68*	*2.20*	*0.87*
LWW PS	0.52%	0.43%	0.09%	0.45%	0.37%	0.08%	0.54%	0.41%	0.13%
	3.49	*3.00*	*1.26*	*2.86*	*2.59*	*0.77*	*2.17*	*1.91*	*1.15*

This table reports excess returns for portfolios sorted on liquidity characteristics (Panels A) and liquidity betas (Panels B). In the first row of Panel A, we first sort each of the 25 portfolios formed using ratings and duration into five portfolios based on size quintile breakpoints. The average excess returns of each of the 25 largest size portfolios are equally weighted and each of the 25 smallest size portfolios are equally weighted. The same sorting procedure is used for the other liquidity characteristics. Similarly, in the first row of Panel B, we first sort each of the 25 portfolios formed using default and term betas into five portfolios based on size beta quintile breakpoints. The average excess returns of each of the 25 largest size-beta portfolios are equally weighted and each of the 25 smallest size-beta portfolios are equally weighted. The same sorting procedure is used for the other liquidity betas. Panels A.1 and B.1 report results for the entire sample period and Panels A.2 and B.2 report results for the TRACE period. t-statistics associated with the average excess returns for each portfolio are reported in italics.

Table 7
Average MADs Using Portfolio Approach in the Spirit of Grinblatt and Titman (1997)

Panel A: Rating/Duration Portfolios Sorted on Liquidity Characteristics

Panel A.1: Sample Period 1995-2015

Sorting Method:	Random Sort	Informed Sort	Difference (Informed - Random)
Size	2.5586%	2.4901%	0.0685%
			(0.000)
Volume	2.5586%	2.4633%	0.0953%
			(0.000)
Zero Frequency	2.5586%	2.4684%	0.0902%
			(0.000)
Spread	2.5586%	2.4746%	0.0840%
			(0.000)
CS Spread	2.5586%	2.4993%	0.0593%
			(0.000)
High-Low Daily Range	2.5586%	2.4514%	0.1072%
			(0.000)
Amihud Liquidity	2.5586%	2.4469%	0.1117%
			(0.000)
Roll's Daily Measure	2.5586%	2.4929%	0.0657%
			(0.000)

Panel A.2: Sample Period 2004-2015			
Sorting Method:	Random Sort	Informed Sort	Difference (Informed - Random)
Size	2.5453%	2.4842%	0.0611% (0.000)
Volume	2.5453%	2.4666%	0.0787% (0.000)
Zero Frequency	2.5453%	2.4707%	0.0746% (0.000)
Spread	2.5453%	2.4898%	0.0555% (0.000)
CS Spread	2.5453%	2.4823%	0.0630% (0.000)
High-Low Daily Range	2.5453%	2.4633%	0.0820% (0.000)
Amihud Liquidity	2.5453%	2.4627%	0.0826% (0.000)
Roll's Daily Measure	2.5453%	2.4859%	0.0594% (0.000)

Panel B: Default/Term Beta Portfolios Sorted on Liquidity Betas

Panel B.1: Sample Period 1995-2015

Sorting Method:	Random Sort	Informed Sort	Difference (Informed - Random)
FF Size	2.6570%	2.5992%	0.0577%
			(0.000)
FF Volume	2.6570%	2.6013%	0.0556%
			(0.000)
FF Zero Frequency	2.6570%	2.5962%	0.0608%
			(0.000)
FF Spread	2.6570%	2.5921%	0.0649%
			(0.000)
FF CS Spread	2.6570%	2.6069%	0.0501%
			(0.000)
FF High-Low Range	2.6570%	2.5917%	0.0653%
			(0.000)
FF Amihud	2.6570%	2.5852%	0.0717%
			(0.000)
FF Roll	2.6570%	2.6003%	0.0567%
			(0.000)
LWW Amihud	2.6570%	2.5978%	0.0591%
			(0.000)
LWW PS	2.6570%	2.6026%	0.0543%
			(0.000)

Panel B.2: Sample Period 2004-2015

Sorting Method:	Random Sort	Informed Sort	Difference (Informed - Random)
FF Size	2.6639%	2.6161%	0.0478%
			(0.000)
FF Volume	2.6639%	2.6185%	0.0454%
			(0.000)
FF Zero Frequency	2.6639%	2.6141%	0.0498%
			(0.000)
FF Spread	2.6639%	2.6067%	0.0572%
			(0.000)
FF CS Spread	2.6639%	2.6088%	0.0551%
			(0.000)
FF High-Low Range	2.6639%	2.6062%	0.0577%
			(0.000)
FF Amihud	2.6639%	2.5985%	0.0654%
			(0.000)
FF Roll	2.6639%	2.6162%	0.0477%
			(0.000)
LWW Amihud	2.6639%	2.6194%	0.0445%
			(0.000)
LWW PS	2.6639%	2.6218%	0.0421%
			(0.000)

This table shows the average mean absolute deviations (MADs) for 125 portfolios constructed using the sorting methodology employed in Table 6. In Panel A the sorting is done based on characteristics and in Panel B, based on betas. Also shown is the average MAD for 1,000 runs of portfolios constructed by randomly sorting bonds into 125 equal-sized portfolios each month using the same approach as in Table 5. Panels A.1 and B.1 report results for the entire sample period and Panels A.2 and B.2 report results for the TRACE period Reported *p*-values in parentheses are based on the percentage of the 1,000 random-sort runs with average MADs less than the informed sort average MAD.

Table 8

Average Excess Returns for Yield Sorts

Portfolios (3 IG & 2HY x 3 sorts on Duration x 3 sorts on Amihud) sorted on Yield

Panel A: Sample Period 1995-2015

	Higher Yielding	Lower Yielding	Difference
ALL Sample	0.62%	0.34%	0.28%
	5.57	*4.86*	*3.91*
IG	0.48%	0.30%	0.17%
	4.67	*4.01*	*2.85*
HY	0.69%	0.44%	0.24%
	3.06	*4.65*	*1.51*

Panel B: Sample Period 2004-2015

	Higher Yielding	Lower Yielding	Difference
ALL Sample	0.63%	0.37%	0.26%
	3.52	*3.45*	*2.42*
IG	0.52%	0.32%	0.20%
	3.26	*2.90*	*2.19*
HY	0.65%	0.41%	0.23%
	2.12	*2.71*	*1.23*

This table presents excess returns for yield-sorted portfolios. The portfolios are constructed as follows: We sort our sample each month into the five ratings portfolios, then we sort each ratings portfolio on duration using tercile breakpoints, and then finally we sort each of the 15 ratings-duration portfolios on the Amihud measure using tercile breakpoints. The result is 45 portfolios each month sorted on ratings, duration, and the Amihud measure. Each of these 45 portfolios is further sorted on yield using tercile breakpoints. We compute the average excess returns for the 45 highest yielding portfolios each month and then average across the sample period. We repeat the process for the lowest yielding portfolios. Panels A reports results for the entire sample period and Panel B, for the TRACE period. t-statistics associated with the average excess returns for each portfolio are reported in italics.

Table 9
Average MADs Using Portfolio Approach

Yield Tercile Sorts within 36 Buckets			
3 IG + 2HY Buckets x 3 Terciles on Duration x 3 Terciles on Amihud			
Sorting Method:	Random Sort	Informed Sort	Difference (Informed - Random)
Panel A: Sample Period 1995-2015			
Bond Universes			
All Sample	2.4469%	2.3580%	0.0889%
			(0.000)
IG	2.1765%	2.1157%	0.0609%
			(0.000)
HY	3.4998%	3.3009%	0.1989%
			(0.000)
Panel B: Sample Period 2004-2015			
Bond Universes			
All Sample	2.4899%	2.3773%	0.1127%
			(0.000)
IG	2.2118%	2.1292%	0.0826%
			(0.000)
HY	3.4509%	3.2341%	0.2169%
			(0.000)

This table reports average MADs for yield-sorted portfolios constructed as follows: We sort our sample each month into the five ratings portfolios, then we sort each ratings portfolio on duration using tercile breakpoints, and then finally we sort each of the 15 ratings-duration portfolios on the Amihud measure using tercile breakpoints. The result is 45 portfolios each month sorted on ratings, duration, and the Amihud measure. Each of these 45 portfolios is further sorted on yield measured as of t-2 using tercile breakpoints, generating 135 portfolios. Also shown is the average MAD for 1,000 runs of portfolios constructed by randomly sorting bonds into 135 equal-sized portfolios each month using the same approach as in Table 5. Panels A reports results for the entire sample period and Panel B, for the TRACE period. Reported *p*-values in parentheses are based on the percentage of the 1,000 random-sort runs with average MADs less than the informed sort average MAD.

Table 10

Rating Changes in the Next Month, and Default Likelihood in Next Year

Panel A: Overall Downgrades using Portfolios Sorted on Yield

Panel A.1: Sample Period 1995-2015

Credit Rating Portfolio	Higher Yielding	Lower Yielding	Difference
1	2.20%	1.03%	1.17%
	6.41	*7.07*	*3.76*
2	1.88%	0.61%	1.27%
	8.06	*4.54*	*7.40*
3	2.58%	0.52%	2.06%
	9.10	*5.84*	*7.52*
4	3.89%	0.69%	3.20%
	11.22	*9.09*	*9.52*
5	4.06%	1.01%	3.05%
	14.04	*7.87*	*11.30*

Panel A.2: Sample Period 2004-2015

Credit Rating Portfolio	Higher Yielding	Lower Yielding	Difference
1	2.32%	0.85%	1.47%
	4.87	*6.42*	*3.51*
2	1.66%	0.67%	0.99%
	8.80	*6.57*	*6.74*
3	2.06%	0.43%	1.62%
	7.71	*7.03*	*6.14*
4	4.11%	0.85%	3.26%
	10.62	*8.79*	*8.69*
5	4.07%	0.84%	3.24%
	14.40	*8.28*	*10.97*

Panel B.1: Overall Upgrades using Portfolios Sorted on Yield				
Panel B.1: Sample Period 1995-2015				
		Higher Yielding	Lower Yielding	Difference
Credit Rating Portfolio	1	0.40%	0.45%	-0.05%
		4.54	*3.98*	*-0.65*
	2	0.74%	1.03%	-0.28%
		5.17	*7.62*	*-1.92*
	3	0.68%	1.82%	-1.13%
		9.15	*10.06*	*-6.67*
	4	1.10%	2.64%	-1.54%
		8.60	*11.23*	*-6.25*
	5	1.10%	3.28%	-2.18%
		10.42	*10.01*	*-6.85*

Panel B.2: Sample Period 2004-2015				
		Higher Yielding	Lower Yielding	Difference
Credit Rating Portfolio	1	0.44%	0.47%	-0.03%
		3.61	*2.79*	*-0.25*
	2	0.53%	0.98%	-0.45%
		8.03	*8.51*	*-4.17*
	3	0.69%	1.64%	-0.95%
		9.04	*10.53*	*-6.65*
	4	1.33%	2.77%	-1.44%
		8.67	*11.60*	*-6.05*
	5	1.47%	3.86%	-2.39%
		10.48	*8.81*	*-5.77*

Panel C: Default Likelihood in Next Year using Portfolios Sorted on Yield				
Panel C.1: Sample Period 1995-2015				
		Higher Yielding	Lower Yielding	Difference
Credit Rating Portfolio	1	0.19%	0.03%	0.16%
		3.35	*3.12*	*3.35*
	2	0.20%	0.01%	0.19%
		3.61	*2.19*	*3.54*
	3	0.60%	0.26%	0.34%
		4.87	*3.54*	*2.79*
	4	1.09%	0.05%	1.04%
		5.92	*2.20*	*5.62*
	5	11.18%	0.67%	10.51%
		19.57	*4.77*	*19.58*

Panel C.2: Sample Period 2004-2015				
		Higher Yielding	Lower Yielding	Difference
Credit Rating Portfolio	1	0.32%	0.04%	0.27%
		3.40	*3.16*	*3.40*
	2	0.32%	0.01%	0.31%
		3.61	*2.20*	*3.54*
	3	0.27%	0.01%	0.26%
		4.42	*1.74*	*4.33*
	4	0.51%	0.03%	0.48%
		4.65	*2.46*	*4.45*
	5	9.58%	0.44%	9.13%
		15.23	*5.22*	*15.90*

This table reports the frequency of subsequent-month credit rating downgrades (Panel A), subsequent-month rating upgrades (Panel B), and subsequent-year default frequencies (Panel C) for portfolios of bonds created as follows. We first sort all bonds each month into five ratings portfolios, 1 being the highest and 5 the lowest, using the ratings breakpoints that most evenly distribute IG bonds into three portfolios and HY bonds into two portfolios. We then sort each rating portfolio on duration using tercile breakpoints and then on the Amihud measure using tercile breakpoints. Each of the resulting portfolios is further sorted on yield using tercile breakpoints. *t*-statistics are reported in italics.

Table 11
Characteristic-based Benchmarks

135 Buckets (3 IG & 2HY x 3 sorts on Duration x 3 sorts on Amihud x Sorts on Yield)

Panel A: Sample Period 1995-2015

1st Sort Variable	2nd Sort Variable	3rd Sort Variable	Random Sort	Informed Sort	Difference (Random – Informed)
Duration	Amihud	Yield	2.8156%	2.3667%	0.4489%
					(0.000)
Duration	Yield	Amihud	2.8156%	2.3715%	0.4441%
					(0.000)
Amihud	Duration	Yield	2.8156%	2.3660%	0.4496%
					(0.000)
Amihud	***Yield***	***Duration***	***2.8156%***	***2.3572%***	***0.4584%***
					(0.000)
Yield	Duration	Amihud	2.8156%	2.3681%	0.4475%
					(0.000)
Yield	Amihud	Duration	2.8156%	2.3606%	0.4550%
					(0.000)

Panel B: Sample Period 2004-2015

1st Sort Variable	2nd Sort Variable	3rd Sort Variable	Random Sort	Informed Sort	Difference (Random – Informed)
Duration	Amihud	Yield	2.8852%	2.4063%	0.4789%
					(0.000)
Duration	Yield	Amihud	2.8852%	2.4076%	0.4776%
					(0.000)
Amihud	Duration	Yield	2.8852%	2.4082%	0.4770%
					(0.000)
Amihud	***Yield***	***Duration***	***2.8852%***	***2.4027%***	***0.4825%***
					(0.000)
Yield	Duration	Amihud	2.8852%	2.4099%	0.4753%
					(0.000)
Yield	Amihud	Duration	2.8852%	2.4068%	0.4784%
					(0.000)

Panel C: Single Sort with 135 buckets on Yield

	Yield Only Sort	Rating/Amihud/ Yield/Duration Sort	Difference (Yield - Rating/Amihud/ Yield/Duration)
Entire Sample	2.5424%	2.3572%	0.1852%
			(0.000)
2004-2015 Period	2.5649%	2.4027%	0.1622%
			(0.000)

This table reports average MADs for portfolios sorted by the characteristics and yield in varying orders. We form 135 benchmark characteristic-based benchmark portfolios by quadruple sorting five ways on a bond's rating and three ways each on duration, the Amihud measure, and yield. We first sort all bonds each month into five ratings portfolios using the ratings breakpoints that most evenly distribute IG bonds into three portfolios and HY bonds into two portfolios. For each ratings portfolio, we then tercile sort on each of duration, Amihud measure, and yield while varying the order of sorting. Panels A reports results for the entire sample period and Panel B, for the TRACE period. Panel C reports based on 135 portfolios that were formed every month based solely on yield. Reported *p*-values in parentheses are based on the percentage of the 1,000 random-sort runs with average MADs less than the informed sort average MAD.

Figure 1

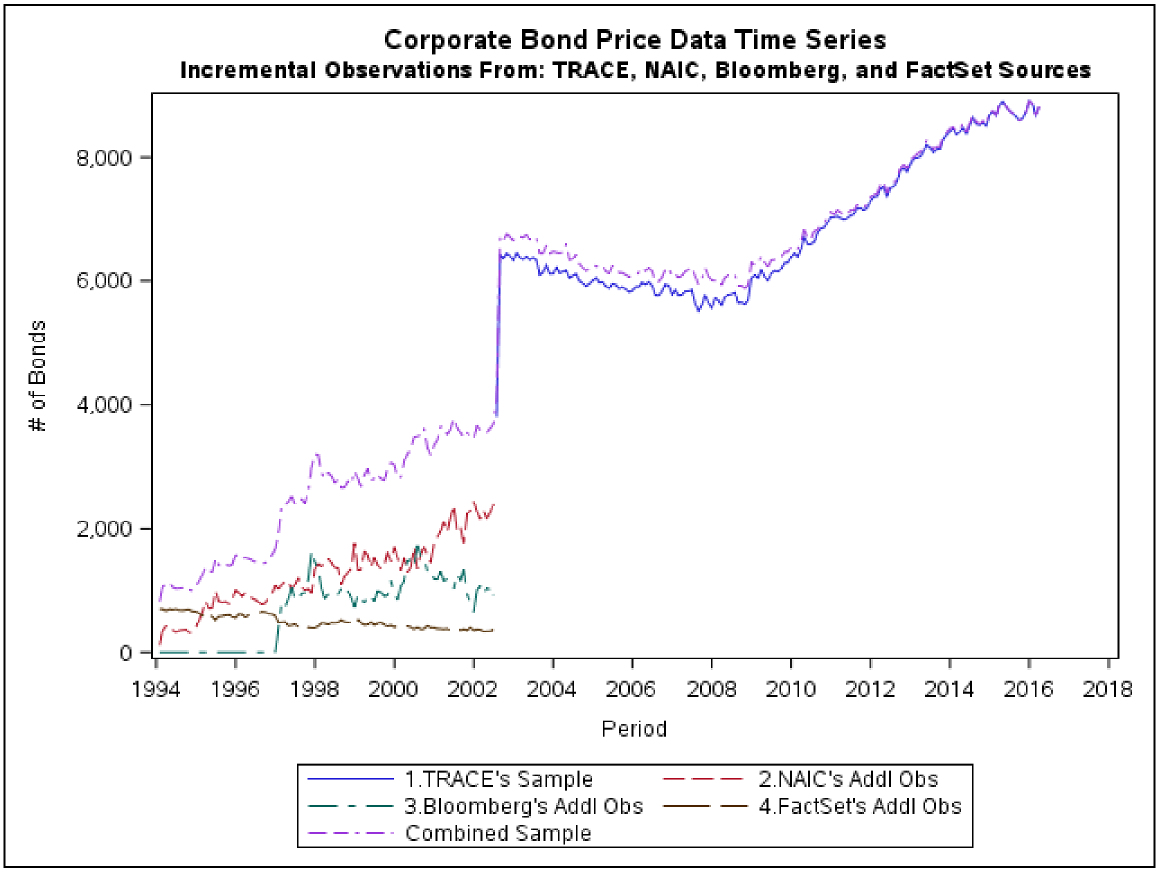

Figure 1 reports the number of unique bonds sourced each month from each of the four data sources: NAIC Transaction database, FactSet, Bloomberg, and Trace Enhanced.

Figure 2

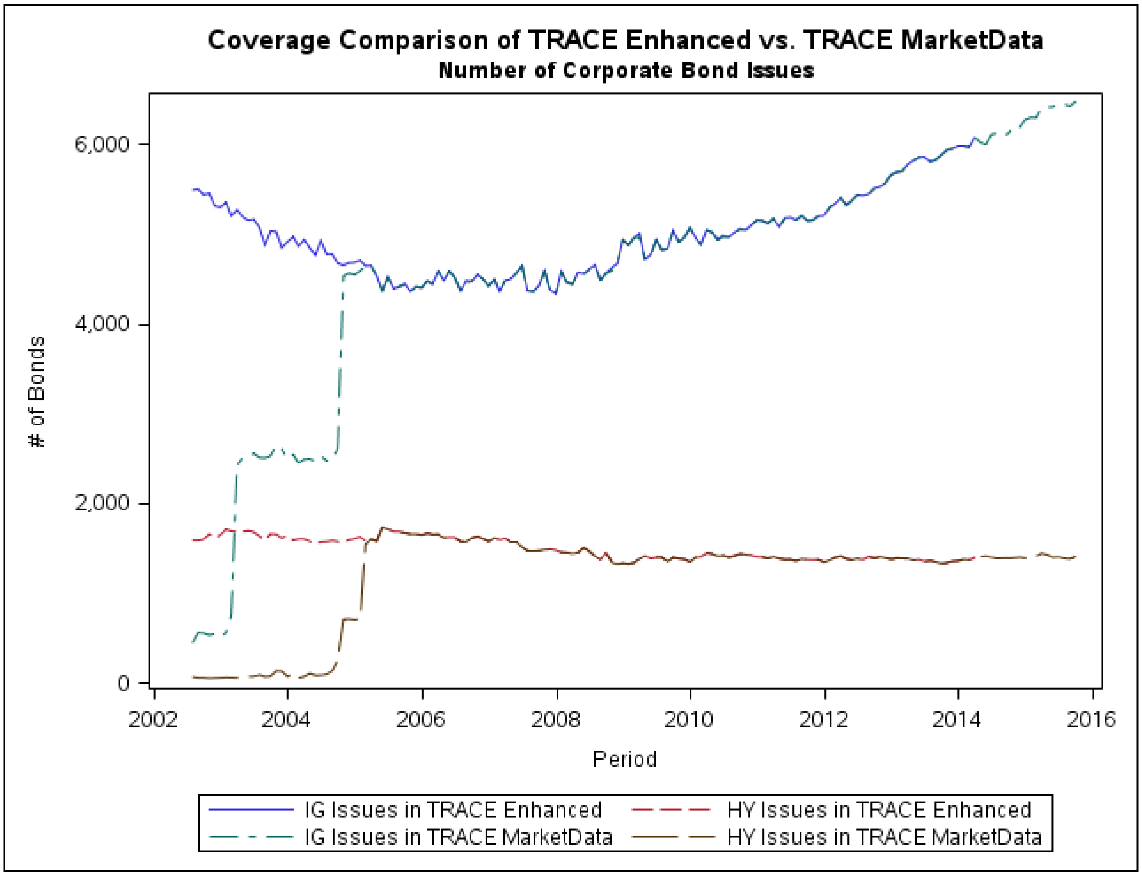

Figure 2 reports the number of IG and HY bonds covered by the TRACE Enhanced and TRACE Standard (MarketData) Databases during the July 2002-December 2015 period.

Figure 3

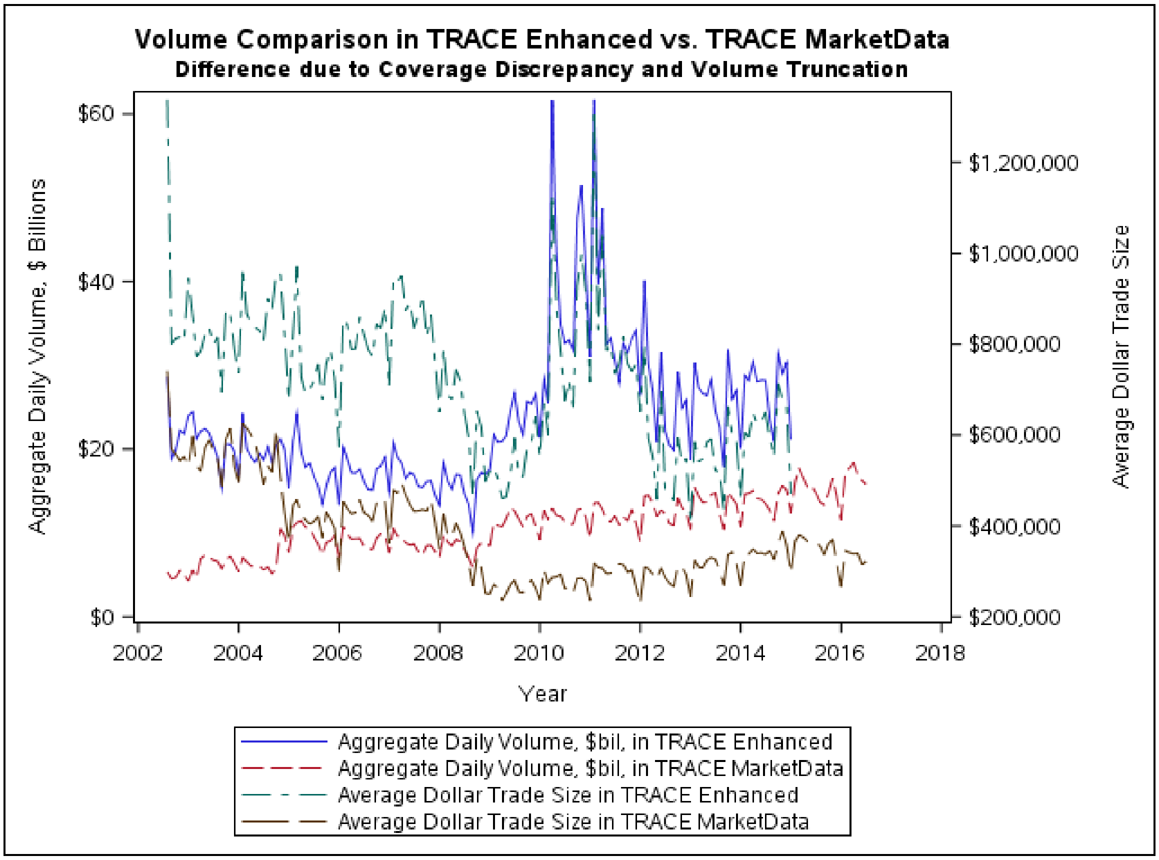

Figure 3 reports daily aggregate volume and average dollar trade sizes for bonds covered in the TRACE Enhanced and TRACE Standard (MarketData) Databases.

Figure 4

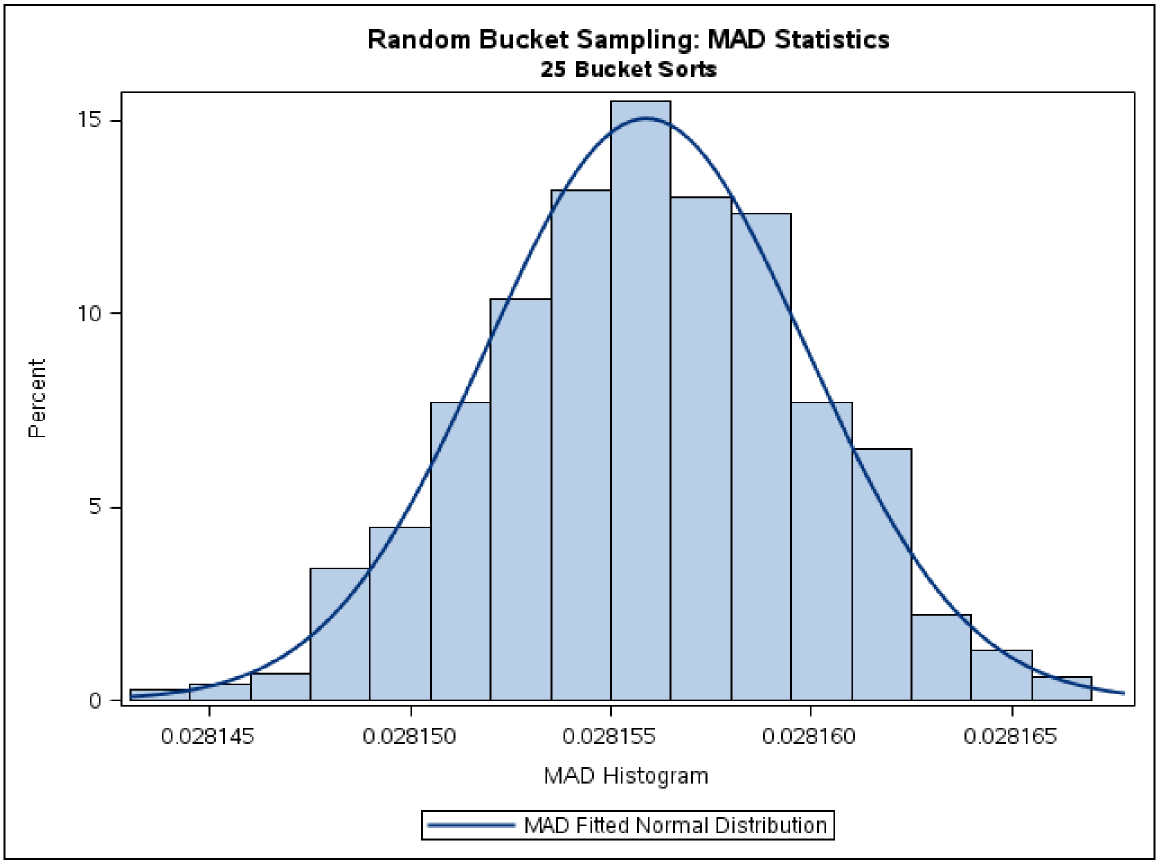

Figure 4 shows the distribution of MAD estimates from bootstrap simulations corresponding to Table 4. In each simulation, every month we randomly place each bond in our sample into one of 25 equally sized portfolios. We compute the MAD for each of the 25 portfolios over the sample period, and then compute an equally weighted average MAD for the 25 portfolios, which is then aggregated across all the sample months. We repeat this process 1,000 times, saving the average MAD from each run.

Figure 5a

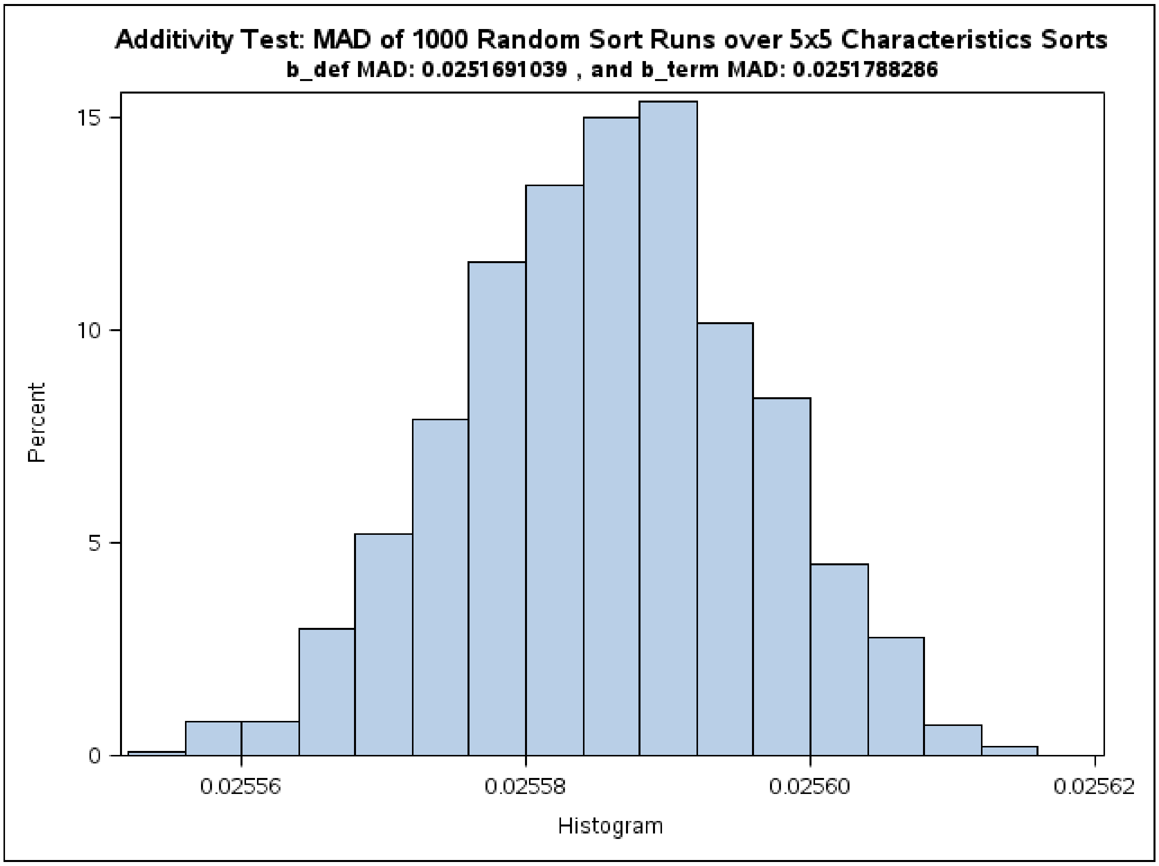

Figure 5a shows the distribution of MAD estimates from bootstrap simulations corresponding to Panel A of Table 5. In each simulation, every month we randomly place each bond in each of the 25 ratings-duration sorted portfolios into 5 different equally sized random portfolios. We compute the MAD measure for each of the resulting 125 portfolios over the sample period, and then compute an equally weighted average MAD across the 125 portfolios, which is then aggregated across all the sample months. We repeat this process 1,000 times, saving the average MAD from each run.

Figure 5b

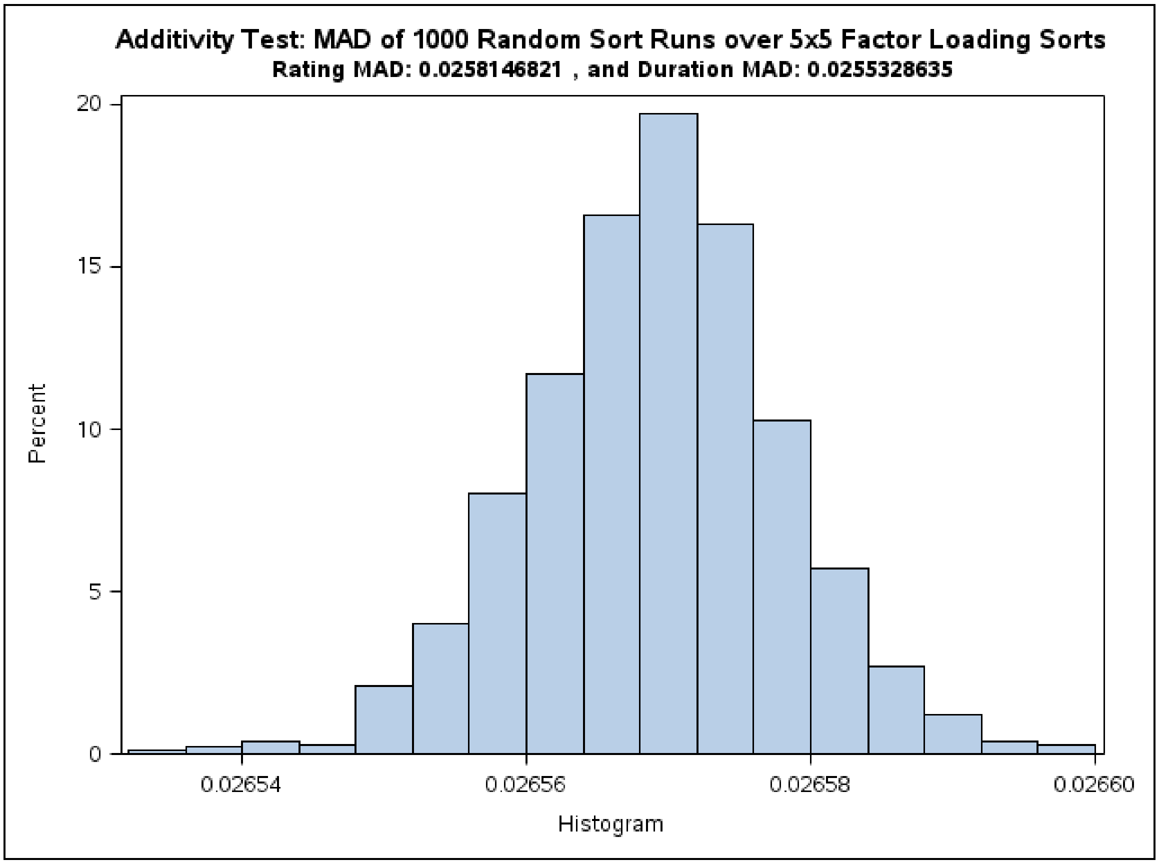

Figure 5b shows the distribution of MAD estimates from bootstrap simulations corresponding to Panel B of Table 5. In each simulation, every month we randomly place each bond in each of the 25 default-beta/term-beta sorted portfolios into 5 different equally sized random portfolios. We compute the MAD measure for each of the resulting 125 portfolios over the sample period, and then compute an equally weighted average MAD across the 125 portfolios, which is then aggregated across all the sample months. We repeat this process 1,000 times, saving the average MAD from each run.

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