Momentum in Corporate Bond Returns

Gergana Jostova
School of Business
George Washington University
jostova@gwu.edu

Stanislava Nikolova *
School of Management
George Mason University
snikolov@gmu.edu

Alexander Philipov
School of Management
George Mason University
aphilipo@gmu.edu

Christof W. Stahel **
School of Management
George Mason University
cstahel@gmu.edu

First draft: April 29, 2008

This Revision: January 15, 2010

* Stanislava Nikolova is currently a Visiting Scholar at the U.S. Securities and Exchange Commission, Washington, DC 20549, *nikolovas@sec.gov*. The Securities and Exchange Commission disclaims responsibility for any private publication or statement of any SEC employee or Commissioner. This paper expresses the author's views and does not necessarily reflect those of the Commission, Commissioners, or other members of the staff.

** Christof W. Stahel is also a Research Fellow at the Federal Deposit Insurance Corporation. The FDIC disclaims responsibility for any private publication or statement of any FDIC employee. This paper expresses the author's views and does not necessarily reflect those of the FDIC.

Momentum in Corporate Bond Returns

ABSTRACT

This paper documents significant price momentum in US corporate bonds over the period from 1973 to 2008. Results are based on 3 million bond-month return observations (on average about 7,000 bonds per month), compiled from two transaction (TRACE and FISD) and three dealer-quote databases (DataStream, Bloomberg, Lehman Brothers). As with equities, momentum profits derive from high credit risk bonds. However, contrary to equities, bond momentum strategies derive their profitability primarily from winners. Hence, short-sale constraints are unlikely to explain the persistent profitability of bond momentum. Bond momentum profits are robust to risk and liquidity considerations, and are prevalent in both quote-based and trade-based datasets.

Introduction

Jegadeesh and Titman (1993) document that stock returns are predictable based on past performance, challenging the foundation of the efficient market hypothesis. They show that stocks that performed well over the past three to twelve months outperform, at the three to twelve month horizon, stocks that performed poorly. While some market anomalies disappear or attenuate upon discovery, stock price momentum has persisted out of sample and is currently among the strongest, economically and statistically, asset-pricing anomalies (see Avramov, Chordia, Jostova, and Philipov (2009)). Moreover, momentum has been documented for a number of other asset classes: international equities, currencies, commodities, and international government bonds (see Rouwenhorst 1998, Blake 1999, Griffin, Ji, and Martin 2003, Gorton, Hayashi, and Rouwenhorst 2008, Asness, Moskowitz, and Pedersen 2009).

For US corporate bonds, however, there is very little research on momentum mainly due to difficulties working with bond data. This scarce research centers around the study by Gebhardt, Hvidkjaer, and Swaminathan (2005b), who find no evidence of momentum among investment-grade company-level bond returns.

Using a composite transaction- and dealer-quote-based dataset of 68,914 individual investment-grade and high-yield bonds, we find strong evidence of momentum profitability in US corporate bonds over the period from 1973 to 2008. Past six-month winners outperform past six-month losers by 61 basis points per month over a six-month holding period. These results are robust to risk and liquidity considerations.

Our corporate bonds sample combines information from DataStream, Lehman Brothers, Bloomberg, TRACE, and FISD.[1] It contains close to 3 million monthly returns from

[1]The Lehman Brothers Database is the *Lehman Brothers Fixed Income Database*. FISD stands for Mergent's *Fixed Income Security Database [FISD]/National Association of Insurance Commissioners*

1973 to 2008 and an average of around 7,000 bonds per month issued by 2,000 companies. DataStream, Bloomberg, and Lehman Brothers are quote-based and generally provide continuous price information over the full sample. In contrast, TRACE and FISD are trade-based and provide prices from actual bond transactions over a subperiod, from 2002 to 2008 and from 1994 to 2008, respectively.

The paper presents results for the overall sample from all databases, as well as for the quote-based and for the trade-based databases separately, since results for the two types of data may differ. Quote-based databases provide pricing information regardless of trading activity and thus offer a more comprehensive sample of both liquid and illiquid bonds. Trade-based databases, on the other hand, are biased towards the most liquid bonds. Since bonds do not trade as frequently as stocks, there may be data gaps that impede the implementation of the momentum strategies which require continuous 6 months of data to form portfolios. Still, we find that bond momentum is strong and profitable in both the quote-based and trade-based samples, suggesting that it is not limited to a particular database and is not the result of stale prices or illiquidity . Surprisingly, bond momentum strategies produce profits of 49 bps in the quote-based database and 80 bps in the trade-based dataset of most liquid bonds. Hence illiquidity is unlikely to explain the momentum anomaly in US corporate bonds.

Momentum profitability is virtually the same in rated and unrated bonds – 60 bps when implemented separately either among the rated or unrated subsamples. Using bond ratings from the various databases and augmenting these with Standard & Poor's bond issue ratings from WRDS, we find that 93% of sample observations have ratings. The sample of rated bonds is therefore quite representative.

Among rated bonds, we find that the momentum strategy is only profitable in non-

[NAIC] Database. See the Data section for more information on each database.

investment grade [NIG] bonds and is non-existent among investment-grade [IG] bonds. The momentum strategy yields a strongly significant 204 bps per month in NIG bonds and an insignificant 9 bps per month in IG bonds. This last result is consistent with Gebhardt, Hvidkjaer, and Swaminathan (2005b), who do not find evidence of momentum profitability at the company level for investment-grade bonds using the Lehman database.

Focusing on rated bonds, we further subdivide the overall sample into quintiles based on rating. The momentum strategy profits (P10-P1) amount to a strongly significant 209 bps per month in the highest credit risk quintile (Q5) and are economically small (ranging between 8 and 18 bps) and statistically insignificant in the remaining four credit risk quintiles.

Stratifying the sample further, we find that momentum profitability is driven exclusively by the worst-rated bonds, specifically the ones rated C and D. While these bonds represent only 1.89% of the bond-month observations in our sample and 2.80% of the total amount outstanding, momentum profits in these bonds are large enough to generate strongly significant momentum in the overall corporate bond universe. This is because when implementing the unconditional momentum strategy across all bonds, high yield bonds tend to appear mostly in the extreme winner and loser portfolios and these are the ones that enter into the momentum strategy. This is analogous to findings in the equity literature that momentum profits are significant only for high credit risk stocks (see Avramov, Chordia, Jostova, and Philipov (2007)). However, for corporate bonds, the subsample that drives momentum profits is even more extreme in terms of credit risk.

Momentum profitability in corporate bonds comes primarily from the long side of the strategy, contrary to momentum in equities. Specifically, investment-grade (high-yield) losers earn 76 (123) bps per month, while investment-grade (high-yield) winners realize 85 (327) bps per month on average. This shows that the difference in momentum profitability between IG and NIG bonds is mostly attributable to the difference between IG and NIG winners – the difference in profits between IG and NIG winner is 242 bps (=327-85) versus 47 bps (=123-76) between IG and NIG losers. This is contrary to equities, where losers tend to contribute more towards momentum profitability in high credit risk stocks relative to low credit risk stocks (see Avramov, Chordia, Jostova, and Philipov (2007)). This is important since it implies that short-sale constraints cannot explain why momentum profitability persists in bonds.

Bond momentum is robust to liquidity and risk considerations. Specifically, profitability remains strong and significant when adjusting returns for duration (as a proxy for interest rate risk), age and amount outstanding (as proxies for liquidity), and credit risk. We adjust returns by subtracting from each monthly bond return the average monthly return of the characteristic decile to which the bond belongs in that month. Again, momentum is strongest and most significant in the worst rated quintile and ranges between an adjusted return of 214 to 232 bps per month depending on the adjustment. Bond momentum is also robust to adjustment for systematic risk. In particular we show that bond momentum remains strong and significant when we adjust for a variety of stock and bond factors, such as changes in the term premium, changes in the default risk premium, as well as the Fama and French (1993) Market, SBM, and HML equity factors.

Momentum profits in corporate bonds do not come solely from periods around rating changes as is the case for equity momentum. For equities, Avramov, Chordia, Jostova, and Philipov (2009) show that most asset-pricing anomalies in equity returns arise during periods around rating downgrades and derive from the short side of the transaction. We find that this is not the case with corporate bond momentum since bond momentum arises from the long side. This suggests that rating downgrades are an unlikely culprit. Moreover, we find that bond momentum is significant even after removing 12 months of data around rating upgrades, downgrades, or both.

The remainder of the paper is organized as follows: Section I discusses the databases and sample used in the analysis. Section II.A investigates momentum in bond returns over the full sample and for separate databases. Section II.B examines momentum in bond returns within subsamples of credit ratings. Section II.C reports robustness tests, and Section III concludes.

I. Data

The corporate bond data used in this study is compiled from five databases: (1) the Lehman Brothers Fixed Income Database [Lehman], (2) DataStream, (3) TRACE, (4) Bloomberg, and (5) Mergent's Fixed Income Securities Database/National Association of Insurance Commissioners Database [FISD]. To the best of our knowledge, it comprises the largest cross-section and longest time-series of US corporate bond data used in empirical studies. It includes 2.94 million bond-month return observations for 68,914 different bonds during the period from January 1973 to December 2008. The subsections below provide more details on the data sources, return calculation, and sample construction.

A. *Bond database description*

The Lehman Brothers Fixed Income Database reports monthly information on the major private and government debt issues traded in the United States from 1973 to March 1998. We identify all U.S. corporate fixed-coupon debentures that are neither convertible, nor puttable, nor backed by mortgages or other assets. We collect data on month-end return, rating, duration, amount outstanding, issue date, and other characteristics. In using the Lehman database, we encounter the same data issues that Gebhardt, Hvidkjaer, and Swaminathan (2005b) report and handle them in a similar way. However, since we supplement the Lehman data with information from other sources, we are less concerned with sample size and hence can exclude from our sample returns calculated from "matrix" prices.[2]

From DataStream, we extract all bonds listed in the database starting in September 1990, which satisfy a set of selection criteria typically used in the corporate bond literature.[3] Specifically, we exclude from our sample non-US dollar denominated bonds, bonds with unusual coupons (e.g. step-up, increasing-rate, pay-in-kind, and split-coupons), and bonds backed by mortgages or other assets. We also eliminate convertible bonds, bonds with warrants, and bonds part of unit deals.

From Bloomberg, we collect historical bond price quotes and characteristics for all publicly traded firms with available credit ratings. We retain only fixed-coupon bonds, which are neither convertible nor callable. We further eliminate from the sample observations with missing coupon data as well as those with odd coupon frequency or

[2] While most prices in the Lehman database reflect "live" dealer quotes, some are "matrix" prices, which are estimated from price quotes of bonds with similar characteristics. To achieve the maximum power when testing, Gebhardt, Hvidkjaer, and Swaminathan (2005b) report estimation results using a sample that contains both dealer quotes and matrix prices. They state that their conclusions are the same when using dealer quotes only.

[3] Although DataStream contains bond data going back to earlier years, data on individual bond returns before September 1990 is limited.

day-count convention, which we consider data entry errors.

The above three databases provide pricing information based on dealer quotes. This may raise concerns that the momentum strategy we identify using quote-based data cannot be easily implemented due to thin or infrequent trading, stale prices, or illiquidity. This is why we consider two additional databases (described below) which are strictly trade-based and all pricing information comes from actual trades, rather than dealer quotes. Momentum results are computed both for the combined dataset as well as separately for the quote-based and trade-based subsamples.[4]

Our fourth source of bond information is the recently developed TRACE system.[5] Introduced in July of 2002, TRACE collects and distributes consolidated information on secondary market transactions in publicly traded TRACE-eligible securities, such as investment-grade, high-yield, and convertible corporate bonds. The system was implemented in phases and by February 2005 covered more than 99 percent of the OTC activity in US corporate bonds.[6] We collect bond prices starting at the inception of the TRACE system up to December 2008. We use the CUSIP Master File, which contains bond characteristics, to eliminate from our sample non-US dollar denominated bonds, bonds with unusual coupons (e.g. step-up, increasing-rate, pay-in-kind, and split-coupons), and bonds backed by mortgages or other assets. We also eliminate convertible bonds, bonds with warrants, bonds that are part of unit deals and preferred shares. As documented by Bessembinder, Kahle, Maxwell, and Xu (2009), there are a number of likely data errors reported in the TRACE database. Following their data cleaning procedure, we eliminate cancelled, corrected, and commission trades from our

[4]Bessembinder, Kahle, Maxwell, and Xu (2009) document that trade-based and quote-based databases are highly consistent with regards to bond price reaction to corporate news events.

[5]TRACE has been used in Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), and Goldstein, Hotchkiss, and Sirri (2007).

[6]See FINRA news release http://www.finra.org/Newsroom/NewsReleases/2005/P013274.

sample. Since TRACE provides intraday prices, we aggregate these into a daily price by calculating the trade-size weighted average for each bond on each day of our sample period.[7]

Our final data source is Mergent's FISD/NAIC database. The FISD portion of the database contains issuance information on all fixed-income securities assigned a CUSIP or likely to be assigned one in the near future. It is probably the most comprehensive source of bond issuance data. The NAIC portion of the database maintains prices for all trades in publicly traded corporate bonds made by insurance companies since 1994. Insurers are required to report this information to the National Association of Insurance Commissioners (NAIC) on a quarterly basis. Mergent Inc. matches the two datasets into a single database, FISD/NAIC.[8] We collect bond prices and characteristics from FISD for the period of 1994-2008 excluding non-US dollar denominated bonds, bonds backed by mortgages or other assets, and bonds that are convertible, pay-in-kind, or part of a unit deal. We also eliminate observations that are obvious data entry errors, e.g. with negative prices, with maturity dates prior to issuance or trade dates, etc.

B. Return Calculation

Returns are readily available in some databases, but need to be calculated for other databases used in this study. We define holding period returns as:

$$RET_{i,t} = \frac{(P_{i,t} + AI_{i,t} + Coupon_{i,t}) - (P_{i,t-1} + AI_{i,t-1})}{P_{i,t-1} + AI_{i,t-1}} \tag{1}$$

[7] This approach is consistent with the findings in Bessembinder, Kahle, Maxwell, and Xu (2009) that a daily price based on trade-size weighted intraday prices is less noisy than the last price of the day.

[8] This database has also been used by Campbell and Taksler (2003), Krishnan, Ritchken, and Thomson (2006), and Cai, Helwege, and Warga (2007).

where for the i^{th} bond in our sample $RET_{i,t}$ is its return from $t-1$ to t, $P_{i,t}$ is its price at time t, $AI_{i,t}$ is its accrued interest at time t, and $Coupon_{i,t}$ is its coupon (if any) paid between time $t-1$ and t. DataStream is the only database that provides accrued interest along with each bond's price quote. For TRACE, Bloomberg, and FISD, we use all of the databases to gather bond information necessary for the calculation of accrued interest. This information includes the bond's first coupon date, its coupon size, coupon payment frequency and day count convention for coupon accrual. Whenever some of these characteristics are missing we make the following assumptions. If the first coupon date is missing, we assume that coupons start accruing from the bond's issuance date, and if the payment frequency is missing, we assume that the bond pays interest semi-annually. If there is no available information on the day count convention used for coupon accrual, we assume that it is 30/360.[9]

We calculate the above holding period returns whenever bond prices are available. The quote-based databases Lehman, DataStream and Bloomberg contain daily bond quotes and we calculate monthly returns as the compounded daily returns at the end of each month. This allows us to correctly account for coupon payments that occur within a month. Since trades occur less often than traders post quotes, TRACE and FISD are more sparsely populated. For these trade-based databases, we compound daily returns as well, but set the monthly return to missing if there is no observed price in the last five trading days of the current or preceding months.[10] Hence, the trade-based databases tend to contain more liquid bonds. There is a small degree of overlap between the databases. For example, 87% of all bond-month observations are single database observations. This large percentage is due to the fact that Lehman, the largest database, spans 20 years as the only available source. When there is overlap, 8% of

[9]We have verified that the results hold for the subset of observations for which we can unambiguously calculate accrued interest without the above assumptions.

[10]The conclusions hold true if we remove this restrictions. See also section C.v

the bond-month observations come from exactly two databases. The biggest overlap is between DataStream and TRACE. Less than 1% of all bond-month observations come from 3 or 4 sources. There are no cases in which all five databases have returns for the same month. When there are returns for a bond from multiple sources in a single month, a single bond return is computed as a the equally weighted average of the returns from different databases.

C. Descriptive statistics

The initial sample constructed by merging all five datasets contains 2,935,348 bond-month observations (see Table I). Among these are obvious data errors. For example, the maximum return in the initial overall sample is 2,648,850%. We eliminate return outliers above 100% per month (using alternative cut-offs of 75%, 150%, and 200% per month has very little impact on the sample size and results). Ultimately, this filter eliminates 0.1% of all observations which results in a final sample containing 2,932,335 bond-month observations. In the robustness checks, when controlling for interest-rate risk and liquidity, we use data on duration, age, and amount outstanding. For these tests, we further filter the sample to eliminate outliers in these variables using a series of hard-coded cutoff points which can be inferred from the minimum and maximum values in Table I.

Table I reports summary statistics for all variables. After filtering, the average monthly holding period return in the sample is 0.79%. The average duration, age, and amount outstanding adjusted for outliers are 5.95 years, 82.33 months, and $116.14 millions, respectively.

For most bonds, we obtain rating information from the individual databases. If there is no rating information for a bond, we assign its Standard & Poor's issue rating from *Credit Ratings* in WRDS where available. We convert the credit ratings into a numerical scale from 1 to 22 with larger numbers reflecting higher credit risk: 1 = AAA, 2 = $AA+$, 3 = AA, ..., 10 = $BBB-$, 11 = $BB+$, ..., 21 = C, 22 = D. Our final database contains rating information for roughly 93% of all bonds, i.e. 7.12% of bond-month observations do not have ratings (see Table I). The average bond rating is 6.93, corresponding approximately to an $A-$ rating. The investment-grade cut-off is 10 ($BBB-$), suggesting that more bonds in our sample are investment-grade.

The number of bond-month observations in Lehman, DataStream, Bloomberg, TRACE, and FISD are 1.71, 0.93, 0.15, 0.33, and 0.06 million, respectively. The average returns in the five databases are 0.81%, 0.76%, 0.65%, 0.79%, and 0.45%, respectively, and the corresponding ratings are 6.34, 7.97, 6.35, 8.28, 6.09. This is consistent with the fact that FISD contains primarily investment-grade bonds since it reports trades by insurance companies, which face restrictions on holding junk bonds. Bonds covered in TRACE have the worst average rating. The ages of the bonds are similar in all databases except for Lehman which contains a larger fraction of older bonds. This is consistent with Alexander, Edwards, and Ferri (2000) who find that bonds trade mostly within 2 years of issuance and subsequently get absorbed into inactive portfolios. Since TRACE and FISD cover exclusively bond trades, they are more heavily populated by younger bonds. Similarly, TRACE and FISD have the lowest average duration among all databases. Finally, the amounts outstanding are largest for FISD and TRACE, and smallest for Lehman, probably because Lehman covers earlier years in the sample.

Figure I displays the time-series of the total number of individual bonds in our sample along with the number of companies associated with these bonds. On average, there are 7,200 bonds by 2,019 companies per month in our sample. There are a minimum of

2,639 bonds by 881 firms in January 1998, and a maximum of 24,831 bonds by 6,544 firms on June 2007. The spikes and troughs in the data are due to the beginning or ending of some of the databases.

II. Results

A. Momentum in US Corporate Bonds

In this section we examine the profitability of a momentum spread strategy, as described in Jegadeesh and Titman (1993), that is long in bonds that performed best in the past and short in bonds that performed worst. Specifically, each month t, bonds are ranked into decile portfolios, P1 (worst) through P10 (best), based on their cumulative returns over months $t-6$ through $t-1$ (formation period). We skip one month (month t) between the formation and holding periods to avoid potential biases from bid-ask bounce and short-term price reversal. Portfolios are then held for six-months between month $t+1$ and $t+6$ (the holding periods for strategy t). Monthly portfolio returns are calculated as equally-weighted averages across their constituent bonds. Following Jegadeesh and Titman (1993), the overall momentum strategy return for month t is the equally-weighted average month-t return of strategies implemented in the prior month and all strategies formed up to six months ago.

Table II presents evidence of significant momentum profits in US corporate bonds. Considering the full sample from all databases (first row), the average return of the loser portfolio (P1) is 0.81% per month (t-value of 5.25), it is 0.65% (t-value of 5.44) for the next worst performer (P2) and thereafter, the returns increase monotonically to 1.42% (t-value of 12.93) for the winner portfolio (P10). All portfolio returns are statistically and economically significant. The momentum strategy (P10-P1) return is a statistically significant 0.61% per month (t-value of 4.88).[11]

Due to the relative illiquidity of bonds, it could be argued that momentum strategies may not be exploited in real time. Indeed, corporate bonds are among the least liquid asset classes.[12] Therefore, price momentum in bonds could be the result of dealer quotes smoothed through time when no actual transactions took place. To examine this further, we split the overall sample into trade-based (TRACE+FISD) and quote-based (Lehman+DataStream+Bloomberg) subsamples. The next two lines of Table II present the results. A bond momentum strategy based on bonds that actually trade produces a strongly significant and economically large profits of 80 bps per month (t-stat of 2.94) – even higher than the profits of 49 bps (t-stat of 4.57) produced by the quote-based subsample. Overall, the results show that price momentum in US corporate bonds is significant and real.

Next, we show that momentum profitability is significant and strong in both rated and unrated bonds. Surprisingly, momentum profits amount to 60 bps per month in both rated and unrated firms and are statistically significant at the 5% level in both subsamples (see last two rows in Table II). Moreover, 93% of the bonds in our sample are rated (see Table I). The sample of rated firms is therefore quite representative and comprehensive. For most of the remaining analysis we focus on rated firms.

Before we proceed, we verify that the documented momentum profits are not compensation for systematic risk. We do this by regressing the time-series of P1 to P10 portfolio returns on a number of common risk factors.[13] Specifically, using GMM and

[11] Results are virtually identical when we use the 75%, 150%, or 200% upper cut-offs for returns. See Data section for return filtering.

[12] See http://www.sifma.org/uploadedFiles/Research/Statistics/SIFMA_USBondMarketIssuance.pdf

[13] As in Fama and French (1989), Balduzzi, Elton, and Green (2001), and Gebhardt, Hvidkjaer, and Swaminathan (2005a).

Newey-West adjusted standard errors, we estimate alphas from models of the following form:

$$r_{pt} = \alpha_p + \boldsymbol{\beta}_p' \boldsymbol{F}_t + e_{pt} \tag{2}$$

where $r_{pt} = R_{pt} - R_{rf,t}$ is the momentum portfolio excess return over the risk free rate or the momentum strategy return difference $r_{pt} = R_{P10,t} - R_{P1,t}$ and $\boldsymbol{F}_t$ contain combinations of the following variables: the change in the term spread, the change in the credit spread, the market, SMB, and HML factors of Fama and French (1993), and the momentum factor of Carhart (1997).

Table III reports the estimated portfolio alphas. Uniformly, the winner P10 portfolio alphas are significant and positive, whereas the loser P1 portfolio alphas are not significant at the 5% level. The momentum strategy P10-P1 portfolio alphas, ranging from 70 to 80 bps, are positive and significant and roughly of similar magnitude as the ones reported for stock portfolios by Jegadeesh and Titman (1993). The alphas for the rated and unrated subsamples reveal similar results. We conclude that the observed momentum strategy profits are abnormal and not compensation for systematic risk.

So far we have shown that bond momentum is robust to quote-based or trade-based pricing information, within subsamples of rated and unrated bonds, and survive adjustments for systematic risk.

The results presented so far contrast with the evidence in Gebhardt, Hvidkjaer, and Swaminathan (2005b) who find no momentum in their sample of investment-grade bonds. They argue that the market for non-investment grade bonds prior to 1992 was small and that the number of non-investment grade bonds in the Lehman database they use is limited. Since our sample is based on multiple sources, we are not facing the same restriction. Table IV reports the distribution of investment (IG) and non-investment grade (NIG) bonds as well as the distribution across rating classes from AAA to D. A S&P rating of $BBB-$ or better is classified as IG and $BB+$ and worse is classified as NIG.

Our sample contains on average about 13.5% NIG bond-months measured across all portfolios (average of NIG percentages in second line of Table IV). However, there are 25.12% NIG bonds in P1 and 37.51% in P10, suggesting that the winner and loser portfolios contain many more NIG observations than the intermediate portfolios, similar to what Avramov, Chordia, Jostova, and Philipov (2007) find in momentum-sorted stock portfolios. These findings suggest that credit risk may play a role in bond momentum, which is a conjecture we investigate next.

B. Credit Risk and Momentum Profitability

Table IV shows that the bond momentum strategy is only profitable among NIG bonds, earning 245 bps per month, and non-existent among IG bonds. This is exactly what Avramov, Chordia, Jostova, and Philipov (2007) find for equity momentum. This finding also explains why Gebhardt, Hvidkjaer, and Swaminathan (2005b) find no momentum in their sample of investment-grade bonds.

To investigate further the relationship between credit risk and momentum profitability, each month t we divide all bonds into quintiles based on their prior month's credit rating. We then repeat the momentum analysis within each quintile. Table V presents momentum portfolio returns and momentum strategy profits for each rating quintile. The average numeric S&P rating of each quintile is presented in the second column. The first quintile contains bonds with an average rating of 1.98, approximately a $AA+$ rating. The last quintile contains bonds with an average rating of 13.61, which roughly corresponds to a non-investment grade rating of $B+$.

Bond momentum is profitable only in the worst rated quintile (Q5), earning on average strongly significant 209 bps per month (t-stat of 7.87). Momentum is insignificant in all four other rating groups, ranging between 8 and 18 bps per month. The average ratings in the four best rated quintiles are all investment-grade. These results are in line with Gebhardt, Hvidkjaer, and Swaminathan's (2005b) findings. Indeed Q5 is the only quintile containing NIG bonds (our sample contains 13.5% NIG bonds on average, shown in Table IV, while Q5 contains the worst 20% of rated bonds).

Table V also shows that bond momentum profitability comes mostly from the long side of the strategy, i.e. the winners. In particular, best rated (Q1) winners realize 84 bps per month on average, while worst rated (Q5) winners earn 334 bps – a difference of 250 bps. Compare this to the losers: Q1 losers earn 74 bps per month, while Q5 losers earn 125 bps – a difference of 51 bps per month, or 5 times smaller. This shows that the difference in momentum profitability between Q1 and Q5 is largely attributable to the difference between Q1 and Q5 winners, contrary to equities where losers account for much of momentum profitability in high credit risk stocks relative to that in low credit risk stocks (see Avramov, Chordia, Jostova, and Philipov (2007)). This is important since it implies that short-sale constraints cannot explain why momentum profitability persists in bonds.

So far we have documented a positive relationship between credit risk and bond momentum profitability using portfolio strategies based on a sequential double sort: first by credit risk then by prior 6-month return. To further pinpoint the segment of bonds driving momentum profitability, we implement the traditional unconditional momentum strategy over subsamples that sequentially exclude bonds with the worst credit rating. Table VI reports the average payoffs from momentum strategies in each diminishing subsample as we progressively drop the remaining worst-rated bonds. The last two columns present the number of bonds and total amount outstanding removed relative to the full sample of rated firms.

Momentum strategy profits using the full sample of rated bonds is 60 bps per month (t-value of 4.86), as previously reported in Table II. After removing all D-rated bonds from the sample, momentum profitability drops to 22 bps (t-value of 1.90) – much smaller, but still significant at the 10% level. Further removing all C rated bonds reduces the momentum payoff to an insignificant 18 bps. Surprisingly, the removed bonds represent 1.89% of the rated bonds in our sample and 2.8% of the amount of rated bonds outstanding. Stock price momentum is also significant only among high credit risk firms (see Avramov, Chordia, Jostova, and Philipov (2007)), but in corporate bonds, the sample driving momentum profits is even more extreme in terms of credit risk. In equities, momentum disappears after excluding firms rated worse than $BB-$.

While these worst-rated bonds represent a minor fraction of all bonds, momentum in them is strong enough to generate significant momentum for the overall corporate bond universe. This is because when implementing the unconditional momentum strategy across all bonds, these worst-rated bonds tend to appear in the extreme winner and loser portfolios generating momentum profits (see Table IV).

To summarize, we find significant momentum in US corporate bonds. This is true both in the quote-based and trade-based datasets and both in rated and unrated bonds, and survives adjustments for systematic risk. Credit risk has a strong impact on bond momentum profitability: momentum is only significant among the worst rated bond quintile and comes primarily from the winners or long side of the strategy. The sample of worst rated bonds driving bond momentum is even more extreme than the sample of worst rated stocks driving equity momentum.

C. Additional Robustness Checks

Next we present a series of tests to check whether the impact of credit risk on momentum profitability is independent of alternative characteristics that have been shown to impact bond returns. We also make sure that momentum profitability is robust to interest-rate risk and liquidity considerations. Finally we discuss data issues and how they could potentially impact our results.

C.i Controlling for interest-rate risk

Bond duration measures the interest-rate sensitivity of bonds. Gebhardt, Hvidkjaer, and Swaminathan (2005a) further argue that bond duration is a good total risk measure for bonds, unlike bond betas which only measure systematic exposure. To control for duration risk, we compute each month duration-adjusted individual bond returns by subtracting from each bond return the average return of the duration decile to which the bond belongs in that month. Then we re-examine the momentum strategy following the approach in Table V using duration-adjusted rather than raw returns. Panel A in Table VII reports the results.

The momentum strategy payoffs for all quintiles are significant and positive - but Q5 momentum profits are multiple times larger than those in the best rated four quintiles. Momentum payoffs in Q5 bonds are 220 bps (t-stat of 7.79) after controlling for duration, while the payoffs in the better rated quintiles range between 19 and 30 bps. This suggests that the impact of credit risk on bond momentum is independent of the impact of duration on returns.

The significance of Q5 momentum profits also shows that bond momentum is robust to adjusting for duration. The higher returns earned by past winners are not due to their higher duration. In particular, Q5 duration-adjusted momentum profits are even slightly higher than Q5 raw momentum profits, suggesting that Q5 momentum losers probably have slightly higher duration than Q5 winners.

C.ii Controlling for the impact of credit risk on bond returns

Theory suggests that higher credit risk bonds should earn higher returns. In this section, we confirm that bond momentum profits are not compensation for credit risk. Specifically, it could be argued that past winners earn higher returns because they have higher credit risk than past losers. In other words, momentum profits compensate for credit risk and are therefore not purely anomalous. To check this, we compute credit-risk-adjusted individual bond returns following the procedure in the above subsection.

Panel B of Table VII shows that after controlling for credit risk, bond momentum is still significant in Q5 stocks – credit risk-adjusted momentum profits are 221 bps (t-stat of 8.35). Past winners do not outperform past losers because of higher credit risk. In fact, the Q5 credit risk-adjusted payoffs are higher than their raw payoffs of 209 bps (Table V), suggesting that Q5 losers have slightly higher credit risk than Q5 winners.

C.iii Controlling for illiquidity

Next we examine whether bond momentum and the impact of credit risk on bond momentum are robust to liquidity considerations, since it has been documented that liquidity affects returns.[14] Moreover, Korajczyk and Sadka (2004) show that profitable momentum returns vanish after trading costs are taken into account in equity markets.

[14] See, among others, Amihud and Mendelson (1986), Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Chen, Lesmond, and Wei (2007).

Furthermore, Lee and Swaminathan (2000) show that liquidity affects the magnitude and persistence of price momentum in equities, and Chen, Lesmond, and Wei (2007) show that more illiquid bonds have higher yield spreads. Chen, Lesmond, and Wei (2007) model bond liquidity as a function of age and amount outstanding. Following these authors, we compute age- and amount outstanding-adjusted individual bond returns and re-examine the profitability of the momentum strategy. Table VII panels C and D report the results. As before momentum profitability in Q5 is significant and strong and much larger than that in the other rating quintiles.

The tests above confirm that (1) bond momentum is robust to risk and liquidity considerations, and that (2) the impact of credit risk on bond momentum profitability is independent of the impact of interest rate risk, credit risk, and liquidity on bond returns.

C.iv Controlling for impact of rating changes

Hand, Holthausen, and Leftwich (1992) find that rating changes, especially downgrades, have a substantial impact on bond returns. However, more recently Ambrose, Cai, and Helwege (2009) show that after controlling for information flow, price pressure effects from downgrading bonds to junk status are negligible, if not non-existent. Still for equities, Avramov, Chordia, Jostova, and Philipov (2009) show that most asset-pricing anomalies in equity returns take place around rating downgrades and derive from the short side of the transaction. True, unlike equity momentum, bond momentum arises from the long side, so rating downgrades are an unlikely culprit. Still since our results are driven by non-investment grade bonds, it is possible that they simply reflect price reactions to rating changes. In order to address this issue, we exclude from our sample bond-month observations from six months before and six months after a rating change and re-evaluated the momentum strategy. In unreported results, we find that bond momentum is significant when periods around rating upgrades, downgrades, or both, are removed. Hence, momentum profits in corporate bonds are not driven by returns around rating changes as is the case for equity momentum profits.

C.v Data issues

It is conceivable that some bonds disappear during the holding period because they default – a much more likely scenario for riskier bonds. Yet we have no record of recovery rates and the databases contain no delisting returns as in CRSP. To investigate whether this is indeed an issue, in unreported results, we count the number of bonds that are in each of the momentum portfolios in month $t + 1$ and $t + 6$ and assess their retention. If the retention rate for P1 is significantly lower than that for P10, we would be concerned about survivorship bias that would likely favor the winner portfolio. We find that of the bonds that enter the P1 and P10 portfolios in month $t + 1$ roughly 88% and 91%, respectively, have a recorded return at the end of the holding period, $t + 6$. The fact that the attrition rate is quite similar across the momentum portfolios suggests that survivorship bias is less of a concern for bond momentum profitability.

As with all empirical work, the quality of the results depends on the quality of the data used in the analysis. One bad dataset could potentially impact the quality of the combined data sample we use. To mitigate potential concerns, we report results for all data, as well as for quote-based and trade-based data separately. Lehman and DataStream provide the most bond-month observations and hence results should be most sensitive to their exclusion. This is why the strong significance of momentum in the trade-based datasets, TRACE and FISD, offers most assurance that the results are not solely due to Lehman or DataStream observations. In addition, in unreported results, we have verified that bond momentum is significant when any single bond dataset is excluded from the overall sample. [15]

III. Conclusions

This paper documents strong evidence of momentum profitability in US corporate bonds over the period from 1973 to 2008. Past six-month winners outperform past six-month losers by 61 basis points per month over a six month holding period.

Results are based on an extensive dataset of 68,914 individual investment-grade and high-yield bonds with an average of 7,000 bonds per month issued by 2,000 companies. Our data consists of a total of 3 million bond-month observations from two transaction- (TRACE and FISD) and three quote-based (Lehman, DataStream, and Bloomberg) datasets. Bond momentum is strong and profitable in both the quote-based and trade-based samples. In particular, the bond momentum strategy produces profits of 49 bps in the quote-based database and 80 bps in the trade-based dataset of most liquid bonds. Hence the momentum anomaly in US corporate bonds is not limited to a particular database, and illiquidity is unlikely to explain it.

Momentum profitability is virtually the same in rated and unrated bonds – 60 bps when implemented separately either among the rated or unrated subsamples. Among rated bonds, we find that the momentum strategy is only profitable in non-investment

[15] Since a discussant raised the question of the source of bond price information in DataStream, we confirmed with DataStream data analysts that "U.S. corporate bond prices contained in the database are indicative prices (i.e. dealer quotes) from various market-makers trading the bonds. This data is further augmented with traded prices for exchange-traded bonds. Unfortunately, DataStream provides no indication of whether a recorded price is indicative (i.e. trade-based), which is similar to how trader quotes are reported in the Lehman Brothers database." Unlike DataStream, the Lehman Brothers database also contains unambiguously identifiable matrix prices based on quoted prices for securities with similar characteristics. For consistency, we exclude such matrix prices from our analysis.

grade [NIG] bonds and is non-existent among investment-grade [IG] bonds. Stratifying the sample further, we find that momentum profitability is driven exclusively by the worst-rated bonds, specifically the ones rated C and D. While these bonds represent only 1.89% of the bond-month observations in our sample and 2.80% of the total amount outstanding, momentum profits in these bonds are large enough to generate strongly significant momentum in the overall corporate bond universe. This is because when implementing the unconditional momentum strategy across all bonds, high-yield bonds tend to appear mostly in the extreme winner and loser portfolios constituting the momentum strategy. Momentum profits are also significant only in high credit risk stocks (see Avramov, Chordia, Jostova, and Philipov (2007)), but in corporate bonds, the sample driving momentum profits is even more extreme in terms of credit risk.

Momentum profitability in corporate bonds comes primarily from winners, contrary to momentum in equities. This is important since it implies that short-sale constraints cannot explain why momentum profitability persists in bonds. Also unlike equities, momentum profits in corporate bonds do not come solely from periods around rating changes and are significant even in stable credit conditions.

Bond momentum is robust to liquidity and risk considerations. It remains strong and significant when adjusting returns for duration (as a proxy for interest rate risk), age and amount outstanding (as proxies for liquidity), credit risk, and systematic risk.

References

Acharya, Viral V., and Lasse H. Pedersen, 2005, Asset Pricing with Liquidity Risk, *Journal of Financial Economics* 77.

Alexander, Gordon J., Amy K. Edwards, and Michael G. Ferri, 2000, The Determinants of the Trading Volume of High Yield Corporate Bonds, *Journal of Financial Markets* 3, 177–204.

Ambrose, Brent W., Nianyun Cai, and Jean Helwege, 2009, Fallen Angels and Price Pressure, Working paper, Available at SSRN: http://ssrn.com/abstract=1405490.

Amihud, Yakov, and Haim Mendelson, 1986, Asset Pricing and the Bid-Ask Spread, *Journal of Financial Economics* 17, 223–249.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse H. Pedersen, 2009, Value and Momentum Everywhere, Working Paper.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2007, Momentum and Credit Rating, *Journal of Finance* 62, 2503–2520.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2009, Asset-Pricing Anomalies and Financial Distress, Working Paper.

Balduzzi, Pierluigi, Edwin J Elton, and T Clifton Green, 2001, Economic news and bond prices: Evidence from the U.S. Treasury market, *Journal of Financial and Quantitative Analysis* 36.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring Abnormal Bond Performance, *Review of Financial Studies* 22, 4219–4258.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, 2006, Market transparency, liquidity externalities, and institutional trading costs in corporate bonds, *Journal of Financial Economics* 82, 251–288.

Blake, LeBaron, 1999, Technical Trading Rule Profitability and Foreign Exchange Intervention, *Journal of International Economics* 49, 125–143.

Cai, Nianyun (Kelly), Jean Helwege, and Arthur Warga, 2007, Underpricing in the Corporate Bond Market, *Review of Financial Studies* 20, 2021–2046.

Campbell, John Y., and Glen B. Taksler, 2003, Equity Volatility and Corporate Bond Yields, *Journal of Finance* 58, 2321–2349.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57–82.

Chen, Long, David A. Lesmond, and Jason Wei, 2007, Corporate Yield Spreads and Bond Liquidity, *Journal of Finance* 62.

Edwards, Amy, Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate Bond Market Transaction Costs and Transparency, *Journal of Finance* 62, 1421–1451.

Fama, Eugene F., and Kenneth R. French, 1989, Business Conditions and Expected Returns on Stocks and Bonds, *Journal of Financial Economics* 25, 23–49.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3–56.

Gebhardt, William R., Soeren Hvidkjaer, and Bhaskaran Swaminathan, 2005a, The cross-section of expected corporate bond returns: Betas or characteristics?, *Journal of Financial Economics* 75, 85–114.

Gebhardt, William R., Soeren Hvidkjaer, and Bhaskaran Swaminathan, 2005b, Stock and Bond Market Interaction: Does Momentum Spill Over?, *Journal of Financial Economics* 75, 651–690.

Goldstein, Michael A., Edith S. Hotchkiss, and Erik Sirri, 2007, Transparency and Liquidity: A Controlled Experiment on Corporate Bonds, *Review of Financial Studies* 20, 235–273.

Gorton, Gary B., Fumio Hayashi, and Geert K. Rouwenhorst, 2008, The Fundamentals of Commodity Futures Returns, Yale ICF Working Paper No. 07-08.

Griffin, John M., Susan Ji, and J. Spencer Martin, 2003, Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole, *Journal of Finance* 58, 2515 – 2547.

Hand, John R. M., Robert W. Holthausen, and Richard W. Leftwich, 1992, The Effect of Bond Rating Agency Announcements on Bond and Stock Prices, *Journal of Finance* 47, 733–752.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Korajczyk, Robert A., and Ronnie Sadka, 2004, Are Momentum Profits Robust to Trading Costs?, *Journal of Finance* 59.

Krishnan, CNV, Peter H. Ritchken, and James B. Thomson, 2006, On Credit Spread Slopes and Predicting Bank Risk, *Journal of Money Credit and Banking* 38, 1545–1574.

Lee, Charles M.C., and Bhaskaran Swaminathan, 2000, Price Momentum and Trading Volume, *Journal of Finance* 55, 2017–2069.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642–685.

Rouwenhorst, K. Geert, 1998, International Momentum Strategies, *Journal of Finance* 53, 267 – 284.

Table I
Descriptive Statistics
(DataStream+Bloomberg+Trace+Lehman+FISD)

The sample includes 68,914 individual US corporate bonds by 11,944 private and public companies and covers the period from January 1973 to December 2008. The first column reports the number of bond-month observations. The last column reports the percentage of missing observations relative to the unfiltered sample of returns (first line of each dataset).

Variable	Observations	Mean	Median	St. Dev.	Minimum	Maximum	Missing (%)
Database: All bonds							
Return (% per month)	2,935,348	2.87	0.65	1,555.08	-100.00	2,648,850.20	–
Return (filtered)	2,932,335	0.79	0.65	4.63	-100.00	100.00	0.10
S&P Rating	2,726,279	6.93	6.00	4.51	1.00	22.00	7.12
Duration (years)	2,734,299	6.11	5.97	5.00	-0.37	5,233.53	6.85
Duration (filtered)	2,705,795	5.95	5.92	3.24	0.00	15.00	7.82
Age (months)	2,835,619	87.57	54.00	101.82	-268.00	1,321.00	3.40
Age (filtered)	2,804,101	82.33	53.00	81.45	0.00	360.00	4.47
Amount Outstanding ($mln)	2,835,267	285.98	98.50	1,501.58	0.00	100,126.87	3.41
Amount Outst. (filtered)	2,614,892	116.14	75.00	118.42	1.00	500.00	10.92
Database: Lehman Brothers							
Return (% per month)	1,713,815	0.89	0.70	6.90	-100.00	967.40	0.01
Return (filtered)	1,713,330	0.81	0.70	3.75	-100.00	100.00	0.04
S&P Rating	1,666,219	6.34	6.00	4.07	1.00	22.00	2.78
Duration (years)	1,713,940	6.27	6.38	3.41	-0.00	40.03	0.00
Duration (filtered)	1,695,908	6.11	6.34	3.03	0.00	15.00	1.05
Age (months)	1,713,941	112.53	72.00	120.03	-268.00	1,321.00	–
Age (filtered)	1,682,994	104.30	71.00	93.21	0.00	360.00	1.81
Amount Outstanding ($mln)	1,713,940	147.38	50.75	1,012.64	0.00	68,829.00	0.00
Amount Outst. (filtered)	1,669,423	87.83	50.00	87.73	1.00	500.00	2.60
Database: DataStream							
Return (% per month)	934,480	2.92	0.53	128.77	-99.83	47,752.65	–
Return (filtered)	932,571	0.76	0.53	5.21	-99.83	100.00	0.20
S&P Rating	803,176	7.97	6.00	5.16	1.00	22.00	14.05
Duration (years)	839,402	6.08	5.51	7.35	-0.37	5,233.53	10.17
Duration (filtered)	830,071	5.88	5.47	3.48	0.00	15.00	11.17
Age (months)	844,766	47.49	36.00	41.00	-19.00	298.00	9.60
Age (filtered)	844,603	47.50	36.00	40.99	0.00	298.00	9.62
Amount Outstanding ($mln)	845,076	315.17	197.00	558.57	0.00	10,000.00	9.57
Amount Outst. (filtered)	726,163	173.89	150.00	142.84	1.00	500.00	22.29
Database: Bloomberg							
Return (% per month)	150,217	0.65	0.67	2.08	-38.69	268.69	–
Return (filtered)	150,215	0.65	0.67	1.85	-38.69	98.17	0.00
S&P Rating	125,593	6.35	6.00	2.83	1.00	22.00	16.39
Duration (years)	77,912	6.02	5.71	3.10	0.00	18.01	48.13
Duration (filtered)	77,840	6.01	5.70	3.09	0.00	15.00	48.18
Age (months)	140,655	58.18	51.00	41.43	1.00	243.00	6.37
Age (filtered)	140,655	58.18	51.00	41.43	1.00	243.00	6.37
Amount Outstanding ($mln)	139,912	283.22	100.00	896.47	0.00	12,670.38	6.86
Amount Outst. (filtered)	127,963	119.79	100.00	128.27	1.00	500.00	14.81
Database: TRACE							
Return (% per month)	325,560	1.56	0.65	113.59	-98.43	60,101.39	–
Return (filtered)	325,006	0.79	0.65	6.60	-98.43	99.35	0.17
S&P Rating	317,854	8.28	6.00	4.44	1.00	22.00	2.37
Duration (years)	307,917	5.21	4.49	3.70	0.00	30.00	5.42
Duration (filtered)	306,586	5.16	4.47	3.62	0.00	15.00	5.83
Age (months)	324,356	52.71	42.00	43.87	-19.00	945.00	0.37
Age (filtered)	324,116	52.45	42.00	41.91	0.00	360.00	0.44
Amount Outstanding ($mln)	324,358	397.72	250.00	511.73	0.00	6,500.00	0.37
Amount Outst. (filtered)	251,046	200.37	200.00	163.17	1.00	500.00	22.89
Database: FISD							
Return (% per month)	59,567	180.48	0.42	32,650.74	-99.99	7,946,548.79	–
Return (filtered)	59,469	0.45	0.41	5.92	-99.99	97.91	0.16
S&P Rating	54,937	6.09	6.00	4.23	1.00	22.00	7.77
Duration (years)	32,572	5.86	5.72	3.06	0.00	27.79	45.32
Duration (filtered)	32,527	5.84	5.72	3.02	0.00	14.90	45.39
Age (months)	59,489	32.28	22.00	35.36	-45.00	430.00	0.13
Age (filtered)	59,311	32.31	22.00	34.98	0.00	360.00	0.43
Amount Outstanding ($mln)	59,567	4,871.00	1,000.00	7,736.90	0.00	100,126.87	–
Amount Outst. (filtered)	19,565	316.23	300.00	141.47	1.01	500.00	67.15

Table II
Bond Momentum

Each month, t, bonds are ranked into decile portfolios P1 through P10 based on their cumulative returns over months $t-6$ through $t-1$ (formation period). The momentum strategy is long the winner portfolio, P10, and short the loser portfolio, P1. These positions are held over a six-months holding period ($t+1$ through $t+6$, i.e. after one month lag). Portfolio returns are equally weighted across their constituent bonds. The overall strategy portfolio return for month t is the equally-weighted average month-t return of strategies implemented in the prior month and all strategies formed up to six months ago. The table presents the average raw monthly profits during the holding period of the momentum portfolios, P1 to P10, as well as the momentum strategy returns (P10-P1). t-statistics are in parentheses (bold if indicating 5% level of significance). The sample period is from January 1973 to December 2008.

	Momentum portfolios (P1=losers, P10 = winners)										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10 - P1
All Databases	0.81	0.65	0.69	0.72	0.74	0.75	0.76	0.78	0.79	1.42	0.61
	(**5.25**)	(**5.44**)	(**6.21**)	(**6.68**)	(**7.11**)	(**7.40**)	(**7.79**)	(**8.24**)	(**8.64**)	(**12.93**)	(**4.88**)
Trade-based Databases	0.36	0.49	0.72	0.70	0.72	0.75	0.69	0.68	0.69	1.21	0.80
	(1.09)	(**2.65**)	(**3.91**)	(**4.23**)	(**5.91**)	(**5.38**)	(**6.46**)	(**5.49**)	(**4.24**)	(**5.90**)	(**2.94**)
Quote-Based Databases	0.95	0.72	0.71	0.73	0.74	0.75	0.76	0.77	0.80	1.45	0.49
	(**7.65**)	(**6.74**)	(**6.78**)	(**6.91**)	(**7.06**)	(**7.23**)	(**7.55**)	(**8.07**)	(**8.78**)	(**13.51**)	(**4.57**)
Rated Bonds	0.79	0.65	0.69	0.72	0.74	0.75	0.76	0.77	0.79	1.40	0.60
	(**5.14**)	(**5.47**)	(**6.21**)	(**6.64**)	(**7.07**)	(**7.34**)	(**7.71**)	(**8.14**)	(**8.52**)	(**12.70**)	(**4.86**)
Unrated Bonds	1.01	0.78	0.76	0.78	0.75	0.85	0.86	0.85	0.86	1.61	0.60
	(**3.71**)	(**3.80**)	(**4.41**)	(**5.05**)	(**6.03**)	(**7.44**)	(**7.77**)	(**7.23**)	(**6.81**)	(**11.01**)	(**2.27**)

Table III

Alphas of Bond Momentum Portfolios

Bond momentum portfolio returns are computed as in Table II. We then run time-series regressions of these portfolio excess returns on systematic factors. We estimate coefficients using GMM and Newey-West adjusted standard errors. The table shows the estimated alphas (with their associated t-statistics in parentheses) from time-series regressions based on the following model specifications:

$$r_{pt} = \alpha_p + \boldsymbol{\beta}_p' \boldsymbol{F}_t + e_{pt}$$

where $r_{pt} = R_{pt} - R_{rf,t}$ is the momentum portfolio excess return over the risk free rate or the momentum strategy return difference $r_{pt} = R_{P10,t} - R_{P1,t}$ and $\boldsymbol{F}_t$ is a vector of factors. For each model $\boldsymbol{F}$ are represented by the following models:

1. $\Delta TERM, \Delta DEF$
2. $mTERM, mDEF$
3. Mkt, SMB, HML
4. Mkt, SMB, HML, MOM
5. $mTERM, mDEF, Mkt, SMB, HM$
6. $mTERM, mDEF, Mkt, SMB, HML, MOM$

where Mkt is the excess return on the market, SMB, HML, and MOM are the returns on the size and book-to-market factors of Fama and French (1993), and momentum factor of Carhart (1997), respectively. $\Delta TERM_t = (TERM_t - TERM_{t-1})$ and $\Delta DEF_t = (DEF_t - DEF_{t-1})$, $mTERM_t = \Delta TERM_t/(1 + TERM_{t-1})$ and $mDEF_t = \Delta DEF_t/(1 + DEF_{t-1})$, respectively. The sample period is from January 1973 to December 2008.

	Momentum portfolios (P1=losers, P10 = winners)										
Model	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10 - P1
					All Bonds						
1.	0.32	0.14	0.18	0.21	0.23	0.24	0.25	0.27	0.30	0.95	0.80
	(1.90)	(1.19)	(1.62)	(1.89)	(**2.08**)	(**2.22**)	(**2.41**)	(**2.64**)	(**2.91**)	(**5.57**)	(**5.46**)
2.	0.32	0.14	0.18	0.21	0.22	0.24	0.25	0.27	0.30	0.95	0.80
	(1.90)	(1.19)	(1.61)	(1.88)	(**2.07**)	(**2.21**)	(**2.40**)	(**2.63**)	(**2.90**)	(**5.57**)	(**5.46**)
3.	0.07	0.00	0.08	0.12	0.14	0.16	0.17	0.18	0.18	0.75	0.75
	(0.39)	(0.02)	(0.65)	(1.08)	(1.28)	(1.41)	(1.58)	(1.72)	(1.80)	(**4.82**)	(**5.17**)
4.	0.18	0.05	0.10	0.13	0.14	0.14	0.15	0.15	0.15	0.75	0.70
	(1.07)	(0.36)	(0.80)	(1.13)	(1.22)	(1.28)	(1.38)	(1.46)	(1.52)	(**4.60**)	(**4.56**)
5.	0.05	-0.02	0.04	0.08	0.10	0.12	0.13	0.14	0.16	0.74	0.76
	(0.31)	(-0.17)	(0.36)	(0.74)	(0.95)	(1.10)	(1.28)	(1.45)	(1.57)	(**4.68**)	(**5.24**)
6.	0.16	0.01	0.05	0.08	0.08	0.09	0.10	0.11	0.12	0.73	0.73
	(0.94)	(0.07)	(0.42)	(0.69)	(0.78)	(0.85)	(0.98)	(1.10)	(1.25)	(**4.46**)	(**4.74**)
					Rated Bonds						
1.	0.30	0.15	0.18	0.21	0.22	0.24	0.25	0.27	0.29	0.92	0.77
	(1.81)	(1.23)	(1.63)	(1.87)	(**2.05**)	(**2.19**)	(**2.37**)	(**2.59**)	(**2.86**)	(**5.40**)	(**5.29**)
2.	0.30	0.15	0.18	0.21	0.22	0.24	0.25	0.27	0.29	0.92	0.77
	(1.80)	(1.23)	(1.63)	(1.86)	(**2.05**)	(**2.19**)	(**2.36**)	(**2.58**)	(**2.86**)	(**5.40**)	(**5.30**)
3.	0.05	0.01	0.08	0.12	0.14	0.15	0.17	0.17	0.18	0.73	0.72
	(0.29)	(0.07)	(0.67)	(1.07)	(1.27)	(1.39)	(1.54)	(1.67)	(1.76)	(**4.66**)	(**5.01**)
4.	0.16	0.05	0.10	0.13	0.14	0.14	0.15	0.15	0.15	0.73	0.68
	(0.93)	(0.41)	(0.82)	(1.10)	(1.21)	(1.25)	(1.35)	(1.42)	(1.48)	(**4.46**)	(**4.42**)
5.	0.04	-0.02	0.04	0.08	0.10	0.11	0.13	0.14	0.15	0.72	0.73
	(0.21)	(-0.13)	(0.38)	(0.73)	(0.94)	(1.07)	(1.24)	(1.40)	(1.52)	(**4.52**)	(**5.09**)
6.	0.14	0.01	0.05	0.07	0.08	0.09	0.10	0.10	0.12	0.71	0.70
	(0.79)	(0.12)	(0.43)	(0.66)	(0.76)	(0.83)	(0.94)	(1.05)	(1.20)	(**4.32**)	(**4.61**)
					Unrated Bonds						
1.	0.52	0.29	0.26	0.28	0.27	0.36	0.37	0.37	0.38	1.14	0.85
	(**2.07**)	(1.59)	(1.76)	(**2.00**)	(**2.12**)	(**2.98**)	(**3.09**)	(**2.81**)	(**2.85**)	(**6.10**)	(**3.83**)
2.	0.52	0.29	0.26	0.28	0.26	0.36	0.37	0.37	0.38	1.14	0.85
	(**2.06**)	(1.58)	(1.76)	(**2.00**)	(**2.12**)	(**2.98**)	(**3.09**)	(**2.81**)	(**2.85**)	(**6.10**)	(**3.83**)
3.	0.31	0.14	0.14	0.24	0.13	0.26	0.25	0.22	0.20	0.96	0.82
	(1.21)	(0.68)	(0.87)	(1.72)	(0.99)	(**2.32**)	(**2.33**)	(1.92)	(1.54)	(**5.39**)	(**3.54**)
4.	0.49	0.21	0.19	0.25	0.13	0.23	0.20	0.18	0.15	0.95	0.75
	(1.69)	(0.96)	(1.09)	(1.65)	(0.99)	(**1.98**)	(1.77)	(1.51)	(1.16)	(**5.13**)	(**2.94**)
5.	0.30	0.13	0.13	0.21	0.12	0.25	0.23	0.20	0.20	0.96	0.83
	(1.18)	(0.65)	(0.76)	(1.44)	(0.93)	(**2.16**)	(**2.19**)	(1.77)	(1.57)	(**5.33**)	(**3.50**)
6.	0.48	0.19	0.17	0.22	0.12	0.22	0.18	0.16	0.15	0.95	0.76
	(1.62)	(0.89)	(0.96)	(1.35)	(0.90)	(1.81)	(1.59)	(1.34)	(1.16)	(**5.02**)	(**2.97**)

Table IV
Composition of Momentum Portfolios

Each month t, all bonds (rated and unrated) with returns for months $t-6$ through $t-1$ (formation period) are ranked into decile portfolios according to their return during the formation period. The first three rows show for each decile portfolio the percentage of bonds that are rated investment-grade (IG), rated non-investment grade (NIG), or unrated. The next three rows show the equally-weighted average return of the three groups in each portfolio. IG represents S&P rating of BBB- or better and NIG represents S&P rating of BB+ or worse. The sample period is from January 1973 to December 2008.

	Momentum portfolios (P1=losers, P10 = winners)										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10 - P1
Distribution of bond-month observations by rating categories											
IG	66.75%	85.84%	87.19%	87.87%	88.00%	87.27%	85.66%	81.88%	75.87%	53.47%	
NIG	25.12	6.77	6.03	6.27	6.47	7.22	8.61	12.37	17.54	37.51	
Unrated	8.13	7.39	6.78	5.85	5.54	5.50	5.73	5.75	6.60	9.02	
Mean portfolio return (in percent) by rating category											
IG	0.76	0.69	0.70	0.72	0.73	0.73	0.74	0.75	0.76	0.85	0.09
NIG	1.23	0.82	0.76	0.71	0.76	0.80	0.87	0.86	1.12	3.27	2.04
Unrated	1.05	0.77	0.75	0.77	0.75	0.83	0.86	0.86	0.87	1.61	0.56
Distribution of bond-month observations by rating											
AAA	12.06%	15.02%	13.63%	12.95%	11.37%	9.50%	8.40%	7.83%	7.38%	6.49%	
AA+	1.55	2.08	1.90	1.73	1.67	1.63	1.67	1.55	1.51	1.08	
AA	6.43	10.09	10.53	10.42	10.03	9.93	9.61	8.56	7.50	4.24	
AA-	4.07	6.22	6.41	6.20	6.37	6.49	6.28	5.66	4.82	2.85	
A+	5.90	9.40	9.84	9.95	10.14	10.48	9.92	8.98	7.30	3.87	
A	11.19	16.30	17.54	18.20	18.83	19.34	18.89	17.53	14.96	9.45	
A-	4.60	6.65	7.28	7.55	7.76	7.72	7.66	7.49	6.60	3.94	
BBB+	5.29	6.44	6.83	7.32	7.59	7.46	7.46	7.45	7.05	4.60	
BBB	9.33	8.61	8.44	8.52	9.01	9.15	9.59	9.79	10.51	8.34	
BBB-	3.97	3.78	3.60	3.79	3.95	4.17	4.53	5.01	5.49	4.74	
BB+	2.53	1.32	1.25	1.33	1.35	1.48	1.74	2.15	2.87	4.05	
BB	3.76	1.32	1.15	1.15	1.05	1.18	1.46	1.90	2.52	3.98	
BB-	1.80	0.75	0.82	0.92	0.97	1.10	1.33	1.89	2.26	2.67	
B+	4.00	1.39	1.25	1.30	1.35	1.51	1.75	2.50	3.42	5.82	
B	3.11	1.18	1.13	1.16	1.22	1.34	1.57	2.32	3.23	5.26	
B-	3.14	0.88	0.77	0.81	0.89	1.03	1.24	1.89	2.75	4.64	
CCC+	1.42	0.36	0.27	0.29	0.30	0.36	0.43	0.65	1.13	2.27	
CCC	1.26	0.27	0.19	0.17	0.19	0.21	0.24	0.40	0.66	1.81	
CCC-	0.67	0.08	0.07	0.06	0.07	0.07	0.10	0.15	0.32	1.02	
CC	0.51	0.05	0.03	0.03	0.04	0.04	0.05	0.06	0.13	0.70	
C	1.38	0.11	0.07	0.07	0.07	0.08	0.08	0.08	0.17	1.51	
D	3.90	0.30	0.21	0.23	0.22	0.21	0.27	0.41	0.82	7.65	
Unrated	8.13	7.39	6.78	5.85	5.54	5.50	5.73	5.75	6.60	9.02	

Table V
Bond Momentum by Rating Groups

Each month, t, bonds from all databases are first divided into quintiles. Within each quintile, we repeat the momentum analysis described in Table II. The average numeric S&P rating of each quintile is presented in the second column. The numerical ratings increase with credit risk: i.e. 1=AAA, 2=AA+, 3=AA, ..., 21=C, 22=D. Ratings 11=BB+ or higher (worse) are considered non-investment grade.

Rating	Average	Momentum portfolios (P1=losers, P10 = winners)										
Sample	Rating	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10 - P1
Q1	1.98	0.74	0.71	0.72	0.71	0.72	0.73	0.73	0.74	0.77	0.84	0.10
		(**5.80**)	(**6.15**)	(**6.37**)	(**6.27**)	(**6.34**)	(**6.48**)	(**6.66**)	(**7.18**)	(**7.80**)	(**7.17**)	(0.91)
Q2	4.32	0.68	0.69	0.70	0.73	0.74	0.74	0.75	0.76	0.76	0.85	0.17
		(**5.09**)	(**5.83**)	(**6.05**)	(**6.57**)	(**6.77**)	(**6.87**)	(**7.31**)	(**7.76**)	(**8.09**)	(**8.35**)	(1.57)
Q3	6.46	0.72	0.69	0.72	0.73	0.75	0.75	0.75	0.76	0.76	0.80	0.08
		(**5.52**)	(**6.22**)	(**6.56**)	(**6.92**)	(**7.20**)	(**7.27**)	(**7.42**)	(**7.79**)	(**8.13**)	(**8.76**)	(0.79)
Q4	8.60	0.74	0.66	0.71	0.74	0.78	0.78	0.80	0.79	0.81	0.93	0.18
		(**4.88**)	(**4.83**)	(**5.91**)	(**6.64**)	(**7.04**)	(**7.34**)	(**7.84**)	(**7.90**)	(**8.44**)	(**9.41**)	(1.66)
Q5	13.61	1.25	0.77	0.69	0.71	0.72	0.77	0.82	0.88	1.04	3.34	2.09
		(**5.92**)	(**4.13**)	(**4.47**)	(**4.90**)	(**5.48**)	(**6.66**)	(**7.79**)	(**8.69**)	(**9.87**)	(**11.56**)	(**7.87**)

Table VI
Bond Momentum in Improving Rating Subsamples

We compute momentum as in Table II sequentially excluding the worst rated bonds. The first column characterizes the subsample. The second column reports the momentum profits (returns of P10-P1) for the corresponding subsample. The next column provides the percentage of rated firms included in the subsample. The last column reports the percentage of amount outstanding of rated bonds included in the subsample. All numbers are in percentages.

Sample	Momentum Profits P10-P1	% of Bonds removed	% of Amount Outstanding removed
AAA−D	0.60 (**4.86**)		
AAA−C	0.22 (1.90)	1.51	2.39
AAA−CC	0.18 (1.57)	1.89	2.80
AAA−CCC	0.16 (1.47)	2.06	2.98
AAA−B-	0.16 (1.40)	2.34	3.36
AAA−B	0.12 (1.20)	2.92	4.07
AAA−B+	0.12 (1.14)	3.71	5.20
AAA−BB-	0.11 (1.08)	5.64	7.97
AAA−BB	0.10 (1.11)	7.94	11.11
AAA−BB+	0.10 (1.12)	10.53	14.16
AAA−BBB-	0.12 (1.30)	12.08	16.41
AAA−BBB	0.11 (1.25)	14.16	18.40
AAA−BBB+	0.11 (1.16)	16.30	21.17
AAA−A-	0.10 (1.10)	20.91	26.97
AAA−A	0.12 (1.22)	30.69	36.48
AAA−A+	0.14 (1.46)	37.93	44.04

Table VII

Bond Momentum based on Characteristic-Adjusted Returns

Each month, characteristic-adjusted returns are computed by subtracting from each monthly bond return the average monthly return of the characteristic decile to which the bond belongs. Bond momentum is then computed as in Table V using characteristic-adjusted rather than raw returns. Panel A presents momentum profits based on duration-adjusted returns; Panel B reports momentum profits adjusted for credit risk; and Panels C and D presents momentum profits for liquidity-adjusted returns, where liquidity is proxied by the age or amount outstanding of the bond. The sample period is from January 1973 to December 2008.

	Momentum portfolios (P1=losers, P10 = winners)										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10 - P1
	Panel A: Duration-Adjusted Returns										
Q1	-0.21	-0.17	-0.07	-0.05	-0.03	-0.04	-0.02	-0.00	-0.00	0.07	0.28
	(**-3.78**)	(**-4.94**)	(**-2.47**)	(-1.54)	(-0.99)	(-1.01)	(-0.57)	(-0.08)	(-0.11)	(1.52)	(**4.36**)
Q2	-0.21	-0.18	-0.07	-0.04	-0.03	-0.02	-0.01	0.02	0.03	0.06	0.27
	(**-3.43**)	(**-4.15**)	(**-2.28**)	(-1.53)	(-1.16)	(-0.70)	(-0.21)	(0.47)	(0.69)	(1.37)	(**3.57**)
Q3	-0.17	-0.11	-0.06	-0.04	-0.02	-0.02	-0.01	0.01	0.02	0.02	0.19
	(**-2.47**)	(**-3.95**)	(**-2.69**)	(-1.58)	(-0.77)	(-0.68)	(-0.27)	(0.37)	(0.50)	(0.48)	(**2.28**)
Q4	-0.13	-0.11	-0.08	-0.03	0.02	0.03	0.04	0.03	0.05	0.17	0.30
	(-1.51)	(-1.85)	(-1.91)	(-1.37)	(0.55)	(0.98)	(1.50)	(1.37)	(1.79)	(**3.87**)	(**3.12**)
Q5	0.46	-0.06	0.02	0.01	-0.01	0.03	0.02	0.08	0.24	2.66	2.20
	(**2.73**)	(-0.44)	(0.24)	(0.12)	(-0.15)	(0.60)	(0.53)	(1.49)	(**4.10**)	(**9.58**)	(**7.79**)
	Panel B: Credit-Risk-Adjusted Returns										
Q1	-0.00	-0.02	-0.02	-0.02	-0.01	-0.02	-0.00	0.01	0.02	0.15	0.15
	(-0.05)	(-0.56)	(-0.66)	(-0.78)	(-0.41)	(-0.85)	(-0.14)	(0.31)	(0.44)	(**2.40**)	(1.49)
Q2	-0.06	-0.06	-0.05	-0.01	-0.01	-0.00	0.01	0.03	0.03	0.10	0.17
	(-0.91)	(-1.42)	(-1.67)	(-0.56)	(-0.49)	(-0.16)	(0.46)	(0.80)	(0.63)	(1.85)	(1.56)
Q3	-0.02	-0.05	-0.02	-0.01	0.02	0.01	0.02	0.02	0.03	0.06	0.09
	(-0.36)	(-1.39)	(-0.56)	(-0.40)	(1.02)	(0.42)	(0.88)	(0.75)	(0.67)	(1.26)	(0.85)
Q4	-0.02	-0.09	-0.06	-0.03	-0.00	0.03	0.03	0.02	0.05	0.17	0.19
	(-0.33)	(-1.80)	(-1.75)	(-1.16)	(-0.18)	(1.13)	(1.32)	(0.72)	(1.03)	(**3.09**)	(1.81)
Q5	0.06	-0.32	-0.33	-0.24	-0.15	-0.03	0.03	0.03	0.07	2.27	2.21
	(0.51)	(**-3.82**)	(**-5.25**)	(**-4.40**)	(**-4.11**)	(-1.12)	(0.71)	(0.72)	(1.32)	(**9.91**)	(**8.35**)
	Panel C: Age-Adjusted Returns										
Q1	-0.12	-0.10	-0.08	-0.08	-0.07	-0.06	-0.06	-0.03	-0.00	0.10	0.22
	(-1.68)	(**-2.01**)	(-1.77)	(-1.83)	(-1.66)	(-1.47)	(-1.39)	(-0.79)	(-0.08)	(1.11)	(1.88)
Q2	-0.17	-0.15	-0.12	-0.08	-0.06	-0.06	-0.06	-0.04	-0.02	0.08	0.24
	(**-2.16**)	(**-3.29**)	(**-3.18**)	(**-2.72**)	(**-2.17**)	(**-2.00**)	(-1.85)	(-1.29)	(-0.40)	(1.35)	(**2.35**)
Q3	-0.14	-0.16	-0.11	-0.09	-0.07	-0.06	-0.06	-0.05	-0.04	0.01	0.15
	(**-2.00**)	(**-4.45**)	(**-3.55**)	(**-3.32**)	(**-2.49**)	(**-2.02**)	(**-2.04**)	(-1.36)	(-0.98)	(0.26)	(1.58)
Q4	-0.10	-0.18	-0.12	-0.08	-0.03	-0.02	-0.02	-0.01	0.01	0.13	0.24
	(-1.23)	(**-2.93**)	(**-2.88**)	(**-2.51**)	(-1.18)	(-0.46)	(-0.89)	(-0.35)	(0.18)	(**2.54**)	(**2.29**)
Q5	0.38	-0.05	-0.09	-0.07	-0.07	-0.04	0.03	0.09	0.21	2.52	2.14
	(**2.15**)	(-0.34)	(-0.86)	(-0.82)	(-0.89)	(-0.77)	(0.56)	(1.67)	(**3.11**)	(**9.26**)	(**8.02**)
	Panel D: Amount-Outstanding-Adjusted Returns										
Q1	-0.08	-0.08	-0.07	-0.06	-0.05	-0.04	-0.03	-0.02	0.00	0.12	0.21
	(-1.31)	(-1.68)	(-1.55)	(-1.51)	(-1.12)	(-1.04)	(-0.85)	(-0.38)	(0.05)	(1.26)	(1.72)
Q2	-0.11	-0.09	-0.10	-0.06	-0.05	-0.04	-0.04	-0.02	-0.01	0.09	0.20
	(-1.32)	(-1.89)	(**-2.58**)	(-1.82)	(-1.73)	(-1.46)	(-1.26)	(-0.43)	(-0.29)	(1.36)	(1.78)
Q3	-0.09	-0.13	-0.10	-0.08	-0.05	-0.05	-0.03	-0.04	-0.02	0.02	0.12
	(-1.90)	(**-3.63**)	(**-3.32**)	(**-3.36**)	(**-1.98**)	(**-2.06**)	(-1.20)	(-1.15)	(-0.43)	(0.44)	(1.39)
Q4	-0.07	-0.18	-0.16	-0.10	-0.04	-0.01	-0.01	0.01	0.04	0.14	0.21
	(-0.84)	(**-2.32**)	(**-2.57**)	(**-2.39**)	(-0.87)	(-0.56)	(-0.39)	(0.27)	(1.05)	(**2.17**)	(1.94)
Q5	0.43	-0.03	-0.11	-0.08	-0.09	-0.05	-0.00	0.08	0.25	2.74	2.32
	(**2.36**)	(-0.21)	(-1.14)	(-0.87)	(-1.18)	(-0.89)	(-0.06)	(1.58)	(**3.49**)	(**9.30**)	(**8.07**)

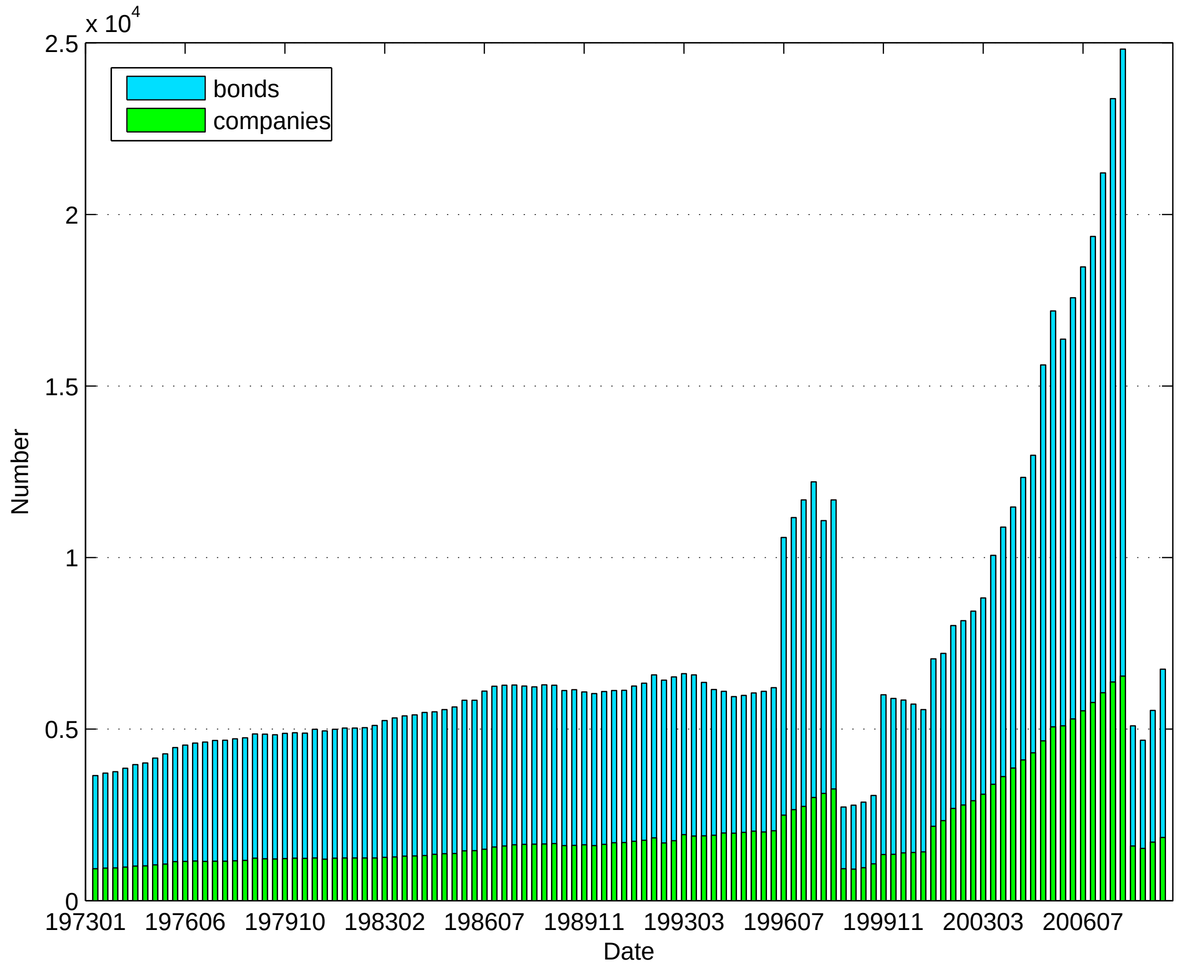

Figure I. Number of bonds and companies over time. The figure presents numbers of bonds and their issuing companies per month from January 1973 to to December 2008 for the overall dataset from Lehman, Datastream, Bloomberg, TRACE, and FISD.