Long-Term Reversals in the Corporate Bond Market*

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Abstract

Long-term reversals in corporate bond returns are economically and statistically significant in a comprehensive sample spanning the period 1977 to 2017. Such reversals are stronger in the high credit risk sector. Bond long-term reversal is not a manifestation of the equity counterpart and is mainly driven by long-term losers. A return-based long-term reversal factor carries a sizable premium and provides strong explanatory power for returns of industry/size/rating/maturity-sorted portfolios of corporate bonds. Our evidence accords with the hypothesis that past returns capture investors' ex-ante risk assessment, so that losing bonds command higher expected returns.

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1 Introduction

There is evidence that contrarian strategies are profitable over long horizons. For example, DeBondt and Thaler (1985) show that stocks with subpar performance over the previous three to five years produce higher returns over the next three- to five-year holding periods than stocks with superior performance over the same period. Richards (1997) and Balvers, Wu, and Gilliland (2000) show that these strategies also yield abnormally high returns across international stock market indices. Such phenomena represent a potential violation of weak-form market efficiency (Fama (1970)), so that advancing the understanding of these reversal-based strategies is important. While previous studies of the strategies mainly focus on equities, debt financing forms a significant portion of firms' capital structures,[1] underscoring the need to study these long-term reversals in corporate bond markets. Whether return predictability patterns in equities extend to bonds is an open question, however, given the markedly differing investing clienteles across equities and bonds.[2] Motivated by these observations, we empirically analyze the profitability of long-term contrarian strategies in the cross-section of corporate bond returns. We first assemble a comprehensive dataset of corporate bonds using both transaction and dealer-quote data from January 1977 to December 2017, yielding more than 1.7 million bond-month observations. Then, we investigate whether returns formed over long horizons can predict cross-sectional differences in future bond returns. We find strong evidence of long-term reversal in corporate bonds even as such reversals attenuate for stocks during our sample period. We also provide explanations for the profitability of long-term contrarian strategies in the corporate bond market.

A vast literature considers explanations for reversals in the cross-section of equities. For example, in rationalizing long-term reversals DeBondt and Thaler (1985, 1987) suggest that investors overweight recent information and drive security prices away from fundamental val-

[1] Graham, Leary, and Roberts (2015) indicate that the average debt-to-assets ratio for public companies was as high as 35% in 2010.

[2] The primary holders of corporate bonds are institutional investors, whereas individual investors play a significant role in the equity market. According to flow of fund data released by the Federal Reserve Board from 1986 to 2017, approximately 78% of corporate bonds were held by institutional investors, including insurance companies, mutual funds, and pension funds. The participation rate of individual investors in the corporate bond market is very low. Retail investors (household sector) play a significant role in the equity market; households (43%), mutual funds (33%), and pension funds (15%).

ues. As investors and analysts extrapolate past information too far into the future, some assets that experience recent bad (good) news become undervalued (overvalued), and subsequently reverse. Loughran and Ritter (1996) also confirm long-term reversals in stock returns. Evidence of short-term (monthly) reversals (Jegadeesh (1990)) is most often attributed to liquidity effects. Thus, Nagel (2012) shows that the returns of short-term reversal strategies can be used as proxies for the returns associated with liquidity provision, and Avramov, Chordia, and Goyal (2006) document a strong relation between short-term return reversals and stock illiquidity.[3] While short-horizon reversals do appear to prevail in corporate bonds (Chordia et. al. (2017); Bai, Bali, and Wen (2017); Khang and King (2004)) no preceding study, to the best of our knowledge, addresses the profitability of *long-horizon* (DeBondt and Thaler (1985)) contrarian strategies in corporate bonds using an extensive sample.[4]

In the spirit of DeBondt and Thaler (1985), we first perform portfolio-level analysis and sort bonds based on their past 36-month cumulative returns (LTR) from month $t-48$ to $t-13$, skipping the 12-month momentum (i.e., from month $t-12$ to $t-2$) and the short-term reversal months (i.e., month $t-1$). We find that bonds in the lowest LTR quintile (long-term losers) generate 5.6% more raw returns per annum than bonds in the highest LTR quintile (long-term winners). We also find that the long-term reversal in bond returns is not a manifestation of the long-term reversal in equity returns. After we control for 11 well-known stock and bond market factors including the stock long-term reversal factor, the risk-adjusted return difference between the lowest and highest LTR quintiles is economically large, 5.2% per annum, and highly significant. We find that the cross-sectional predictability of LTR holds for one-month-ahead returns, as well as for 12-, 24-, and 36-month ahead returns.[5]

[3]Roll (1984) proposes a model in which the bid-ask spread generates negative serial correlation in time-series of stock returns. Admati and Pfleiderer (1989), Keim (1989), Lo and MacKinlay (1990), Hasbrouck (1991), Mech (1993), and Conrad, Gultekin, and Kaul (1997) show that microstructure issues such as the bid-ask bounce and transaction costs can generate autocorrelation in security returns. Boudoukh, Richardson, and Whitelaw (1994) demonstrate that a large portion of documented serial correlation is attributable to institutional factors such as trading and non-trading periods, market frictions such as the bid-ask spread, or other microstructure effects.

[4]Previous work also finds that corporate bond returns exhibit the medium-term (six to 12 month) momentum effect of Jegadeesh and Titman (1993) (see, for example, Jostova, Nikolova, Philipov, and Stahel (2013); Gebhardt, Hvidkjaer, and Swaminathan (2005); Pospisil and Zhang (2010); and Ho and Wang (2018)). We address the relation between momentum and long-term contrarian strategies in the corporate bond market within Section 5.

[5]Ellul, Jotikasthira, and Lundblad (2011) show that insurance companies that are relatively more con-

We also test the significance of LTR using bond-level cross-sectional regressions. The Fama-MacBeth (1973) regression results echo the portfolio-level analysis, indicating that the LTR of corporate bonds predicts their future returns. After simultaneously accounting for bond momentum and short-term return reversals and controlling for a number of bond characteristics in cross-sectional regressions, the predictive power of LTR remains economically and statistically significant. We rely on the value-weighted trivariate portfolios using credit rating as the first sorting variable, time-to-maturity as the second sorting variable, and the LTR as the third sorting variable to construct a long-term reversal factor (LTR^{Bond}). We find that the factor generates significantly positive return premia, with particularly higher magnitudes during economic downturns and high economic uncertainty periods. Further, long-established stock and bond market factors do not materially explain variations in LTR^{Bond}; the adjusted-R^2 values from the corresponding time-series regressions are modest.

Given the evidence that corporate bond returns depend on past returns, an important issue is the collective role of past returns (and, in particular, long-term reversals) in explaining the cross-section of bond returns. Accordingly, we consider the performance of return-based factors, including LTR^{Bond}, in explaining the cross-section of corporate bond returns. We find that a parsimonious set of bond market factors based on long- and short-term reversals, as well as momentum, outperforms a number of standard factor models in predicting the returns of industry- and size/rating/maturity-sorted portfolios. We also analyze the performance of return-based factors versus the recently proposed ones of Bai, Bali, and Wen (2017), which capture downside risk, credit risk, and liquidity risk. We show that our long-term reversal factor adds substantial explanatory power to their factors for explaining the returns of the industry- and size/rating/maturity-sorted portfolios. Overall, the joint explanatory power of return-based corporate bond factors is comparable to that of the Bai, Bali, and Wen (2017) factors, with LTR^{Bond} playing an important role.[6]

We next explore rationales for long-term reversals in corporate bonds. Reversal of long-

strained by regulation are more likely to sell downgraded bonds, which exhibit price declines and subsequent *short-term* reversals. In contrast, our study uncovers *long-term* reversal using data for the period 1977–2017 (Ellul et al. (2011) focus on transaction data of insurance companies over the period 2001–2005).

[6]The explanatory power of LTR^{Bond} is pervasive across bonds with different sizes, credit risk, and maturity. In Section 4.2, we show that LTR^{Bond} explains not only the abnormal returns of low credit quality bonds, but also those of bonds with high credit quality and large issue sizes.

term return performance could mean correction of overreaction, but, alternatively, also could imply increases in required returns after a decline in prices (due to an increase in risk). We find that LTR is mainly driven by long-term losers, and these bonds experience increases in credit risk during the portfolio formation period. These results hold when credit risk is measured both by ratings as well as financial statement metrics, indicating that they are robust to the subjectivity inherent in credit ratings.[7] Notably, although LTR itself is driven by a subset of bonds, its role in pricing the cross-section of bonds is pervasive. These findings are consistent with the risk hypothesis. Turning to the potential alternative explanation, while models of overreaction in equities (Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999)) suggest that momentum should be followed by reversals,[8] in the corporate bond market, momentum portfolios do not experience long-run reversals, unlike in equities (Jegadeesh and Titman (2001)). In addition, the overreaction hypothesis suggests either a symmetric reversal for winners and losers, or greater profits for the winners under short-selling constraints (since arbitrageurs would short the winners), but long-term reversals are driven by losers. Finally, while we would expect non-institutions to overreact more than institutions, bonds that are held proportionally less by institutions do not show stronger evidence of long-term reversals. On balance, the evidence supports the idea that long-term reversal in losing bonds captures an increase in required returns owing to the increased risk of holding losing bonds, and past returns measure investors' ex-ante assessment of bond risk that extends beyond available metrics for credit quality.

This paper proceeds as follows. Section 2 describes the data and variables used in our empirical analyses. Section 3 examines the cross-sectional relation between long-term reversal and the future returns of corporate bonds. Section 4 introduces a new long-term reversal factor for corporate bonds, and examines the explanatory power of return-based bond factors for alternative test portfolios. Section 5 investigates the source of long-term reversals in the corporate bond market. Section 6 concludes.

[7]The reversals prevail in both January and non-January months. Thus, the role of tax loss selling, as proposed by George and Hwang (2007) for equities, is mitigated in bonds.

[8]Greenwood and Shleifer (2014) suggest that trends in returns convey information on future returns if investors extrapolate expectations from the past (thus causing momentum). If rational agents are risk averse, they should demand a premium for absorbing the trades of the extrapolators. This premium should cause long-term reversals in a manner similar to Hong and Stein (1999).

2 Data and Variable Definitions

2.1 Corporate Bond Data

The corporate bond dataset is compiled from six major sources: the Lehman Brothers fixed income database (Lehman), Datastream, the National Association of Insurance Commissioners database (NAIC), Bloomberg, the enhanced version of the Trade Reporting and Compliance Engine (TRACE), and the Mergent fixed income securities database (FISD). The Lehman data cover the sample period from January 1973 to March 1998, and Datastream reports corporate bond information from January 1990 to June 2014. Both Lehman and Datastream provide prices based on dealer quotes. NAIC reports the transaction information by insurance companies for the period from January 1994 to July 2013. Bloomberg provides daily bond prices from January 1997 to December 2004, and the TRACE records the transactions of the entire corporate bond market from July 2002 to December 2017. The two datasets, NAIC and TRACE, provide prices based on real transactions.

We highlight the following filtering criteria in order to choose qualified bonds. Specifically, we remove bonds that (i) are not listed or traded in the U.S. public market; (ii) are structured notes, mortgage-backed, asset- backed, agency-backed, or equity-linked; (iii) are convertible; (iv) trade under \$5; (v) have floating coupon rates; and (vi) have less than one year to maturity. Among all six corporate bond datasets, TRACE provides the most detailed information on bond transactions at the intraday frequency. Following Bessembinder, Maxwell, and Venkataraman (2006), who highlight the importance of using TRACE transaction data, we rely on the transaction records reported in the enhanced version of TRACE for the sample period from July 2002 to December 2017. The TRACE dataset offers the best-quality corporate bond transactions, with intraday observations on price, trading volume, and buy and sell indicators. For TRACE data, we adopt the filtering criteria proposed by Bai, Bali, and Wen (2017) and further eliminate bond transactions that (vii) are labeled as when-issued, locked-in, or have special sales conditions; (viii) are canceled, (ix) have more than a two-day settlement, and (x) have a trading volume smaller than \$10,000. We then merge corporate bond pricing data with the Mergent fixed income securities database to obtain bond characteristics such as the offering amount, offering date, maturity date, coupon rate, coupon type, interest payment frequency, bond type, bond rating, bond option features, and issuer information.

Finally, we adopt the following principle to handle overlapping observations among different data sets. If two or more datasets have overlapping observations at any point in time, we give priority to the dataset that reports the transaction-based bond prices. For example, TRACE will dominate other datasets in 2002 – 2017. If there are no transaction data or the coverage of the data is too small, we give priority to the dataset that has a relatively larger coverage on bonds/firms and can be better matched to the bond characteristic data, FISD. For example, Bloomberg daily quotes data are preferred to those of Datastream for the period for 1998 to 2002 because of its larger coverage and higher percentage of matching rate to FISD.

2.2 Corporate Bond Returns

The monthly corporate bond return at time t is computed as

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

where $P_{i,t}$ is the transaction price, $AI_{i,t}$ is accrued interest, and $Coupon_{i,t}$ is the coupon payment, if any, of bond i in month t. We denote $R_{i,t}$ as bond i's excess return, $R_{i,t} = r_{i,t} - r_{f,t}$, where $r_{f,t}$ is the risk-free rate proxied by the one-month Treasury bill rate. The quote-based datasets of Lehman and Datastream provide month-end prices and returns. The NAIC and Bloomberg data provide daily prices and the time-stamped TRACE data provide intraday clean prices. For TRACE intraday data, we first calculate the daily clean price as the trading volume-weighted average of intraday prices to minimize the effect of bid-ask spreads in prices, following Bessembinder et al. (2009). We then convert the bond prices from daily to monthly frequency. Specifically, our method identifies two scenarios for a return to be realized at the end of month t: (i) from the end of month $t-1$ to the end of month t, and (ii) from the beginning of month t to the end of month t. We calculate monthly returns for both scenarios, where the end (beginning) of each month refers to the last (first) five trading days within the month. If there are multiple trading records in the five-day window, the one closest to the last trading day of the month is selected. If a monthly return can be realized under both scenarios, the realized return in the first scenario (from month-end $t-1$ to month-end t) is selected.

2.3 Accounting for Defaulting Bond Returns

Corporate bonds occasionally default prior to reaching maturity. If default returns are simply treated as missing observations, return estimates can be overstated, particularly for high-yield bonds and long-term losers. To address this potential return bias, we follow Cici, Gibson, and Moussawi (2017) and compute a composite default return for all defaulted bonds. Specifically, we search for any price information on defaulted issues after the default event. We then compute median returns on these defaulted issues in the $(-1, +1)$ month window around the default date and use the median return of -40.17% for defaulting investment-grade (IG) issues and -17.67% for defaulting non-investment-grade (NIG) issues, which reflect higher expected default probability for high yield ex-ante. For IG and NIG issues that default without post-default prices, we use the corresponding IG and NIG default return averages as proxies for default-month returns.[9] Using the in-sample composite default-month returns for defaulting bonds of similar credit quality, but without valid post-default pricing information, enables us to avoid the delisting bias documented in previous research on equity returns (Shumway (1997)).

2.4 Bond Characteristics

We measure the size of a bond using amount outstanding ($ million) and the maturity of a bond using time-to-maturity in years. We measure the credit quality of corporate bonds via their credit ratings which capture information on bond default probability and the loss severity. We collect bond-level rating information from Mergent FISD historical ratings. All

[9] In Section 3.5, we provide two robustness checks regarding bond default returns. First, we use a more conservative measure of defaulting return, -100%, for bonds that default. Second, we eliminate all bonds rated C or below in the formation month in the univariate portfolio test. Our results remain similar and thus we follow the Cici, Gibson, and Moussawi (2017) approach throughout the paper for defaulting bond returns.

ratings are assigned a number to facilitate the analysis, for example, 1 refers to a AAA rating, 2 refers to AA+, ..., and 21 refers to CCC. Investment-grade bonds have ratings from 1 (AAA) to 10 (BBB-). Non-investment-grade bonds have ratings above 10. A larger number indicates higher credit risk, or lower credit quality. We determine a bond's rating as the average of ratings provided by S&P and Moody's when both are available, or as the rating provided by one of the two rating agencies when only one rating is available. Following Roll (1984), bond-level illiquidity (ILLIQ) is calculated as the (negative of the) autocovariance of the price changes.

Our final sample includes 27,718 bonds issued by 8,748 unique firms, yielding a total of 1,782,998 bond-month return observations during the sample period from January 1977 to December 2017. Panel A of Table 1 reports the time-series average of the bond long-term return reversal (LTR), bond characteristics (rating, maturity, size), and bond-level illiquidity. The sample contains bonds with an average rating of 7.88 (i.e., BBB+), an average issue size of $279 million, and an average of time-to-maturity of 12.66 years. Among the full sample of bonds, about 75% are investment-grade and the remaining 25% are high-yield bonds.

2.5 Summary Statistics

Following DeBondt and Thaler (1985), we quantify long-term reversal (LTR) with the past 36-month cumulative returns from month $t-48$ to $t-13$, skipping the 12-month momentum and the short-term reversal months.[10] Panel A of Table 1 shows that the average of LTR is 28.25% with a standard deviation 19.69%. Panel B of Table 1 presents the correlation matrix for the bond-level long-term reversal and other bond characteristics such as rating, maturity, size, and illiquidity. As shown in Panel B, credit rating and maturity are positively associated with long-term reversal, indicating that bonds with higher credit risk and longer maturity (i.e., higher interest rate risk) have stronger long-term return reversals. Bond size and bond illiquidity are negatively correlated with LTR, implying that smaller and illiquid bonds have

[10]Similar to Jegadeesh (1990), we measure the short-term reversal (STR) of a bond for month t using its previous month return, that is, R_{t-1}. Following Jegadeesh and Titman (1993), we define bond momentum as the past 11-month cumulative returns from months $t-12$ to $t-2$, skipping the short-term reversal month $t-1$.

stronger long-term return reversals.

3 Long-Term Reversals in Corporate Bonds

3.1 Univariate Portfolio Analysis

We first examine the significance of long-term reversal in corporate bond returns using portfolio-level analysis. For each month from January 1977 to December 2017, we form quintile portfolios by sorting corporate bonds based on their past 36-month cumulative returns (LTR) from months $t-48$ to $t-13$. Quintile 1 contains the bonds with the lowest LTR (long-term losers) and quintile 5 contains the bonds with the highest LTR (long-term winners). To mitigate the impact of illiquid and small bond transactions, we report in Table 2 the results from the value-weighted portfolios using the bond's outstanding dollar values as weights.

Moving from quintile 1 to quintile 5, the average excess return on the LTR portfolios decreases from 1.02% to 0.55% per month. This result produces a monthly average return difference of -0.47% between quintiles 5 and 1 with a Newey-West t-statistic of -3.27, indicating that corporate bonds in the lowest LTR quintile generate an economically and statistically significant 5.64% per annum higher returns than bonds in the highest LTR quintile.

Although Table 2 focuses on one-month-ahead return predictability, Table A.1 of the online appendix presents longer term predictability results based on the univariate portfolios sorted by LTR for the 12-, 24-, and 36-month ahead returns. The results confirm a significant long-term reversal effect in the corporate bond market for long-term investment horizons. Following DeBondt and Thaler (1985), we also use non-overlapping three-year periods for portfolio formation, and the subsequent three years as the test period. Table A.2 of the online appendix confirms the long-term reversal effect using this method.

The economic and statistical significance of the long-term reversal effect in the corporate bond market is even more striking because there is no significant long-term reversal effect in the equity market for the same time period. Using Kenneth French's value-weighted decile portfolios of stocks sorted by LTR, we find for the period January 1977 – December 2017 that the average excess return on decile 1 (LTR-equity losers) is 0.90% per month and the average excess return on decile 10 (LTR-equity winners) is 0.70% per month, providing a negative but economically and statistically insignificant average return spread of -0.20% per month (t-stat. = -0.77).

In addition to the average excess returns, Table 2 presents the intercepts (alphas) from the regression of the quintile bond excess portfolio returns on well-known stock and bond market factors — the excess stock market return (MKT^{Stock}), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM^{Stock}), and a liquidity factor (LIQ), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003). We also include the short-term stock return reversal factor (STR^{Stock}) and the long-term stock return reversal factor (LTR^{Stock}) to investigate whether these equity market factors can explain our findings.[11] The third column of Table 2 shows that, similar to the average excess returns, the 7-factor alpha on the LTR portfolios also decreases from 1.07% to 0.47% per month, moving from the low-LTR to the high-LTR quintile, yielding a significant alpha difference of -0.60% per month (t-stat.= -3.31).

Beyond well-known stock market factors, we also test whether the significant return difference between high-LTR and low-LTR bonds can be explained by prominent bond market factors. Following Bai, Bali, and Wen (2017), we use the 4-factor model with the aggregate corporate bond market, the downside risk, the credit risk, and the liquidity risk factors of corporate bonds. The excess bond market return (MKT^{Bond}) is proxied by the Merrill Lynch Aggregate Bond Market Index returns in excess of the one-month T-bill return.[12] Following Bai, Bali, and Wen (2017), the downside risk factor (DRF) is the value-weighted average return difference between the highest-VaR portfolio minus the lowest-VaR portfolio within each rating portfolio. The liquidity risk factor (LRF) is generated based on the monthly change (i.e., innovations) in aggregate illiquidity.[13] The credit risk factor (CRF) is the value-weighted

[11]The factors MKT^{Stock} (excess market return), SMB (small minus big), HML (high minus low), MOM^{Stock} (momentum-winner minus momentum-loser), STR^{Stock} (short-term-loser minus short-term-winner), and LTR^{Stock} (long-term-loser minus long-term-winner) are described in and obtained from Kenneth French's online data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. The LIQ (liquidity risk) factor is available at Lubos Pastor's online data library: http://faculty.chicagobooth.edu/lubos.pastor/research.

[12]We also consider alternative bond market proxies such as the Barclays Aggregate Bond Index and the value-weighted average returns of all corporate bonds in our sample minus the one-month Treasury bill rate. The results from these alternative bond market factors turn out to be similar to those reported in our tables.

[13]Following Roll (1984), bond-level illiquidity is calculated as the autocovariance of the price changes.

average return difference between the highest-rating portfolio minus the lowest-rating portfolio within each illiquidity portfolio. Similar to our earlier findings for the average excess returns and the 7-factor alphas from equity market factors, the fourth column of Table 2 shows that, moving from the low- to the high-LTR quintile, the 4-factor alpha from bond market factors decreases from 0.51% to 0.09% per month. The corresponding 4-factor alpha difference between quintiles 5 and 1 is negative and significant; -0.43% per month with a t-statistic of -3.59. The fifth column of Table 2 presents the 11-factor alpha for each quintile from the combined seven stock and four bond market factors. Consistent with our earlier results, moving from the low- to the high-LTR quintile, the 11-factor alpha decreases from 0.47% to 0.03% per month, providing a significant alpha spread of -0.44% per month (t-stat.$= -3.76$). These results indicate that after we control for well-known equity and bond market factors, the return difference between the high- and low-LTR bonds remains negative and highly significant.

In addition to the 4-factor model of Bai, Bali, and Wen (2017), we test whether the significant return spread between the high-LTR and low-LTR bonds is explained by alternative bond market factors. Following Elton et al. (2001) and Bessembinder et al. (2009), we use the aggregate corporate bond market (MKT^{Bond}), default spread (DEF), and term spread (TERM) factors.[14] In addition to MKT^{Bond}, DEF, and TERM, we also use the liquidity factor (LIQ^{Bond}) for the corporate bond market, which is generated based on the monthly change (i.e., innovations) in aggregate illiquidity. Following Bai, Bali, and Wen (2017), we also include the short-term bond return reversal factor (STR^{Bond}), constructed from 5×5 bivariate portfolios of credit rating and bond short-term reversal. Finally, following the original momentum finding of Jostova et al. (2013), we use the bond momentum factor (MOM^{Bond}) constructed from 5×5 bivariate portfolios of credit rating and bond momentum. We estimate the alpha on LTR-sorted quintile portfolios using these alternative factor models; (i) the 3-factor model

The aggregate illiquidity of the corporate bond market is proxied by the value-weighted average illiquidity of individual corporate bonds.

[14]In accordance with Fama and French (1993), we construct the default factor (DEF) as the difference between the return on a market portfolio of long-term corporate bonds (the composite portfolio on the corporate bond module of Ibbotson Associates) and the long-term government bond return. The term factor (TERM) is defined as the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one-month Treasury bill rate.

with MKT^{Bond}, DEF, and TERM, (ii) the 4-factor model with MKT^{Bond}, DEF, TERM, and LIQ^{Bond}, and (iii) the 6-factor model with MKT^{Bond}, DEF, TERM, LIQ^{Bond}, STR^{Bond}, and MOM^{Bond}.

Table A.3 of the online appendix shows that the 3-factor, 4-factor, and 6-factor alpha spreads between the high-LTR and low-LTR quintiles are negative and highly significant; -0.47 (t-stat. $= -3.27$), -0.40 (t-stat. $= -3.65$), and -0.44 (t-stat. $= -3.93$), respectively. However, as presented in Table A.3, the alphas are positive for all quintiles, indicating that MKT^{Bond}, DEF, TERM, LIQ^{Bond}, STR^{Bond}, and MOM^{Bond} do not well capture the cross-sectional and time-series variations in LTR-sorted portfolios. Thus, we will continue with the 4-factor model of Bai, Bali, and Wen (2017) that explains a much larger amount of variation in LTR-sorted portfolios and produces a positive (negative) alpha for LTR-losers (LTR-winners), as one would expect.

Notably, as reported in Table 2, the 11-factor alpha of bonds in quintile 1 (long-term losers) is positive and economically and statistically significant, whereas the corresponding alpha of bonds in quintile 5 (long-term winners) is statistically insignificant. Hence, we conclude that the significantly negative alpha spread between high- and low-LTR bonds is due to the outperformance of long-term losers, but not to the underperformance of long-term winners. Examining the average characteristics of individual bonds in the LTR-sorted portfolios, we find that low-LTR bonds in quintile 1 (long-term losers) have a higher market beta, lower liquidity and size, and higher credit risk.

Figure 1 presents the cumulative monthly post-formation returns of the corporate bonds sorted by long-term reversal (LTR). Following DeBondt and Thaler (1985), in Figure 1 we use non-overlapping three-year periods for portfolio formation, and use the subsequent three years as the test period. Cumulative abnormal returns are calculated based on the 4-factor model of Bai, Bali, and Wen (2017) with the aggregate corporate bond market (MKT^{Bond}), the downside risk factor (DRF^{Bond}), the credit risk factor (CRF^{Bond}), and the liquidity risk factor (LRF^{Bond}). Figure 1 indicates that long-term losers outperform winners on average for the 36-month post-formation periods and the effect is asymmetric; i.e., it is much larger for losers than for winners.

3.2 Bivariate Portfolio Analysis

Table 3 presents the results from the bivariate sorts of LTR and a number of potential bond return predictors. Quintile portfolios are formed every month from January 1977 to December 2017 by first sorting corporate bonds into five quintiles based on their credit ratings, maturity, size, illiquidity, bond market beta (β^{Bond}), previous month return (STR^{Bond}), or momentum (MOM^{Bond}); then within each quintile portfolio of a control variable, bonds are sorted further into five sub-quintiles based on their LTR. This methodology, under each characteristic-sorted quintile, produces sub-quintile portfolios of bonds with dispersion in LTR but that have nearly identical characteristics, such as rating, maturity, size, and illiquidity. The portfolios are value-weighted using the amounts outstanding as weights. LTR,1 (LTR,5) represents the lowest (highest) LTR-ranked bond quintiles within each of the five bond characteristic-ranked quintiles.

The first column of Table 3 shows that the 11-factor alpha decreases from the low-LTR quintile to the high-LTR quintile, averaged across the quintile portfolios of credit rating. More importantly, after controlling for credit rating, the 11-factor alpha difference between high- and low-LTR bonds remains negative, −0.32% per month, and highly significant with a t-statistic of −2.60. Similarly, other bond characteristics, such as time-to-maturity, size, or illiquidity, do not explain the high (low) returns on the low (high) LTR bonds. Specifically, controlling for maturity, size, and illiquidity in 5×5 bivariate portfolios, the 11-factor alpha spreads between the lowest- and highest-LTR quintiles are, respectively, −0.37%, −0.38%, −0.33% per month, and significant with the corresponding t-statistics of −2.62, −2.78, and −2.63. Moreover, the last three columns of Table 3 show that after we control for additional bond market risk and past return characteristics (β^{Bond}, STR^{Bond}, and MOM^{Bond}), the alpha spreads between the low- and high-LTR quintiles are negative, in the range of −0.29% and −0.35% per month, and highly significant. These results indicate that the long-term reversal in corporate bonds is distinct from other bond return characteristics such as short-term reversals and momentum.

3.3 Return Premia over Time

We now investigate the significance of long-term return reversal over time. Table 4 reports the average return spreads and the corresponding t-statistics from the value-weighted quintile portfolios of LTR across different sample periods. Since illiquidity and systematic risk premia (including default, market and macroeconomic risk premia) are higher during financial and economic downturns, we first examine the return premia on the LTR of corporate bonds during good and bad states of the economy, determined based on the Chicago Fed National Activity Index (CFNAI).[15] Table 4 shows that the value-weighted average return spread between LTR-losers and LTR-winners is higher at 1.42% per month (t-stat. = 3.03) during bad states (CFNAI ≤ 0), whereas it is much lower at 0.23% per month (t-stat. = 3.37) during good states (CFNAI > 0).

Second, we investigate the significance of return premia conditioning on macroeconomic uncertainty and find that the premia on the LTR are higher during high economic uncertainty periods when the JLN index is above its historical median (JLN $>$ JLN^{Median}), compared to periods of low economic uncertainty (JLN $\leq$ JLN^{Median});[16] 0.71% per month (t-stat. = 3.74) during high uncertainty periods, whereas much lower at 0.17% per month (t-stat. = 2.41) during low uncertainty periods.

Third, we test the significance of return premia conditioning on aggregate default risk, and find that the LTR premia are significantly high during periods of high default risk (ΔDEF > 0), but lower during periods of low default risk (ΔDEF ≤ 0); 0.66% per month (t-stat. = 2.49) during states of high default risk versus 0.49% per month (t-stat. = 3.73) during states of low default risk.

Fourth, we examine the significance of return premia conditioning on aggregate illiquidity, and find that the premia on LTR are higher during periods of high aggregate illiquidity (ILLIQ$^{agg} > Median$), compared to periods of low aggregate illiquidity (ILLIQ^{agg} $\leq$

[15]The CFNAI is a monthly index designed to assess overall economic activity and related inflationary pressure. It is a weighted average of 85 existing monthly indicators of national economic activity, and constructed to have an average value of zero and a standard deviation of one. An index value below (above) zero corresponds to a bad (good) state.

[16]Jurado, Ludvigson, and Ng (2015) develop a factor-based estimate of economic uncertainty. We obtain the one-month-ahead economic uncertainty index (JLN) from Sydney Ludvigson's website: https://www.sydneyludvigson.com/data-and-appendixes/.

$Median$);[17] 0.58% per month (t-stat. = 3.67) during periods of high bond market illiquidity, whereas much lower but still significant at 0.30% per month (t-stat. = 2.35) during periods of high bond market liquidity.

Finally, we check whether the long-term reversal effect remains significant when the recent financial crisis period is eliminated from the asset pricing tests. Specifically, we removed the entire year of 2008 (12 months), the entire two years of 2008 and 2009 (24 months), and the widely recognized crisis period from July 2007 to March 2009 (21 months). The value-weighted average return spread between the LTR-losers and LTR-winners remains economically and statistically significant after excluding these three alternative periods of financial crisis; 0.40% (t-stat. = 9.28) excluding the period from January 2008 to December 2008, 0.31% (t-stat. = 10.01) excluding the period from January 2008 to December 2009, and 0.37% (t-stat. = 9.24) excluding the period from July 2007 to March 2009.

3.4 Fama-MacBeth Regressions

We have so far tested the significance of long-term reversal (LTR) at the portfolio level. We now examine the cross-sectional relation between LTR and expected returns at the bond level using Fama and MacBeth (1973) regressions. We present the time-series averages of the slope coefficients from the regressions of one-month-ahead excess bond returns on LTR and the control variables, including the bond market beta (β^{Bond}), default beta (β^{DEF}), term beta (β^{TERM}), bond-level illiquidity (ILLIQ), credit rating, year-to-maturity (MAT), and bond amount outstanding (SIZE). Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot LTR_{i,t} + \sum_{k=1}^{K} \lambda_{i,k} Controls_{k,t} + \epsilon_{i,t+1}, \tag{2}$$

where $R_{i,t+1}$ is the excess return on bond i in month t+1.

Table 5 reports the time series average of the intercepts, the slope coefficients (λ's), and the adjusted R^2 values over the 492 months from January 1977 to December 2017. The Newey-

[17] Aggregate illiquidity (ILLIQ^{agg}) in the corporate bond market is proxied by the value-weighted average of the bond-level illiquidity measures of Roll (1984).

West adjusted t-statistics are reported in parentheses. The univariate regression results show a negative and significant relation between LTR and the cross-section of future bond returns. In Regression (1), the average slope $\lambda_{1,t}$ from the monthly regressions of excess returns on LTR alone is -0.014 with a t-statistic of -3.49. The economic magnitude of the associated effect is similar to that documented in Table 2 for the univariate quintile portfolios of LTR. The spread in average LTR between quintiles 5 and 1 is approximately 54%, and multiplying this spread by the average slope of -0.014 yields an estimated monthly return difference of 76 basis points (bps).[18]

Regression specification (2) in Table 5 shows that after we control for β^{Bond}, β^{DEF}, β^{TERM}, illiquidity, credit rating, maturity, and size, the average slope coefficient of LTR remains negative and highly significant. In other words, controlling for bond characteristics does not affect the significance of long-term return reversals in the corporate bond market.

Regression (3) tests the cross-sectional predictive power of LTR while controlling for the other past bond return characteristics simultaneously, namely, the bond short-term reversal and bond momentum. Consistent with Bai, Bali, and Wen (2017) and Jostova et al. (2013), regression (3) shows a significantly negative (positive) relation between STR (MOM) and future bond returns. The average slopes on STR and MOM are economically and statistically significant at -0.034 (t-stat. $= -5.50$) and 0.017 (t-stat. $= 2.57$), respectively. Importantly, the average slope coefficient of LTR remains negative and highly significant, -0.009 (t-stat. $= -3.53$), indicating that LTR is distinct from short-term reversal and momentum in corporate bond returns. The last specification, Regression (4), presents results from the multivariate regressions with all bond return characteristics (STR, MOM, and LTR) while simultaneously controlling for β^{Bond}, β^{DEF}, β^{TERM}, illiquidity, credit rating, maturity, and size. Similar to our findings in Regression (2), the cross-sectional relation between future bond returns and LTR is negative and highly significant. The negative average slope of -0.007 on LTR in Regression (4) represents an economic effect of 0.38% per month, controlling for everything

[18]Note that the ordinary least squares (OLS) methodology used in the Fama-MacBeth regressions gives an equal weight to each cross-sectional observation so that the regression results are more aligned with the equal-weighted portfolios. That is why the economic significance of LTR obtained from Fama-MacBeth regressions, 0.76% per month, is somewhat higher than the 0.47% per month obtained from the value-weighted portfolios (see Table 2).

else.[19] These results show that the long-term reversal has distinct, significant information beyond bond size, maturity, rating, liquidity, market risk, and default risk, and it is a strong and robust predictor of future bond returns.

3.5 Robustness Checks

3.5.1 Long-term reversal effect in the long-run

In addition to one-month-ahead predictability, we investigate the longer-term predictive power of LTR in the corporate bond market. Table A.1 of the online appendix presents the results from the value-weighted quintile portfolios sorted by LTR to predict the 12-, 24-, and 36-month-ahead returns. The results confirm a significant long-term reversal effect in the corporate bond market for long-term investment horizons.

3.5.2 Non-overlapping samples

We also investigate the long-term reversal effect using a non-overlapping sample of bond returns. Following DeBondt and Thaler (1985), we use non-overlapping three-year periods for portfolio formation, and use the subsequent three years as the test period. Table A.2 of the online appendix presents results for the long-term reversal effect using this method. The results are similar to those reported in Table 2 and show that bonds with poor performance over the past three years (LTR-losers) produce higher risk-adjusted returns over the next three years than bonds with superior performance (LTR-winners) over the same period. Figure 1 demonstrates the post-formation cumulative abnormal returns for the LTR-sorted portfolios, indicating that long-term losers outperform winners on average for each of the 36-month post-formation periods.

3.5.3 Alternative measures of defaulting bond returns

We provide two additional robustness checks regarding bond default returns. First, instead of the Cici, Gibson, and Moussawi (2017) approach, we use a more conservative measure of

[19] Among the control variables, only credit rating and illiquidity have robust and significant average slope coefficients, indicating significantly positive credit risk and illiquidity premia in the corporate bond market, consistent with the findings of Bai, Bali, and Wen (2017).

defaulting return, −100%, for bonds that default. Second, since bonds with higher credit risk are more likely to default, we eliminate all bonds rated C or below in the formation month in the univariate portfolio test and reexamine the long-term reversal effect. Table A.4 of the online appendix shows that the results turn out to be similar to those reported in Table 2.

3.5.4 Firm-level evidence

Our empirical analyses have thus far been based on bond-level data, since we test whether the past return characteristics of individual bonds predict their future returns. To control for the effect of multiple bonds issued by the same firm, for each month we pick one bond of median size or the most liquid bond as representative of the firm and replicate our portfolio-level analysis and cross-sectional regressions using this firm-level dataset. As presented in Panel A of Table A.5 in the online appendix, the value-weighted quintile portfolios indicate significant long-term reversal in the cross-section of firm-level bond returns. Specifically, the value-weighted average return and 11-factor alpha spreads between LTR-winners and LTR-losers are -0.41% (t-stat. = -3.32) and -0.55% (t-stat. = -3.50), respectively. In Panel B when the most liquid bond is chosen as the representative of the firm, the long-term reversal effect remains highly significant.

As shown in Table A.6 of the online appendix, our main findings from the firm-level regressions remain qualitatively similar to those obtained from the bond-level regressions. Both the univariate and multivariate regression results present a negative and highly significant relation between future firm-level bond returns and LTR.

4 A Long-Term Reversal Factor for Corporate Bonds

In this section, we first introduce a novel long-term reversal factor for corporate bonds, LTR^{Bond}, and then investigate the economic and statistical significance of the factor. Second, we test whether the factor is explained by well-established stock and bond market factors. Third, we examine the explanatory power of a return-based four-factor model for alternative test portfolios of corporate bonds. Finally, we compare the performance of the return-based four-factor model relative to the bond risk factors of Bai, Bali, and Wen (2017).

4.1 The LTR Factor

As discussed previously, corporate bonds with strong long-term reversal effects also have higher credit risk and longer maturity both at the bond and portfolio levels. Thus, it is natural to use credit risk (proxied by credit rating) and time-to-maturity as the primary sorting variables in the construction of this new LTR factor.

To construct the return-based long-term reversal factor, we form mimicking portfolios by first sorting bonds into terciles based on their credit rating; then, within each rating portfolio, we further sort the bonds into sub-terciles based on their time-to-maturity; finally, we further sort the bonds into terciles based on LTR. Thus, for each month from January 1977 to December 2017, the long-term reversal factor (LTR^{Bond}) is constructed using 3×3×3 trivariate conditional sorts of credit rating, time-to-maturity, and LTR. LTR^{Bond} is the value-weighted average return difference between the lowest LTR minus the highest LTR portfolio across the rating and maturity portfolios.

Over the period from January 1977 to December 2017, the corporate bond market risk premium, MKT^{Bond}, is 0.27% per month with a t-statistic of 3.15. The value-weighted LTR^{Bond} factor has a statistically significant and economically larger premium of 0.47% per month (t-stat.= 6.12). The annualized Sharpe ratio for the LTR^{Bond} factor is 1.11, which is higher than the Sharpe ratios for the aggregate stock and bond market factors. Over the same period of January 1977 – December 2017, the stock market risk premium, MKT^{Stock}, is 0.64% per month with a t-statistic of 3.22, yielding an annualized Sharpe ratio of 0.50 for the aggregate equity market factor. For the same time period 1977 – 2017, the annualized Sharpe ratio of the aggregate bond market factor is 0.49, and that of the *stock* LTR factor from Kenneth French's online data library, LTR^{Stock}, is 0.36. The correlation between the LTR^{Bond} and the LTR^{Stock} is modest, at 0.18. The mean return on LTR^{Stock} is 0.15% per month and is statistically indistinguishable from zero (t-stat. = 1.14) for the period January 1977 – December 2017. However, for the earlier period from January 1931 to December 1976, the mean return on LTR^{Stock} is positive and significant, at 0.46% per month (t-stat. = 2.32). Hence, the *stock*

LTR factor attenuates in our sample period.

The correlation between equities and non-investment-grade bonds tends to be higher than that between equities and investment-grade bonds.[20] One may therefore think that the long-term reversal in bonds is simply an artefact of similar reversals in the equities associated with non-investment-grade bonds. To investigate this possibility, we identify equities corresponding to the non-investment-grade bonds and form quintile portfolios by sorting these stocks based on their past 36-month cumulative returns (LTR). Table A.7 of the online appendix shows that stocks associated with non-investment-grade bonds do not exhibit long-term reversals.

Finally, we investigate whether long-established stock and bond market factors explain the newly proposed LTR factor for corporate bonds. We conduct a formal test using the following time-series regressions:

$$LTR_t^{Bond} = \alpha + \sum_{k=1}^{K} \beta_k \cdot Factor_{k,t}^{Stock} + \sum_{l=1}^{L} \beta_l \cdot Factor_{l,t}^{Bond} + \varepsilon_t, \tag{3}$$

where LTR_t^{Bond} is the new long-term reversal factor. $Factor_{k,t}^{Stock}$ denotes a vector of existing stock market factors and $Factor_{k,t}^{Bond}$ denotes a vector of existing bond market factors. Panel A of Table A.8 in the online appendix shows that all of the intercepts (alphas) are economically and statistically significant ranging from 0.35% to 0.49% per month, indicating that the existing stock and bond market factors are not sufficient to capture the information content in the long-term reversal factor of corporate bonds.[21]

4.2 Alternative Test Portfolios

In this section, we examine the explanatory power of the newly proposed long-term reversal factor for the cross-sectional variation in bond returns. First, we show that the commonly used stock and bond market factors do not perform as well as the long-term reversal factor

[20] Confirming this observation, in our sample, the correlation between the monthly returns of non-investment-grade bonds (investment-grade bonds) and equities is 0.26 (0.14). The generally low correlation between equity and bond returns is consistent with Kapadia and Pu (2012) and Chordia et al. (2017).

[21] To address a potential concern about seasonality in corporate bond returns (George and Hwang (2007)), we construct the LTR^{Bond} factor using only non-January months. Panel B of Table A.8 in the online appendix shows that the alpha of the LTR^{Bond} factor remains highly significant, both economically and statistically, after removing Januaries from the sample.

in explaining the cross-sectional variation in the returns of bond portfolios. Second, the long-term reversal factor helps improve the performance of the risk-based factors of Bai, Bali, and Wen (2017). Finally, the collective explanatory power of return-based factors in corporate bonds is comparable to that of the Bai, Bali, and Wen (2017) factors, with the long-term reversal factor playing an important role.

We rely on three different sets of test portfolios of corporate bonds. The first set is based on 5×5 independently sorted bivariate portfolios of size and maturity. The second involves 5×5 independently sorted bivariate portfolios of size and rating. The third is 12-industry portfolios of corporate bonds. We then examine the relative performance of factor models in explaining the time-series and cross-sectional variations in the 25-size/maturity, 25-size/rating, and 12-industry sorted portfolios of corporate bonds. The monthly returns of the test portfolios cover the period from January 1977 to December 2017.

We now assess how much cross-sectional variation in returns can be explained by the following models:

- Model 1: Stock Factors + Bond Factors
- Model 2: Stock Factors + Bond Factors + LTR^{Bond}
- Model 3: Stock Factors + Bond Factors + LTR^{Bond} + MOM^{Bond} + STR^{Bond}
- Model 4: Stock Factors + Bond Factors + DRF + CRF + LRF
- Model 5: Stock Factors + Bond Factors + DRF + CRF + LRF + LTR^{Bond}
- Model 6: Stock Factors+Bond Factors+DRF+CRF+LRF+LTR^{Bond}+MOM^{Bond}+STR^{Bond}

where the stock market factors include MKT^{Stock}, SMB (size factor), HML (book-to-market factor), RMW (profitability factor), CMA (investment factor), LIQ^{Stock} (stock liquidity factor), STR^{Stock} (stock short-term reversal factor), MOM^{Stock} (stock momentum factor), and LTR^{Stock} (stock long-term reversal factor). The bond market factors include MKT^{Bond}, DEF, and TERM. MKT^{Bond} is the excess bond market return, LTR^{Bond} is the long-term reversal factor proposed in Section 4.1, MOM^{Bond} is the bond momentum factor, constructed in this paper following the original momentum finding of Jostova et al. (2013), STR^{Bond} is the short-term reversal factor in Bai, Bali, and Wen (2017), DRF, CRF, and LRF are the downside risk, credit risk, and liquidity risk factors of Bai, Bali, and Wen (2017).

4.2.1 25-Size/Maturity-Sorted Portfolios

Table 6 reports the adjusted R^2 values from the time-series regressions of the 25-size/maturity-sorted portfolios' excess returns on the six different factor models. Panel A of Table 6 shows that the commonly used stock and bond market factors do not play a material role in the cross-sectional variation of bond returns. Specifically, the adjusted R^2 from Model 1, averaged across the 25 portfolios, is low at 15%, implying that a large fraction of the variance in the returns of the 25 bond portfolios is not explained by the factors. Compared to Model 1, the average R^2 from Model 2 with the long-term reversal factor is much stronger. As shown in Panel B of Table 6, when we augment Model 1 with the long-term reversal factor (LTR^{Bond}), the average adjusted R^2 increases significantly from 15% to 44%, indicating that the new long-term reversal factor of corporate bonds captures significant cross-sectional information about the portfolio returns that is not fully picked up by the long established stock and bond market factors.

In Panel C of Table 6, we augment the long-term reversal factor with the short-term reversal and momentum factors (Model 3). The results in Panel C show that the return-based factor model performs well in explaining the cross-sectional variation in the returns of bond portfolios, with an average R^2 of 50%. Consistent with the findings of Bai, Bali, and Wen (2017), the risk-based factor model (Model 4) delivers a high adjusted R^2 at 60% for the 25 size/maturity-sorted portfolios. A notable point in Table 6 is that adding the long-term reversal factor alone to the risk-based DRF, CRF, and LRF factors (Model 5) significantly improves the explanatory power. Panels D and E of Table 6 show that compared to the performance of the risk-based factors (Model 4), the adjusted R^2 from Model 5 increases from 60% to 73%. Finally, compared to Model 5, the short-term reversal and momentum factors in Model 6 continue to improve the explanatory power by adding 4% adjusted R^2 for the size/maturity-sorted portfolios.

As an alternative way of evaluating the relative performance of the factor models, we focus on the magnitude and statistical significance of the alphas on the 25-size/maturity-sorted portfolios generated by the alternative factor models. Panel A of Table 6 shows that the long established stock and bond factors generate economically significant alphas for almost all 25 portfolios, ranging from 0.21% to 0.58% per month. As shown in the last row of Panel A, the average alpha across the 25 portfolios is large at 0.37% per month with a highly significant p-value, according to the Gibbons, Ross, and Shanken (1989, GRS) test. However, Panel B of Table 6 presents substantially different results compared to Panel A. The factor model with LTR^{Bond} generates economically and statistically *insignificant* alphas for 23 out of 25 portfolios. As shown in the last row of Panel B, the average alpha across the 25 portfolios is very low and economically weak at 0.17% per month. Panel C shows that the absolute magnitude of the alphas continues to decrease after adding the momentum and short-term reversal factors. Finally, combining the risk-based and return-based factors (Model 6 in Panel F) yields an economically insignificant alpha of 0.03% per month.

Overall, the results in Table 6 confirm the superior performance of LTR^{Bond} in capturing the cross-sectional variation in the returns of the 25-size/maturity-sorted portfolios of corporate bonds. The long-term reversal factor not only contributes significantly to the performance of the return-based four-factor model, but it also improves the performance of the risk-based factors of Bai, Bali, and Wen (2017).

4.2.2 25-Size/Rating-Sorted Portfolios

In this section, we investigate the relative performance of the factor models based on the 25-size/rating portfolios. Panel A of Table 7 shows that the adjusted R^2, averaged across the 25-size/rating portfolios, is 13% for Model 1. Similar to our earlier findings from the size/maturity-sorted portfolios, Panel B of Table 7 reports that the average adjusted R^2 significantly increases to 42%, when the new long-term reversal factor is included. Although the risk-based factor model of Bai, Bali, and Wen (2017) again delivers a high adjusted R^2 of 54% (Model 4, Panel D), adding the long-term reversal factor to the risk-based factors enhances the explanatory power of the Bai, Bali, and Wen (2017) model by 10% (Model 5, Panel E). Finally, as presented in Panel F of Table 7, the short-term reversal and momentum factors in Model 6 continue to boost the explanatory power by adding 4% R^2 for the 25 size/rating-sorted portfolios.

As reported in the last row of Panel A, the average alpha across the 25 portfolios is economically large at 0.37% per month, and highly significant with a p-value less than 0.01, according to the GRS test. In contrast, the model with LTR^{Bond} (Model 2) generates economically and statistically *insignificant* alphas for all 25 portfolios. As presented in the last row of Panel B, the average alpha across the 25 portfolios is much lower at 0.18% per month.[22] Panel C shows that the economic significance of the alphas continues to decline after adding the momentum and short-term reversal factors. Panels D and E of Table 7 show that adding the long-term reversal factor alone to the risk-based factors of Bai, Bali, and Wen (2017) (Model 5) significantly reduces the average alpha from 0.11% to 0.06% per month. Finally, combining the risk-based and return-based factors (Model 6 in Panel F) produces an economically insignificant alpha of 0.04% per month.

4.2.3 12-Industry-Sorted Portfolios

Finally, we test the relative performance of the factor models using the 12-industry portfolios of corporate bonds based on the Fama-French (1997) industry classification. As shown in Panel A of Table 8, Model 1 (with only MKT^{Bond}) generates economically significant alphas for 9 out of the 12 portfolios. As shown in the last column of Panel A, the average alpha for the 12-industry portfolios generated by Model 1 is 0.39% per month and highly significant with a p-value less than 0.01, according to the GRS test. Similar to our findings for the 25-size/maturity- and 25-size/rating-sorted portfolios, Model 2 provides a more accurate characterization of the returns on 12-industry portfolios. Model 2 with LTR^{Bond} generates economically and statistically *insignificant* alphas at the 5% (10%) level for 10 (12) out of 12 portfolios. As shown in the last two columns of Panel A, the average alpha across the 12 portfolios is 0.16% per month. Panel A of Table 8 shows that the absolute magnitude of the alphas declines after adding

[22]Panel B of Table 7 shows that Model 2 with the LTR factor explains the abnormal returns of high credit quality bonds, not just the abnormal returns of low quality bonds. The LTR factor in Model 2 also explains the abnormal returns of large bonds with high credit quality as their alphas are statistically insignificant.

the momentum and short-term reversal factors (Model 3). Including the long-term reversal factor by itself to the risk-based factor model of Bai, Bali, and Wen (2017) (Model 5) further decreases the average alpha from 0.11% to 0.08% per month. Similar to our earlier findings in Tables 6 and 7, combining the risk-based and return-based factors (Model 6) generates an economically insignificant alpha of 0.03% per month.

The first row in Panel C of Table 8 confirms that existing factors a limited role in explaining the cross-sectional variation in industry portfolios of corporate bonds. Specifically, the adjusted R^2, averaged across the 12-industry portfolios, is 21% for Model 1. Similar to our findings from the size/maturity- and size-rating-sorted portfolios, the second row in Panel C of Table 8 reports that the average adjusted R^2 significantly increases to 41%, after including the new long-term reversal factor in the market model specification. The results from Models 3 and 4 in Table 8, Panel C, indicate that the performance of the return-based factor model with LTR^{Bond}, MOM^{Bond}, and STR^{Bond} ($R^2 = 47\%$) is somewhat better than that of the risk-based factor model with DRF, CRF, and LRF ($R^2 = 43\%$). Moreover, adding the long-term reversal factor to the risk-based factors augments the explanatory power of the Bai, Bali, and Wen (2017) model by 59% (Model 5). Finally, as presented in the last row of Panel C in Table 8, the short-term reversal and momentum factors (Model 6) increase the explanatory power of Model 5 by adding 5% R^2 for the 12-industry portfolios.

Overall, these results show that LTR^{Bond} performs well in predicting the cross-sectional variation in the returns of the 12-industry portfolios of corporate bonds. In the next section, we examine rationales for long-term reversals in the corporate bond market.

5 Why Does the LTR Factor Command a Premium?

Why does LTR^{Bond} command a premium? One possible hypothesis is that bond prices overreact, followed by corrections. An alternative hypothesis is that losers experience increases in risk, so that the higher returns of losers represent increases in required returns.

We term the overreaction and risk hypotheses as OH and RH, respectively. It is challenging to distinguish between these potential explanations. Nonetheless, in the ensuing analysis, we make progress on this issue by first making some general observations to guide our empirical tests (we drop the superscript from LTR^{Bond} for convenience):

H1. The OH by itself does not predict asymmetry in LTR, since investors' overreaction could manifest itself in both rising and falling prices. Considering frictions, however, it is challenging to short corporate bonds (Edwards, Harris, and Piwowar (2007)). This implies that long-term winners (the short leg of the arbitrage portfolio) are expected to be more profitable than long-term losers (the long leg) due to short-selling constraints impeding arbitrageurs (Shleifer and Vishny (1997)) trading on other investors' misreactions. Thus, the OH suggests either a symmetric reaction, or greater profitability for long-term winners.

H2. Since a predominant source of risk for bonds is downside risk, viz. Bai, Bali, and Wen (2017), under RH, we expect LTR to be stronger for losers (i.e., bonds which have lost value due to increasing risk).

H3. Under RH, LTR returns should load positively on factors that command a positive premium in bond markets.

H4. Under RH, LTR hedge portfolio profits (alphas) should attenuate when we control for bond risk factors.

H5. Under RH, LTR losers should experience an increase in credit risk over the portfolio formation period. Since subjective credit ratings might themselves be biased, RH would receive stronger support if losers experience heightened default risk as measured by financial performance metrics in addition to credit ratings.

H6. The behavioral models of overreaction (Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999)) indicate that momentum should be followed by reversals. If LTR is driven by these forces, we expect to see bond momentum portfolios experience reversals in the long-run. Such evidence would support OH.

H7. We expect institutions to be more sophisticated than individuals (Kumar (2009)). Hence, under OH, bonds that are held proportionally more by institutions should exhibit weaker evidence of LTR.

5.1 Long-term Reversal and Default Risk

The evidence in Section 3.1 already indicates that the profitability of long-term contrarian strategies emanates from the strong positive performance of past losers, rather than negative returns in winners, which supports H2 above rather than H1. To follow up, we now investigate whether the strength of the long-term reversal effect in corporate bonds is uniform across bonds with high and low default risk. As discussed in Section 3.1, when we compute the average portfolio characteristics of bonds in the univariate quintile portfolios, we find that LTR-losers are more sensitive to fluctuations in the aggregate bond market portfolio, that is, LTR-losers have greater market risk compared to LTR-winners. We extend this analysis by estimating bond exposure to aggregate default and interest rate risk. For each month in our sample, we simultaneously estimate individual bond exposures to the change in default and term spreads along with their exposure to the aggregate bond market using the past 36 months of data. Panel A of Table 9 shows that the average market beta of LTR-losers is 1.22, whereas the average market beta of LTR-winners is lower at 0.52. Similarly, the average exposure to aggregate default risk decreases from 4.80 to 3.50, when moving from the LTR-loser to the LTR-winner quintile. Consistent with our findings from the bond exposures to the aggregate market and aggregate default risk factors (β^{Bond} and β^{DEF}), LTR-losers have greater exposure to interest rate risk with $\beta^{TERM} = 1.96$, compared to LTR-winners with $\beta^{TERM} = 0.15$. That LTR losers have greater exposure to risk factors accords with H3, and thus, with RH.

We additionally examine the link between bond exposure to aggregate default risk and long-term reversal by forming value-weighted bivariate portfolios based on β^{DEF} and LTR. Specifically, we first sort corporate bonds into five quintiles based on their exposure to aggregate default risk (β^{DEF}). Then, within each β^{DEF} portfolio, bonds are sorted further into five sub-quintiles based on LTR. Panel B of Table 9 shows that the alpha spread between high-LTR and low-LTR quintiles is economically insignificant in the first two quintiles of β^{DEF}. Another noteworthy point in Panel B is that the alpha spread between LTR-winners and

LTR-losers is again largest in the highest β^{DEF} quintile; -1.13% per month with a t-statistic of -5.23, implying that the long-term reversal effect is strongest in the sample of bonds with high exposure to aggregate default risk. Overall, Table 9 shows that the long-term reversal effect is confined to the three quintiles with high credit risk and the three quintiles with high default beta. This result again supports H3, and hence, RH.

Next, we test whether the LTR effect is explained by downside risk, credit risk, and liquidity risk collectively. Table A.9 of the online appendix shows that the average return on the LTR factor reduces from 0.47% (t-stat. = 6.12) to 0.43% per month (t-stat. = 5.19) controlling for the aggregate bond market portfolio, implying that bond market risk explains only 4 basis points per month of the original LTR loser-minus-winner premium. The third row of Table A.9 shows that controlling for the downside risk (DRF), credit risk (CRF), and liquidity risk (LRF) factors of Bai, Bali, and Wen (2017) reduces the alpha from 0.47% to 0.20% per month (t-stat. = 2.54), indicating that downside risk, credit risk, and liquidity risk as a group explain an additional 23 bps per month. It is important to note that the loadings on the DRF, CRF, and LRF factors are all positive and statistically significant (supporting RH in H3), and the regression R^2 increases from 1.93% to 56.72% after including the DRF, CRF, and LRF factors to the CAPM specification, suggesting that time-varying expected returns may play a significant role in explaining the observed bond price reversals. However, the common risk factors of aggregate market, downside, credit, and liquidity as a whole explain 27 basis points per month, leaving 20 bps per month of the LTR premium unexplained. To the extent that the bond factor model attenuates LTR, and LTR profits are related to factor loadings, our tests support RH (based on H4 above).

Finally, following Lettau and Ludvigson (2001a), we use the log consumption-wealth ratio (CAY) as a conditioning variable and examine the ability of the consumption CAPM (CCAP-M) to explain the long-term reversal effect in the corporate bond market.[23] The last row in Table A.9 of the online appendix shows that the slope coefficient on CAY is negative but

[23]Lettau and Ludvigson (2001a) show that the conditional version of the consumption CAPM performs better than the unconditional CAPM and the three-factor Fama-French (1993) model in explaining the cross-sectional variation in equity returns. Lettau and Ludvigson (2001b) also provide evidence that CAY is a strong predictor of future excess returns on the U.S equity market portfolio controlling for the dividend yield, the dividend payout ratio, and several other popular time-series return predictors.

statistically insignificant. Moreover, the alpha and the adjusted R^2 remain almost the same, indicating that the CCAPM conditioned on CAY does not explain the conditional LTR premium. Overall, these results show that the conditional asset pricing model that expresses the stochastic discount factor, not as an unconditional linear model as in the static CAPM, but as a conditional factor model of DRF, CRF, LRF, and CAY does not explain the long-term reversals in corporate bonds. Thus, the four factor model specific to the bond market appears to work better in explaining LTR.

5.2 Long-term Reversal, Ratings Downgrade, and Changes in Financial Distress

We now further test whether long-term reversals capture time variation in expected returns — i.e., whether an increase in discount rates generates an immediate price drop, followed by higher expected future returns. Given our evidence that long-term reversals are stronger for losers, we examine whether losers have recently experienced an increase in credit risk (i.e., credit rating downgrade) which results in an immediate negative price response, followed by higher future returns. Thus, we compute the average change in credit ratings across the portfolio formation window for losers and winners separately. As shown in Panel A of Table 10, long-term losers indeed experience significant increases in credit risk (or ratings downgrades) during the portfolio formation window. Specifically, the average change in ratings (or average increase in the numerical score) for bonds in quintile 1 is economically large, at 0.38, 1.00, 1.87, and 2.90 for the 12-, 24-, 36-, and 48-month measurement windows, respectively. However, the average change in ratings for long-term winners is almost zero for all measurement windows, suggesting that winners do not experience an improvement in credit risk on average. As reported in the last row of Table 10, Panel A, the average differences in ratings changes between losers and winners are all significant at −0.35, −0.99, −1.87, and −2.86, respectively, for the 12-, 24-, 36-, and 48-month measurement windows. Overall, the results provide support for the discount rate channel, especially that related to long-term losers, in driving long-term reversals in corporate bonds.[24]

Panel B of Table 10 shows the negative price response associated with a ratings downgrade. We form quintile portfolios based on the change in credit ratings from month $t-48$ to month $t-13$ (i.e., the same measurement window as LTR) and report the portfolio formation period returns associated with each quintile. Consistent with a negative price response to an increase in credit risk, bonds with ratings downgrades tend to experience lower returns, supporting RH in H5.

Bar-Isaac and Shapiro (2013) show that credit rating quality is not bias-free and it depends on economic fundamentals and varies over the business cycle, indicating countercyclical ratings quality. If credit rating agencies herd, especially for downgraded securities and especially during bad times, it is possible that credit ratings might be biased. To address any potential concerns about the subjectivity of credit ratings, we replicate Table 10 using two proxies of financial distress: the failure probability measure of Campbell, Hilscher, and Szilagyi (2008) and the O-score measure of Ohlson (1980). Confirming our findings from credit ratings, Table 11 shows that long-term losers indeed experience significant increases in financial distress during the portfolio formation window, and financial distress is an important source of the long-term reversal effect. Thus, the source of reversals in the bond market extends to alternative measures of credit/distress risk that are not based on credit ratings.

The fact that losers from months $t-48$ to $t-13$ experience increases in credit risk in months $t-12$ to t implies a role for bond markets in anticipating distress. To provide more direct evidence on this issue, we investigate whether long-term returns signal future shifts in credit risk. We examine the cross-sectional relation between LTR and alternative measures of credit risk at the bond level using Fama and MacBeth (1973) regressions. Table 12 reports the results from the Fama-MacBeth regressions of two measures of credit risk in month $t+1$ on the past 3-year return (LTR) ending in month t, with and without the control variables. Regressions (1) to (3) show a positive and significant relation between LTR and the distance-to-default (DD) after controlling for other bond characteristics, indicating that long-term losers experience larger increases in future credit risk (or losers experience a lower distance-to-

[24]Our results are consistent with Kisgen (2006, 2009), who finds that firms with fundamentals near rating change boundaries are more likely to reduce leverage (to address increased default risk) than other firms.

default). Consistent with these results, Regressions (4) to (6) show a negative and significant relation between LTR and the credit default spread (CDS), indicating that long-term losers are exposed to larger future shifts in credit risk. In sum, the results in Table 12 show that long-term reversal has distinct, significant information beyond bond size, maturity, liquidity, and market risk, and is a strong predictor of future shifts in corporate bond default and credit quality. This evidence also indicates that bond returns aid in price discovery by providing material information about future firm outcomes.

To summarize, reversals emanate from losing bonds, and such bonds are more prone to experiencing rating downgrades. Note that while LTR itself is primarily driven by this subset of bonds, the role of LTR in pricing the cross-section of bond returns is pervasive (Section 4). Overall, the totality of the evidence thus far supports RH.

5.3 Further Tests of the Overreaction Hypothesis

As mentioned in H6, the behavioral models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) suggest that intermediate-term momentum should be followed by longer-term reversals. Supporting this notion, Jegadeesh and Titman (2001) indicate that momentum portfolios for equities exhibit reversals in the long-run. We now test if a similar finding holds for corporate bonds. Panel A of Table 13 shows that momentum portfolios themselves yield significant returns over medium-term horizons, with 11-factor alphas ranging from 0.23% to 0.27% per month. However, the returns on these momentum portfolios do not reverse in the long-run from three to five years after portfolio formation. Panel B of Table 13 shows that portfolios formed on long-term bond returns do show reversals even four years after portfolio formation, with alphas ranging from −0.14% to −0.43% per month. Moreover, for the long-term reversal portfolios, there is no evidence of momentum even five years after the portfolio formation period, as the alpha spread between LTR-winners and LTR-losers is negative and statistically significant, −0.21% per month (t-stat. = −2.43), for months $t+13$ to $t+60$.[25] These results collectively suggest that momentum and long-term reversal in corporate

[25]The alpha spreads between LTR-winners and LTR-losers are negative and significant for one-year to five-year after portfolio formation month, except for months 49 to 60. Although LTR-losers outperform LTR-winners by 9 basis points per month, the risk-adjusted return (11-factor alpha) spread is statistically

bonds follow a pattern different from that in equities or in standard behavioral models. Thus, the theoretical behavioral models apply to equity markets, rather than to bonds. This is evidence indicative of RH rather than OH stated in H6.

We next examine H7 using corporate bond holdings data from the Thompson Reuter's eMAXX fixed income database. This database has comprehensive coverage of quarterly fixed income holdings for U.S. institutional investors such as insurance companies and mutual funds.[26] For a given bond i at quarter t, the institutional ownership measure is defined as

$$INST_{it} = \sum_j \left(\frac{Holding_{ijt}}{OutstandingAmt_{it}} \right) = \sum_j h_{jt} \tag{4}$$

where $INST_{it}$ is the institutional ownership of bond i in quarter t, $Holding_{ijt}$ denotes the par amount holdings of investor j on bond i in quarter t (from the eMAXX data), $OutstandingAmt_{it}$ is the outstanding amount of the bond i (from the Mergent FISD database), and h_{jt} is the fraction of the outstanding amount controlled by investor j, in percentage.

To test H7, we investigate whether the strength of the long-term reversal effect in corporate bonds is uniform across bonds with high and low institutional ownership. Specifically, we form value-weighted bivariate portfolios by independently sorting corporate bonds into 5×5 quintile portfolios based on institutional ownership (INST) prior to portfolio formation month (i.e., prior to month $t-48$) and long-term reversal (LTR), proxied by the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal months. Table 14 reports the 11-factor alpha for each of the 25 portfolios for month $t+1$ and shows that the 11-factor alpha spread between high-LTR and low-LTR quintiles is economically and statistically significant in all quintiles of institutional ownership. However, the magnitude of the alpha spreads is uniform across all INST quintiles. Specifically, the 11-factor alpha spreads between LTR-winners and LTR-losers are -0.46% (t-stat. $= -2.63$) and -0.45% (t-stat. $= -2.55$) for the low and high institutional ownership quintiles, respectively, indicating that the long-term reversal effect does not differ in bonds with low vs. high institutional ownership.

insignificant for four years after portfolio formation.

[26]eMAXX reports the quarterly holdings based on regulatory disclosure to the National Association of Insurance Commissioners (NAIC) and the Securities and Exchange Commission (SEC) for insurance companies and mutual funds, respectively. For major pension funds, it is a voluntary disclosure.

Thus, the evidence in Table 14 is at odds with H7.

Overall, though we cannot completely rule out the overreaction hypothesis, the findings support RH as the likeliest explanation for the profitability of LTR^{Bond}. The results accord with the notion that LTR^{Bond} represents investors' ex-ante assessment of credit risk that is not captured by extant bond risk factors or default risk metrics. In turn, this risk is priced in the cross-section of bond returns.

6 Conclusion

We show that contrarian strategies based on long-term returns are statistically and economically profitable in the corporate bond market. The dependence of corporate bond returns on past long-run returns obtains even as it disappears for equities during our sample period. We introduce a novel corporate bond factor based on the long-term reversal and show that the premium on this factor survives long-established stock and bond market factors. We further examine the explanatory power of the newly proposed long-term reversal factor for alternative test portfolios constructed based on bond size, rating, maturity, and industry. We find that a four-factor model with the bond market factor, the long-term reversal factor, and two other return-based factors (short-term reversals and momentum) outperforms existing factor models in predicting the returns of the industry- and size/rating/maturity-sorted portfolios of corporate bonds. Moreover, the empirical performance of the past return-based factors is found to be comparable to the risk-based factor model of Bai, Bali, and Wen (2017), with the long-term reversal factor playing a significant role.

Are long-term reversals in bonds compensation for risk or overreaction? We make progress on this issue via a series of tests. We show that the long-term reversal effect is principally driven by losers that also experience an increase in credit risk, where such risk is measured either by metrics based on financial statements or the more subjective published bond ratings. Although long-term reversals are driven by a subset of bonds, the role of the long-term reversal factor in pricing the cross-section of bonds is pervasive. The overreaction hypothesis suggests that under short-selling constraints, we would expect greater profits for winners rather than losers, since arbitrageurs would face costs in shorting winners. However, bond market reversals are driven by losers. Further, bond market momentum is not followed by reversals, so that long-term reversals in bonds are independent of intermediate-term momentum. This implies that behavioral theories of momentum followed by reversals apply more to equity markets than bonds. Finally, while lower institutional holdings might imply a less sophisticated clientele more prone to overreaction, we find that long-term reversals are not stronger in bonds reported to be held proportionally less by institutions.

On balance, our findings support the notion that long-term reversals represent an increase in required returns for bonds with increasing risk and consequently falling prices. In turn, the evidence indicates that past returns capture investors' ex-ante risk assessment that is not captured by the standard metrics for credit quality we consider, and that commands a premium in the cross-section of corporate debt. Our work raises at least two issues. First, does the role of past long-run returns in explaining future corporate bond returns extend to international markets? Second, does the pattern of long-term reversals extend to other asset classes? These and other topics are left for future research.

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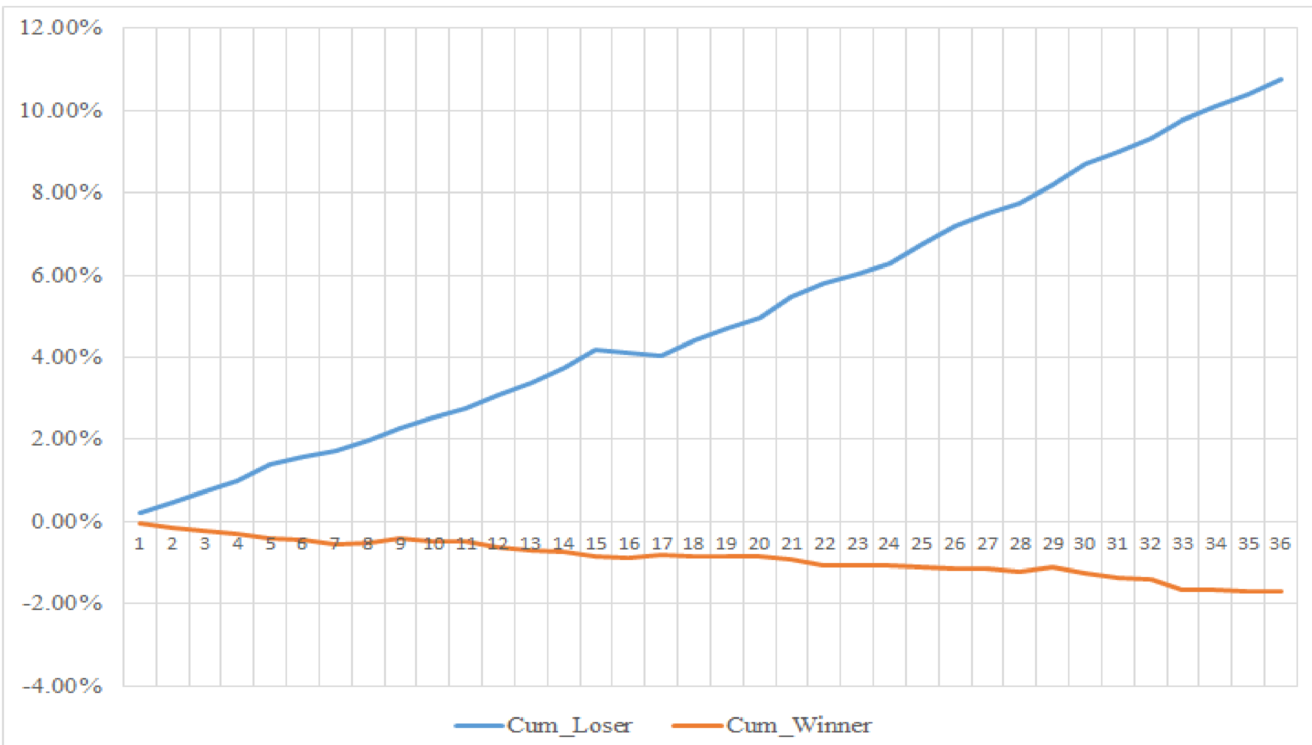
Figure 1: Post-formation Cumulative Return for the LTR-sorted Portfolios



This figure presents the cumulative monthly post-formation returns of the corporate bonds sorted by long-term reversal (LTR). Following DeBondt and Thaler (1985), we use non-overlapping three-year periods for portfolio formation, and use the subsequent three years as the test period. Cumulative abnormal returns are estimated using the 4-factor alphas for LTR-losers and LTR-winners based on the aggregate corporate bond market (MKT^{Bond}), the downside risk factor (DRF^{Bond}), the credit risk factor (CRF^{Bond}), and the liquidity risk factor (LRF^{Bond}) of Bai, Bali, and Wen (2017). The sample covers the period from January 1977 to December 2017.

Table 1: Descriptive Statistics

Panel A reports the number of bond-month observations, the cross-sectional mean, median, standard deviation and monthly return percentiles of corporate bonds, and bond characteristics including credit rating, time-to-maturity (Maturity, year), amount outstanding (Size, $ million), illiquidity (ILLIQ), and long-term reversal (LTR). Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. Numerical ratings of 10 or below (BBB- or better) are considered investment-grade, and ratings of 11 or higher (BB+ or worse) are labeled high yield. ILLIQ is calculated as the autocovariance of the price changes. LTR is the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and the short-term reversal month in $t-1$. Panel B reports the time-series average of the cross-sectional correlations. The sample period is from January 1977 to December 2017.

Panel A: Cross-sectional statistics over the sample period of January 1977 – December 2017

					Percentiles					
	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Bond return (%)	1,782,998	0.69	0.64	2.84	-6.59	-2.74	-0.31	1.64	4.18	8.68
Rating	1,782,998	7.88	7.13	3.94	2.1	2.84	5.14	9.54	15.86	19.91
Time-to-maturity (maturity, year)	1,782,998	12.66	10.28	8.4	3.01	3.67	6.75	16.9	27.64	34.67
Amount Out (size, $million)	1,782,998	279.12	204.24	284.07	25.69	40.23	101.85	346.54	797.66	1450.15
ILLIQ	1,782,998	4.76	1.24	16.52	0.03	0.12	0.55	2.97	19.04	74.19
LTR (%)	1,782,998	28.25	26.58	19.69	-18.88	-7.17	19.89	33.34	55.49	95.49

Panel B: Average cross-sectional correlations

	Rating	Maturity	Size	ILLIQ	LTR
Rating	1	-0.151	-0.119	0.277	0.101
Maturity		1	0.070	0.027	0.035
Size			1	-0.033	-0.041
ILLIQ				1	-0.044
LTR					1

Table 2: Univariate Portfolios of Corporate Bonds Sorted by Long-term Reversal

Quintile portfolios are formed every month from January 1977 to December 2017 by sorting corporate bonds based on their long-term reversal (LTR), proxied by the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal month. Quintile 1 is the portfolio with the lowest LTR, and Quintile 5 is the portfolio with the highest LTR. Table reports the average LTR, the next-month average excess return, the 7-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 11-factor alpha for each quintile. The last five columns report average portfolio characteristics including bond beta (β^{Bond}), illiquidity (ILLIQ), credit rating, time-to-maturity (years), and amount outstanding (size, in $billion) for each quintile. The last row shows the differences in monthly average returns, and the differences in alphas with respect to the factor models. The 7-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the stock momentum factor (MOM^{Stock}), the stock liquidity factor (LIQ^{Stock}), the short-term reversal factor (STR^{Stock}), and the long-term reversal factor (LTR^{Stock}). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the downside risk factor (DRF^{Bond}), the credit risk factor (CRF^{Bond}), and the liquidity risk factor (LRF^{Bond}). The 11-factor model combines 7 stock market factors and 4 bond market factors. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor stock	4-factor bond	11-factor	Average portfolio characteristics				
	LTR	return	alpha	alpha	alpha	β^{Bond}	ILLIQ	Rating	Maturity	Size
Low	-7.14	1.02	1.07	0.51	0.47	1.15	15.40	8.05	10.89	0.28
		(5.21)	(4.17)	(5.30)	(5.05)					
2	19.62	0.45	0.41	0.20	0.19	0.86	3.29	6.74	10.49	0.29
		(3.68)	(2.92)	(2.24)	(1.91)					
3	24.38	0.34	0.26	0.08	0.05	0.76	2.32	6.61	10.92	0.31
		(3.12)	(2.34)	(0.77)	(1.23)					
4	29.22	0.33	0.25	-0.05	-0.08	0.79	2.17	6.89	12.24	0.29
		(3.10)	(2.29)	(-0.10)	(-0.68)					
High	47.52	0.55	0.47	0.09	0.03	0.32	6.25	8.94	12.85	0.26
		(5.16)	(4.10)	(0.29)	(0.44)					
High − Low		-0.47***	-0.60***	-0.43***	-0.44***					
Return/Alpha diff.		(-3.27)	(-3.31)	(-3.59)	(-3.76)					

Table 3: Bivariate Portfolios of Corporate Bonds Sorted by Long-term Reversal Controlling for Bond Characteristics

Quintile portfolios are formed every month from January 1977 to December 2017 by sorting corporate bonds based on credit rating, maturity, size, illiquidity, bond market beta (β^{Bond}), previous month return (STR^{Bond}), or previous 11-month cumulative returns (MOM^{Bond}). Then, within each control quintile, corporate bonds are further sorted into sub-quintiles based on their long-term reversal (LTR), proxied by the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal month. "LTR,1" is the portfolio of corporate bonds with the lowest LTR within each quintile portfolio and "LTR,5" is the portfolio of corporate bonds with the highest LTR within each quintile portfolio. The portfolios are value-weighted using amount outstanding as weights. Table shows the 11-factor alpha for each quintile. The last row shows the differences in alphas with respect to the 11-factor model, which combines the 7 stock and 4 bond market factors. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Control variable	Credit rating	Maturity	Size	Illiquidity	β^{Bond}	STR^{Bond}	MOM^{Bond}
LTR,1	0.47	0.55	0.60	0.45	0.46	0.36	0.36
	(4.12)	(3.25)	(3.02)	(3.48)	(3.38)	(4.35)	(3.28)
LTR,2	0.17	0.16	0.23	0.18	0.15	0.12	0.12
	(1.99)	(1.87)	(1.83)	(1.97)	(1.76)	(2.16)	(1.46)
LTR,3	0.17	0.07	0.14	0.17	0.10	0.07	0.10
	(2.00)	(1.28)	(1.65)	(1.65)	(1.37)	(1.44)	(1.21)
LTR,4	0.15	-0.06	-0.11	-0.10	-0.11	-0.04	-0.09
	(1.73)	(-0.10)	(-1.44)	(-1.16)	(-1.36)	(-0.04)	(-1.05)
LTR,5	0.14	0.28	0.22	0.13	0.18	0.01	0.04
	(2.91)	(2.67)	(2.72)	(2.30)	(2.75)	(3.48)	(1.49)
LTR,5 - LTR,1	-0.32**	-0.37**	-0.38***	-0.33***	-0.29**	-0.35**	-0.32***
Return/Alpha diff.	(-2.60)	(-2.62)	(-2.78)	(-2.63)	(-2.58)	(-2.42)	(-3.64)

Table 4: LTR Return Premia Over Time

This table reports the average monthly return spreads and their t-statistics from the long-short univariate portfolios of corporate bonds sorted by LTR, conditioning on different states of the economy (CFNAI), macroeconomic uncertainty index (JLN), default risk (ΔDEF), and illiquidity (ILLIQ). The LTR^{premia} is the average return on the LTR-based strategy buying LTR-losers (quintile 1) and selling LTR-winners (quintile 5). The long-short portfolios are value-weighted using amount outstanding as weights. LTR^{premia} covers the period from January 1977 to December 2017.

	LTR^{premia}	
	Mean	t-stat
Non-recessionary periods (CFNAI > 0)	0.23	3.37
Recessionary periods (CFNAI ≤ 0)	1.42	3.03
Low macroeconomic uncertainty (JLN $\leq$ JLN^{Median})	0.17	2.41
High macroeconomic uncertainty (JLN $>$ JLN^{Median})	0.71	3.74
Aggregate default risk decrease (ΔDEF ≤ 0)	0.49	3.37
Aggregate default risk increases (ΔDEF > 0)	0.66	2.49
Low aggregate illiqudity (ILLIQ $\leq$ ILLIQ^{Median})	0.30	2.35
High aggregate illiquidity (ILLIQ $>$ ILLIQ^{Median})	0.58	3.67

Table 5: Fama-MacBeth Cross-Sectional Regressions

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the long-term reversal (LTR), with and without controls. Bond characteristics include time-to-maturity (years) and amount outstanding (size, in $billion). Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. β^{Bond} is the individual bond exposure to the aggregate bond market portfolio, proxied by the Merrill Lynch U.S. Aggregate Bond Index. β^{DEF} is the default beta and β^{TERM} is the term beta. ILLIQ is the Roll's measure of bond-level illiquidity. STR is the short-term reversal proxied by previous month return. MOM is the bond momentum, defined as the past 11-month cumulative returns from $t-12$ to $t-2$, skipping month $t-1$. The Fama and MacBeth regressions are run each month for the period from January 1977 to December 2017. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last column reports the average adjusted R^2 values. Numbers in bold denote statistical significance at the 5% level or below.

	Intercept	LTR	STR	MOM	β^{Bond}	β^{DEF}	β^{TERM}	Rating	Maturity	Size	ILLIQ	Adj. R^2
(1)	0.801	**-0.014**										0.022
	(3.84)	(-3.49)										
(2)	-0.131	**-0.008**			0.005	0.118	-0.264	**0.066**	0.012	0.001	**0.050**	0.209
	(-1.55)	(-3.78)			(0.08)	(1.83)	(-1.40)	(7.44)	(1.40)	(0.01)	(6.43)	
(3)	0.510	**-0.009**	**-0.034**	**0.017**								0.151
	(3.92)	(-3.53)	(-5.50)	(2.57)								
(4)	0.233	**-0.007**	**-0.128**	**0.023**	-0.041	-0.144	0.011	**0.051**	0.007	0.054	**0.050**	0.279
	(0.93)	(-2.36)	(-4.17)	(2.19)	(-0.24)	(-1.14)	(0.12)	(6.85)	(1.71)	(0.76)	(2.79)	

Table 6: Explanatory Power of Alternative Factor Models for Size and Maturity-Sorted Bond Portfolios

The table reports the intercepts (alphas), the t-statistics, and the adjusted R^2 values for the time-series regressions of the test portfolios' excess returns on alternative factor models. The 25 test portfolios are formed by independently sorting corporate bonds into 5 by 5 quintile portfolios based on size (amount outstanding) and maturity and then constructed from the intersections of the size and maturity quintiles. The portfolios are value-weighted using amount outstanding as weights. The stock factors include MKT^{Stock}, SMB, HML, RMW, CMA, STR^{Stock}, MOM^{Stock}, LTR^{Stock}, and LIQ^{Stock}. The bond factors include MKT^{Bond}, DEF, TERM, and LIQ^{Bond}.

The alternative models include:

Model 1: Stock Factors + Bond Factors
Model 2: Stock Factors + Bond Factors + LTR^{Bond}
Model 3: Stock Factors + Bond Factors + LTR^{Bond} + MOM^{Bond} + STR^{Bond}

Model 4: Stock Factors + Bond Factors + DRF + CRF + LRF
Model 5: Stock Factors + Bond Factors + DRF + CRF + LRF + LTR^{Bond}
Model 6: Stock Factors + Bond Factors + DRF + CRF + LRF + LTR^{Bond} + MOM^{Bond} + STR^{Bond}

Panel A: Model 1

Alpha (α)	Short	2	3	4	Long
Small	0.36	0.44	0.48	0.35	0.36
2	0.31	0.37	0.40	0.28	0.41
3	0.31	0.35	0.30	0.38	0.47
4	0.28	0.31	0.32	0.34	0.43
Big	0.21	0.32	0.45	0.42	0.58
Average $\|\alpha\|$	0.37				
p-GRS	< 0.01				

t-statistics	Short	2	3	4	Long
Small	2.10	1.82	1.94	1.76	1.72
2	2.99	2.39	2.27	0.93	2.23
3	4.22	3.11	2.13	2.85	2.63
4	3.50	3.01	2.18	2.35	2.09
Big	2.55	2.93	2.68	2.66	2.49

Adj. R^2	Short	2	3	4	Long
Small	0.10	0.05	0.05	0.08	0.09
2	0.14	0.21	0.19	0.07	0.09
3	0.27	0.28	0.35	0.24	0.16
4	0.24	0.25	0.29	0.14	0.09
Big	0.12	0.09	0.12	0.04	0.02
Average R^2	0.15				

Panel B: Model 2

	Short	2	3	4	Long
Small	0.12	0.12	0.22	0.17	0.18
2	0.16	0.08	0.10	0.03	0.19
3	0.14	0.13	0.05	0.22	0.31
4	0.11	0.11	0.09	0.17	0.29
Big	0.13	0.19	0.23	0.31	0.40
Average $\|\alpha\|$	0.17				
p-GRS	0.02				

	Short	2	3	4	Long
Small	0.68	0.49	0.87	0.82	0.83
2	1.55	0.55	0.58	-0.09	1.03
3	2.10	1.23	0.36	1.61	1.66
4	1.48	1.11	0.61	1.18	1.36
Big	1.51	1.73	1.38	1.88	2.06

	Short	2	3	4	Long
Small	0.36	0.26	0.19	0.22	0.22
2	0.44	0.68	0.59	0.22	0.30
3	0.94	0.81	0.86	0.53	0.34
4	0.82	0.77	0.70	0.36	0.19
Big	0.29	0.28	0.36	0.10	0.04
Average R^2	0.44				

Panel C: Model 3

	Short	2	3	4	Long
Small	0.07	0.09	-0.09	0.10	0.13
2	0.07	0.06	0.08	0.07	0.12
3	0.05	0.06	-0.05	-0.09	-0.11
4	-0.05	-0.07	-0.06	0.08	0.12
Big	-0.05	0.09	0.08	0.11	0.15
Average $\|\alpha\|$	0.08				
p-GRS	0.01				

	Short	2	3	4	Long
Small	0.80	0.76	-0.66	0.89	1.10
2	1.35	0.77	0.86	0.43	1.15
3	1.38	1.07	-0.74	-1.26	-1.11
4	-1.36	-1.34	-0.73	1.07	1.07
Big	1.17	1.55	0.92	1.25	1.13

	Short	2	3	4	Long
Small	0.38	0.32	0.18	0.24	0.24
2	0.44	0.77	0.71	0.22	0.36
3	0.99	0.94	0.98	0.65	0.43
4	0.92	0.92	0.84	0.46	0.30
Big	0.31	0.32	0.37	0.12	0.19
Average R^2	0.50				

Panel D: Model 4

	Alpha (α)				
	Short	2	3	4	Long
Small	-0.06	-0.18	-0.16	-0.12	-0.15
2	0.00	-0.04	-0.05	-0.41	-0.05
3	0.17	0.04	-0.03	0.05	0.08
4	0.15	0.14	-0.01	0.04	0.06
Big	0.00	0.02	-0.02	0.05	0.05
Average $\lvert\alpha\rvert$	0.10				
p-GRS	0.02				

	t-statistics				
	Short	2	3	4	Long
Small	-1.56	-2.14	-2.44	-2.61	-3.04
2	0.08	-1.19	-1.27	-4.45	-1.08
3	2.43	1.55	-0.77	1.22	1.56
4	2.73	1.78	-0.36	1.02	0.89
Big	-0.18	0.70	-0.61	1.13	0.82

	Adj. R^2				
	Short	2	3	4	Long
Small	0.67	0.72	0.69	0.62	0.62
2	0.70	0.63	0.65	0.65	0.60
3	0.68	0.65	0.69	0.51	0.42
4	0.67	0.59	0.60	0.38	0.34
Big	0.65	0.60	0.69	0.46	0.46
Average R^2	0.60				

Panel E: Model 5

	Short	2	3	4	Long
Small	-0.03	-0.11	-0.06	-0.06	-0.09
2	-0.01	-0.04	-0.06	-0.21	-0.04
3	0.02	0.00	-0.03	0.01	0.03
4	0.01	0.00	-0.02	0.01	0.04
Big	0.01	0.01	-0.01	0.04	0.08
Average $\lvert\alpha\rvert$	0.04				
p-GRS	0.01				

Short	2	3	4	Long
-0.82	-2.54	-1.29	-1.46	-2.03
-0.37	-1.53	-1.74	-3.93	-1.17
1.10	-0.13	-1.09	0.38	0.73
0.58	0.08	-0.74	0.31	0.66
0.83	0.58	-0.33	0.98	1.44

	Short	2	3	4	Long
Small	0.60	0.63	0.64	0.71	0.67
2	0.67	0.75	0.76	0.72	0.78
3	0.72	0.79	0.83	0.82	0.77
4	0.71	0.77	0.80	0.78	0.73
Big	0.68	0.73	0.75	0.75	0.72
Average R^2	0.73				

Panel F: Model 6

	Alpha (α)				
	Short	2	3	4	Long
Small	0.00	-0.08	-0.06	-0.03	-0.02
2	0.01	-0.02	0.00	-0.14	0.02
3	0.02	0.01	-0.01	0.04	0.05
4	0.03	0.02	-0.01	0.03	0.06
Big	0.02	0.03	-0.01	0.05	0.06
Average $\lvert\alpha\rvert$	0.03				
p-GRS	0.01				

t-statistics				
Short	2	3	4	Long
-0.06	-1.37	-0.91	-0.48	-0.41
0.41	-0.58	-0.08	-2.04	0.31
0.95	0.32	-0.17	0.83	0.81
1.29	0.69	-0.13	0.67	0.91
0.85	1.07	-0.25	0.91	0.91

	Adj. R^2				
	Short	2	3	4	Long
Small	0.63	0.66	0.67	0.75	0.72
2	0.71	0.80	0.80	0.75	0.83
3	0.77	0.83	0.88	0.86	0.82
4	0.75	0.83	0.85	0.83	0.78
Big	0.71	0.76	0.78	0.79	0.76
Average R^2	0.77				

Table 7: Explanatory Power of Alternative Factor Models for Size and Rating-Sorted Bond Portfolios

The table reports the intercepts (alphas), the t-statistics, and the adjusted R^2 values for the time-series regressions of the test portfolios' excess returns on alternative factor models. The 25 test portfolios are formed by independently sorting corporate bonds into 5 by 5 quintile portfolios based on size (amount outstanding) and rating and then constructed from the intersections of the size and rating quintiles. The portfolios are value-weighted using amount outstanding as weights. Stock factors include MKT^{Stock}, SMB, HML, MOM^{Stock}, LIQ^{Stock}, RMW, and CMA. Bond factors include MKT^{Bond}, DEF, TERM, and LIQ^{Bond}.

The alternative models include:

Model 1: Stock Factors + Bond Factors
Model 2: Stock Factors + Bond Factors + LTR^{Bond}
Model 3: Stock Factors + Bond Factors + LTR^{Bond} + MOM^{Bond} + STR^{Bond}

Model 4: Stock Factors + Bond Factors + DRF + CRF + LRF
Model 5: Stock Factors + Bond Factors + DRF + CRF + LRF + LTR^{Bond}
Model 6: Stock Factors + Bond Factors + DRF + CRF + LRF + LTR^{Bond} + MOM^{Bond} + STR^{Bond}

Panel A: Model 1

Alpha (α)	Low	2	3	4	High
Small	0.22	0.12	0.37	0.76	1.26
2	0.22	0.21	0.23	0.29	0.64
3	0.25	0.29	0.30	0.28	0.44
4	0.29	0.28	0.27	0.24	0.47
Big	0.28	0.29	0.34	0.28	0.71
Average $\|\alpha\|$	0.37				
p-GRS	< 0.01				

t-statistics	Low	2	3	4	High
Small	1.60	0.57	1.38	2.34	2.68
2	1.63	1.18	1.60	1.59	2.27
3	2.51	2.57	2.77	2.23	2.08
4	2.79	2.28	2.22	1.92	1.92
Big	2.32	2.10	2.36	1.86	2.41

Adj. R^2	Low	2	3	4	High
Small	0.09	0.05	0.05	-0.01	-0.01
2	0.04	0.01	0.04	0.02	0.00
3	0.05	0.16	0.15	0.14	0.07
4	0.07	0.21	0.33	0.30	0.19
Big	0.14	0.18	0.38	0.30	0.24
Average R^2	0.13				

Panel B: Model 2

	Low	2	3	4	High
Small	-0.12	-0.06	0.15	0.44	0.65
2	0.13	0.12	0.12	0.14	0.32
3	0.15	-0.18	0.18	0.16	0.24
4	0.18	0.18	0.16	0.14	0.21
Big	0.12	0.17	0.19	0.16	0.35
Average $\|\alpha\|$	0.18				
p-GRS	0.02				

	Low	2	3	4	High
Small	-0.96	-0.34	0.65	1.46	1.38
2	1.02	0.74	0.88	0.77	1.18
3	1.51	-1.68	1.69	1.31	1.15
4	1.77	1.53	1.42	1.17	1.09
Big	1.43	1.29	1.40	1.09	1.15

	Low	2	3	4	High
Small	0.47	0.62	0.69	0.46	0.28
2	0.31	0.52	0.61	0.35	0.49
3	0.24	0.32	0.40	0.60	0.66
4	0.12	0.33	0.41	0.56	0.51
Big	0.22	0.33	0.39	0.41	0.30
Average R^2	0.42				

Panel C: Model 3

	Low	2	3	4	High
Small	-0.12	-0.11	0.01	0.17	0.57
2	0.13	0.12	-0.11	-0.16	0.24
3	0.14	0.17	0.14	-0.10	0.13
4	0.24	0.22	0.17	0.13	0.13
Big	-0.24	-0.22	0.23	0.12	0.12
Average $\|\alpha\|$	0.16				
p-GRS	0.02				

	Low	2	3	4	High
Small	-1.20	-0.73	0.06	0.63	1.34
2	0.98	0.85	-0.80	-0.93	1.78
3	1.90	1.92	1.94	-0.89	1.40
4	2.24	1.71	1.46	1.12	1.21
Big	-1.90	-1.53	1.63	0.83	1.84

	Low	2	3	4	High
Small	0.22	0.18	0.14	0.01	0.06
2	0.15	0.10	0.23	0.14	0.23
3	0.33	0.43	0.54	0.55	0.31
4	0.80	0.81	0.94	0.91	0.77
Big	0.49	0.95	0.84	0.89	0.53
Average R^2	0.46				

Panel D: Model 4

Alpha (α)

	Low	2	3	4	High
Small	-0.07	-0.28	-0.26	0.00	-0.22
2	-0.05	-0.10	-0.07	-0.09	-0.05
3	0.13	0.05	0.14	0.04	-0.09
4	0.38	0.05	0.08	0.01	-0.11
Big	0.04	0.04	0.07	-0.05	-0.03
Average $\|\alpha\|$	0.11				
p-GRS	0.02				

t-statistics

	Low	2	3	4	High
Small	-0.64	-2.45	-1.65	0.01	-2.06
2	-0.45	-1.53	-0.68	-0.60	-0.26
3	1.56	1.69	1.55	0.36	-0.70
4	2.23	1.48	0.82	0.13	-0.66
Big	1.25	0.37	0.64	-0.47	-0.88

Adj. R^2

	Low	2	3	4	High
Small	0.52	0.49	0.66	0.53	0.69
2	0.50	0.48	0.57	0.48	0.77
3	0.43	0.41	0.43	0.53	0.76
4	0.40	0.36	0.43	0.50	0.71
Big	0.48	0.52	0.46	0.57	0.83
Average R^2	0.54				

Panel E: Model 5

	Low	2	3	4	High
Small	-0.02	-0.14	-0.11	-0.20	-0.03
2	-0.02	-0.08	-0.02	-0.05	-0.14
3	0.05	0.05	0.04	-0.02	-0.08
4	0.06	0.06	0.02	-0.02	-0.08
Big	0.06	0.04	0.04	-0.03	-0.01
Average $\|\alpha\|$	0.06				
p-GRS	0.01				

	Low	2	3	4	High
Small	-0.41	-2.03	-1.50	-2.17	-0.25
2	-0.55	-1.44	-0.34	-0.83	-2.17
3	1.51	1.26	1.15	-0.51	-1.42
4	1.66	1.29	0.45	-0.43	-1.18
Big	1.62	0.98	0.86	-0.65	-0.08

	Low	2	3	4	High
Small	0.59	0.55	0.71	0.70	0.77
2	0.58	0.55	0.63	0.53	0.89
3	0.53	0.50	0.52	0.65	0.89
4	0.51	0.45	0.54	0.62	0.83
Big	0.58	0.61	0.56	0.67	0.94
Average R^2	0.64				

Panel F: Model 6

	Low	2	3	4	High
Small	0.01	-0.05	-0.11	-0.05	-0.07
2	0.01	-0.02	-0.01	0.00	-0.04
3	0.05	0.06	0.05	0.00	-0.04
4	0.06	0.06	0.03	0.01	-0.03
Big	0.05	0.04	0.04	-0.01	0.00
Average $\|\alpha\|$	0.04				
p-GRS	0.01				

	Low	2	3	4	High
Small	0.06	-0.87	-1.83	-0.77	-0.70
2	-0.08	-0.55	-0.33	-0.01	-0.74
3	1.64	1.95	1.65	-0.03	-0.86
4	2.22	1.70	0.97	0.20	-0.55
Big	1.56	1.05	1.13	-0.30	-0.09

	Low	2	3	4	High
Small	0.62	0.62	0.57	0.56	0.63
2	0.59	0.59	0.56	0.53	0.64
3	0.74	0.68	0.60	0.61	0.64
4	0.75	0.56	0.71	0.70	0.71
Big	0.80	0.95	0.95	0.87	0.97
Average R^2	0.68				

Table 8: Explanatory Power of Alternative Factor Models for Industry-Sorted Portfolios of Corporate Bonds

The table reports the intercepts (alphas), the t-statistics, and the adjusted R^2 values for the time-series regressions of the test portfolios' excess returns on alternative factor models. The industry portfolios are formed by univariate sorting corporate bonds into 12 portfolios based on the Fama-French industry classifications. The portfolios are value-weighted using amount outstanding as weights. The alternative models are the same as in Table 6.

Panel A: Alpha

Industry #	1	2	3	4	5	6	7	8	9	10	11	12	Average	
Description	NoDur	Durables	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Finance	Other	Alpha	p-GRS
Model 1	0.28	0.67	0.54	0.53	0.42	0.35	0.42	0.17	0.34	0.28	0.21	0.47	0.39	< 0.01
Model 2	-0.12	0.20	0.25	0.28	0.23	0.14	0.18	0.08	0.13	0.12	-0.06	0.16	0.16	0.02
Model 3	-0.09	0.20	0.19	0.17	0.15	0.12	0.16	-0.06	0.10	0.11	-0.08	0.15	0.13	0.02
Model 4	-0.07	0.19	0.15	0.13	0.13	-0.10	0.13	-0.06	0.08	0.09	0.07	0.13	0.11	0.02
Model 5	0.05	0.08	-0.10	0.15	0.13	-0.06	0.09	0.05	0.04	-0.06	0.03	0.06	0.08	0.02
Model 6	0.03	0.06	0.07	-0.10	0.18	0.04	-0.05	0.03	0.02	-0.03	0.01	0.04	0.03	0.02

Panel B: t-statistics

Industry #	1	2	3	4	5	6	7	8	9	10	11	12
Description	NoDur	Durables	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Finance	Other
Model 1	2.27	1.25	2.32	0.82	1.17	1.94	2.22	2.17	1.84	1.74	2.18	2.14
Model 2	-0.73	0.65	1.83	0.72	1.03	1.33	1.61	1.71	1.20	1.21	-1.13	1.33
Model 3	-1.23	1.23	3.21	1.34	1.83	2.09	2.41	-0.42	1.77	1.65	-1.61	1.31
Model 4	-1.26	0.70	1.29	0.42	0.74	-1.09	1.42	-1.47	0.92	1.11	1.41	1.21
Model 5	1.07	0.38	-1.13	0.56	0.85	-0.90	1.27	1.53	0.60	-0.94	0.85	0.82
Model 6	1.05	0.40	1.06	-0.52	0.99	0.73	-0.98	1.43	0.44	-0.63	0.68	0.72

Panel C: Adj. R^2

Industry #	1	2	3	4	5	6	7	8	9	10	11	12	Average
Description	NoDur	Durables	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Finance	Other	R^2
Model 1	0.32	0.05	0.16	0.03	0.11	0.19	0.22	0.43	0.20	0.23	0.35	0.20	0.21
Model 2	0.59	0.16	0.33	0.05	0.19	0.39	0.44	0.76	0.41	0.44	0.75	0.47	0.41
Model 3	0.61	0.19	0.38	0.19	0.40	0.42	0.47	0.76	0.45	0.44	0.80	0.52	0.47
Model 4	0.60	0.21	0.33	0.28	0.31	0.36	0.40	0.77	0.42	0.41	0.68	0.43	0.43
Model 5	0.85	0.23	0.50	0.09	0.27	0.53	0.61	1.02	0.64	0.60	1.03	0.70	0.59
Model 6	0.86	0.25	0.56	0.12	0.58	0.56	0.64	1.02	0.66	0.60	1.09	0.74	0.64

Table 9: Bivariate Portfolios of Long-term Reversal Controlling for Default Beta

Panel A reports the univariate LTR portfolios' exposure to the three bond market factors: MKT^{Bond}, DEF, and TERM. In Panel B, quintile portfolios are formed every month from January 1977 to December 2017 by first sorting corporate bonds based on default beta (β^{DEF}) into quintiles, then within each β^{DEF} portfolio, corporate bonds are sorted into sub-quintiles based on their LTR. Panel B reports the 11-factor alphas for each of the 25 portfolios. The 11-factor model combines 7 stock market factors and 4 bond market factors. The alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: LTR exposure to the standard bond market factors

	β^{Bond}	β^{DEF}	β^{TERM}
Low LTR	1.22	4.80	1.96
2	0.48	2.90	0.38
3	0.34	2.89	0.22
4	0.33	3.30	0.13
High LTR	0.52	3.50	0.15

Panel B: First sort on β^{DEF} then on LTR, 11-factor alpha

	Low LTR	2	3	4	High LTR	High − Low
Low β^{DEF}	0.06	0.04	0.06	0.08	0.03	-0.03
	(0.78)	(0.68)	(1.06)	(1.36)	(0.82)	(-0.37)
2	0.09	0.04	0.00	-0.02	0.02	-0.17*
	(1.12)	(0.83)	(0.07)	(-0.45)	(0.64)	(-1.91)
3	0.31	0.13	0.08	-0.07	0.07	-0.25**
	(2.50)	(2.04)	(1.37)	(-1.42)	(1.87)	(-2.50)
4	0.45	0.19	0.14	-0.08	0.09	-0.36***
	(2.77)	(2.65)	(2.20)	(-1.19)	(1.99)	(-3.06)
High β^{DEF}	1.98	1.02	0.92	0.85	0.85	-1.13***
	(7.04)	(3.35)	(3.61)	(4.04)	(5.86)	(-5.23)

Table 10: Long-term Reversal and Credit Ratings Downgrade

In Panel A, quintile portfolios are formed every month by sorting corporate bonds based on their long-term reversal (LTR), proxied by the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal months. Panel A reports the average change in credit ratings for the 12-, 24-, 36-, and 48-month portfolio formation windows for bonds in each quintile. The last row in Panel A shows the average differences in change in ratings between quintiles 5 and 1. In Panel B, portfolios are formed every month based on the change in ratings from $t-48$ to $t-13$. Panel B reports the corresponding average cumulative bond excess returns, as well as the average return and the 11-factor alpha for month t. Hodrick (1992) t-statistics are given in parentheses to account for overlapping longer-horizon returns. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2017.

Panel A: Quintile portfolios sorted by LTR

	ΔRating			
	$t-12:t$	$t-24:t$	$t-36:t$	$t-48:t$
Low LTR (Loser)	0.38	1.00	1.87	2.90
2	0.27	0.59	0.93	1.31
3	0.25	0.48	0.72	0.92
4	0.21	0.40	0.58	0.71
High LTR (Winner)	0.03	0.01	0.00	0.04
High − Low	-0.35***	-0.99***	-1.87***	-2.86***
t-stat	(-3.02)	(-5.21)	(-10.34)	(-12.58)

Panel B: Quintile portfolios sorted by change in ratings

	Cumulative returns from $t-48:t-13$	Average return for month t	11-factor alpha for month t
Low ΔRating	35.14	1.20	0.89
2	26.21	0.48	0.34
3	13.12	0.44	0.31
4	-2.68	0.46	0.32
High ΔRating	-8.53	0.67	0.46
High − Low	-43.67***	-0.52***	-0.44***
t-stat	(-12.80)	(-4.06)	(-3.88)

Table 11: Long-term Reversal and Changes in Financial Distress

Quintile portfolios are formed every month by sorting corporate bonds based on their long-term reversal (LTR), proxied by the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal months. Panel A reports the average change in financial distress (ΔFinancial distress) for the 12-, 24-, 36-, and 48-month portfolio formation windows for bonds in each quintile. Two proxies for financial distress are used: the failure probability measure of Campbell, Hilscher, and Szilagyi (2008) and the O-score measure of Ohlson (1980). The last row shows the average differences in change in financial distress between quintiles 5 and 1. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2017.

Panel A: Financial distress proxied by failure probability

	ΔFailure proability			
	$t-12:t$	$t-24:t$	$t-36:t$	$t-48:t$
Low LTR (Loser)	0.27	0.33	0.46	0.52
2	0.19	0.22	0.24	0.22
3	0.12	0.12	0.15	0.11
4	0.10	0.09	0.09	0.10
High LTR (Winner)	0.03	0.01	0.01	0.01
High − Low	-0.23***	-0.32***	-0.46***	-0.51***
t-stat	(-3.92)	(-4.35)	(-4.68)	(-6.38)

Panel B: Financial distress proxied by O-score

	ΔO-score			
	$t-12:t$	$t-24:t$	$t-36:t$	$t-48:t$
Low LTR (Loser)	-2.97	-3.62	-5.20	-5.70
2	-1.81	-2.03	-2.27	-2.58
3	-0.57	-0.56	-0.66	-0.93
4	0.52	0.48	0.85	0.78
High LTR (Winner)	2.25	1.80	3.04	3.76
High − Low	5.22***	5.42***	8.23***	9.46***
t-stat	(3.74)	(3.92)	(5.43)	(8.84)

Table 12: Does Long-term Reversal Signal Future Shifts in Credit Risk?

This table reports average slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead measures of credit risk on long-term reversal (LTR), with and without control variables. The two measures of credit risk are the distance-to-default (DD) and the credit default spread (CDS). LTR is defined as the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and the short-term reversal month. Bond characteristics include time-to-maturity (years), amount outstanding (size), illiquidity (ILLIQ), and bond market beta (β^{Bond}). The Fama and MacBeth regressions are run each month for the period from January 1977 to December 2017. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last column reports the average adjusted R^2 values. Numbers in bold denote statistical significance at the 5% level or better.

Model	Dep.var	LTR	Maturity	Size	ILLIQ	β^{Bond}	Adj. R^2
(1)	DD	**0.004**					0.047
		(4.21)					
(2)	DD	**0.003**	0.029	0.964	-0.085		0.176
		(3.85)	(12.95)	(5.25)	(-7.50)		
(3)	DD	**0.003**	0.009	0.548	-0.045	0.307	0.308
		(3.49)	(3.94)	(3.67)	(-5.08)	(0.49)	
(4)	RCDS	**-0.031**					0.056
		(-3.83)					
(5)	RCDS	**-0.021**	-0.052	-2.402	0.335		0.232
		(-3.75)	(-10.64)	(-5.96)	(8.00)		
(6)	RCDS	**-0.020**	-0.010	-1.472	0.237	-0.569	0.361
		(-4.73)	(-1.78)	(-4.08)	(6.93)	(-3.92)	

Table 13: Longer Horizons Momentum and Long-term Reversal Returns

This table reports the 11-factor alphas for the long-short momentum portfolio (Panel A) and the long-term reversal portfolio (Panel B) one, two, three, four, and five years after portfolio formation. Momentum is defined as the past 11-month cumulative returns from $t-12$ to $t-2$, skipping month $t-1$. LTR is the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and the short-term reversal month in $t-1$. The alphas are based on the 11-factor model that combines 7 stock market factors and 4 bond market factors in Table 2. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Momentum portfolios

	Months 1 to 12	Months 13 to 24	Months 25 to 36	Months 37 to 48	Months 49 to 60	Months 13 to 60
			11-factor alpha			
High − Low	0.23***	0.21**	0.13**	0.06	0.09	0.10
	(2.76)	(2.58)	(2.26)	(0.85)	(1.26)	(1.21)

Panel B: Long-term reversal portfolios

	Months 1 to 12	Months 13 to 24	Months 25 to 36	Months 37 to 48	Months 49 to 60	Months 13 to 60
			11-factor alpha			
High − Low	-0.43***	-0.31***	-0.28***	-0.14**	-0.09	-0.21**
	(-3.96)	(-3.06)	(-2.92)	(-2.30)	(-1.35)	(-2.43)

Table 14: Bivariate Portfolios of Long-term Reversal and Institutional Ownership

Quintile portfolios are formed every month prior to the portfolio formation month (i.e., prior to month $t-48$) by independently sorting corporate bonds based on their institutional ownership (INST) and long-term reversal (LTR) into 5×5 quintiles. LTR is proxied by the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal months. INST is defined as the total percentage of amount outstanding held by all investors. Table reports the 11-factor alphas for each of the 25 portfolios for month $t+1$. The 11-factor model combines 7 stock market factors and 4 bond market factors. The alphas are defined in monthly percentage terms. The last column of the table reports the average institutional ownership for each INST quintile. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2001 to December 2017.

	Low LTR	2	3	4	High LTR	High − Low	Average INST (%)
INST,1	1.06	0.64	0.35	0.49	0.54	-0.46**	12.65
	(3.34)	(3.73)	(2.32)	(3.64)	(4.12)	(-2.63)	
INST,2	0.48	0.25	0.17	0.20	-0.04	-0.52**	32.08
	(2.96)	(4.33)	(2.78)	(2.02)	(-0.73)	(-2.68)	
INST,3	0.45	0.24	0.25	0.13	-0.03	-0.48**	45.12
	(3.36)	(3.23)	(2.81)	(1.29)	(-0.22)	(-2.43)	
INST,4	0.83	0.18	0.15	0.23	0.34	-0.49**	54.67
	(3.73)	(3.50)	(2.51)	(2.46)	(0.57)	(-2.51)	
INST,5	0.42	0.23	0.21	0.25	-0.03	-0.45**	73.08
	(3.78)	(2.47)	(2.48)	(2.51)	(-0.60)	(-2.55)	

Long-Term Reversals in the Corporate Bond Market

Online Appendix

To save space in the paper, we present the robustness check results in the Online Appendix. Table A.1 confirms a significant long-term reversal effect for the 12-, 24-, and 36-month ahead returns. Table A.2 presents similar results for the long-term reversal effect using non-overlapping three-year testing period. Table A.3 shows similar results for the LTR-sorted portfolios using alternative factor models. Table A.4 presents results of the long-term reversal effect using alternative measures of defaulting bond returns. Table A.5 presents results from the firm-level univariate portfolios of corporate bonds sorted by LTR using the median size bond or the most liquid bond as the representative for the firm. Table A.6 presents results from the firm-level Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the LTR, with and without controls. Table A.7 shows that stocks associated with non-investment-grade bonds do not exhibit long-term reversal during the same period as corporate bonds. Table A.8 shows that commonly used stock and bond market factors do not explain the long-term reversal factor return. Table A.9 reports the intercepts (α), factor loadings, and their t-statistics from time-series regressions of the long-term reversal factor on the bond market factor (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), the liquidity risk factor (LRF) in Bai, Bali, and Wen (2017), and the consumption-to-wealth ratio (CAY).

Table A.1: Longer-term Predictability from Univariate Portfolios of Corporate Bonds Sorted by Long-term Reversal

Quintile portfolios are formed every month from January 1977 to December 2017 by sorting corporate bonds based on their past 36-month cumulative returns (LTR) from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal month. Quintile 1 is the portfolio with the lowest LTR, and Quintile 5 is the portfolio with the highest LTR. Table reports the average excess return and the 11-factor alpha for each quintile, for 12-, 24-, and 36-month ahead returns. The 11-factor model combines 7 stock market factors and 4 bond market factors. The 7-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the stock momentum factor (MOM^{Stock}), the stock liquidity factor (LIQ^{Stock}), the short-term reversal factor (STR^{Stock}), and the long-term reversal factor (LTR^{Stock}). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the downside risk factor (DRF^{Bond}), the credit risk factor (CRF^{Bond}), and the liquidity risk factor (LRF^{Bond}). Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Average return			11-factor alpha		
	12-month ahead	24-month ahead	36-month ahead	12-month ahead	24-month ahead	36-month ahead
Low	0.71	0.75	0.61	0.39	0.44	0.37
	(5.01)	(3.78)	(4.13)	(3.49)	(2.53)	(2.71)
2	0.38	0.35	0.45	0.14	0.11	0.22
	(3.43)	(3.23)	(3.71)	(2.10)	(1.65)	(3.14)
3	0.34	0.33	0.38	0.11	0.09	0.14
	(3.05)	(3.09)	(3.35)	(1.67)	(1.51)	(2.32)
4	0.37	0.34	0.39	-0.12	-0.09	-0.13
	(2.88)	(3.22)	(3.51)	(-1.47)	(-0.85)	(-1.39)
High	0.51	0.49	0.41	0.21	0.21	0.16
	(4.02)	(4.48)	(4.60)	(2.59)	(3.18)	(4.39)
High - Low	-0.20***	-0.26***	-0.20**	-0.17**	-0.23**	-0.21**
Return/Alpha diff.	(-3.02)	(-2.79)	(-2.11)	(-2.26)	(-2.54)	(-2.36)

Table A.2: Univariate Portfolios of Long-term Reversal using a Non-overlapping Sample

Quintile portfolios are formed every month from January 1977 to December 2017 by sorting corporate bonds based on their past 36-month cumulative returns (LTR) from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal month. Quintile 1 is the portfolio with the lowest LTR, and Quintile 5 is the portfolio with the highest LTR. The portfolios are held for 36-months and then rebalance. Table reports the average LTR, the next-month average excess return, the 7-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 11-factor alpha for each quintile. The last five columns report average portfolio characteristics including bond beta (β^{Bond}), illiquidity (ILLIQ), credit rating, time-to-maturity (years), and amount outstanding (size, in $billion) for each quintile. The last row shows the differences in monthly average returns, and the differences in alphas with respect to the factor models. The 7-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the stock momentum factor (MOM^{Stock}), the stock liquidity factor (LIQ^{Stock}), the short-term reversal factor (STR^{Stock}), and the long-term reversal factor (LTR^{Stock}). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the downside risk factor (DRF^{Bond}), the credit risk factor (CRF^{Bond}), and the liquidity risk factor (LRF^{Bond}). The 11-factor model combines 7 stock market factors and 4 bond market factors. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average LTR	Average return	7-factor stock alpha	4-factor bond alpha	11-factor alpha	Average portfolio characteristics				
						β^{Bond}	ILLIQ	Rating	Maturity	Size
Low	-6.55	0.91	0.91	0.42	0.58	1.26	15.72	8.37	10.79	0.27
		(4.15)	(3.33)	(2.51)	(2.85)					
2	19.25	0.39	0.31	0.12	0.15	0.75	5.58	6.93	10.68	0.29
		(3.62)	(2.71)	(1.77)	(2.07)					
3	25.08	0.33	0.26	-0.07	-0.12	0.68	2.71	6.63	11.74	0.29
		(3.25)	(2.46)	(-1.33)	(-1.29)					
4	31.20	0.35	0.27	-0.15	-0.10	0.64	2.38	6.90	12.24	0.27
		(3.35)	(2.53)	(-1.27)	(-1.29)					
High	51.17	0.46	0.39	-0.06	0.17	0.56	3.33	8.32	12.24	0.27
		(4.45)	(3.58)	(-1.01)	(1.47)					
High − Low		-0.45***	-0.53**	-0.48**	-0.41**					
Return/Alpha diff.		(-2.81)	(-2.55)	(-2.40)	(-2.52)					

Table A.3: Univariate Portfolios of Long-term Reversal using Alternative Factor Models

Quintile portfolios are formed every month from January 1977 to December 2017 by sorting corporate bonds based on their past 36-month cumulative returns (LTR) from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal month. Quintile 1 is the portfolio with the lowest LTR, and Quintile 5 is the portfolio with the highest LTR. Table reports the next-month average excess return and factor alphas from bond market factors for each quintile. The 3-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), and the term spread factor (TERM). The 4-factor model with bond market factors adds the bond liquidity factor (LIQ^{Bond}). The 6-factor model with bond market factors adds the bond momentum factor (MOM^{Bond}) and the bond short-term reversal factor (STR^{Bond}). Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average return	3-factor bond alpha	4-factor bond alpha	6-factor bond alpha
Low	1.02	0.59	0.60	0.60
	(5.21)	(4.59)	(4.93)	(4.77)
2	0.45	0.12	0.13	0.13
	(3.68)	(1.92)	(2.06)	(2.26)
3	0.34	0.03	0.03	0.04
	(3.12)	(0.56)	(0.62)	(0.94)
4	0.33	0.01	0.01	0.03
	(3.10)	(0.20)	(0.24)	(0.31)
High	0.55	0.20	0.16	0.18
	(5.16)	(4.11)	(4.19)	(3.93)
High − Low	-0.47***	-0.40***	-0.44***	-0.42***
Return/Alpha diff.	(-3.27)	(-3.65)	(-3.93)	(-3.56)

Table A.4: Long-term Reversal Effect Using Alternative Measures of Defaulting Bond Returns

Quintile portfolios are formed every month from January 1977 to December 2017 by sorting corporate bonds based on their past 36-month cumulative returns (LTR) from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal month. Quintile 1 is the portfolio with the lowest LTR, and Quintile 5 is the portfolio with the highest LTR. Panel A uses default returns of -100% for bonds that default in the formation month t. Panel B of the table eliminates all bonds rated C or below in the formation month t. Table reports the next-month average excess return, the 7-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 11-factor alpha for each quintile. The last row shows the differences in monthly average returns, and the differences in alphas with respect to the factor models. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Using default returns of -100%

Quintiles	Average return	7-factor stock alpha	4-factor bond alpha	11-factor alpha
Low	0.90	0.91	0.36	0.28
	(4.79)	(3.83)	(2.94)	(2.82)
2	0.40	0.34	0.09	0.17
	(3.35)	(2.59)	(1.30)	(1.99)
3	0.30	0.22	0.03	0.07
	(2.77)	(1.94)	(0.45)	(1.03)
4	0.28	0.19	-0.01	0.03
	(2.64)	(1.76)	(-0.10)	(0.57)
High	0.42	0.35	-0.04	-0.14
	(2.22)	(2.26)	(-0.54)	(-0.77)
High − Low	-0.48***	-0.56***	-0.40**	-0.42**
Return/Alpha diff.	(-3.53)	(-3.34)	(-2.40)	(-2.59)

Panel B: Eliminating bonds with ratings C or below in the formation month

Quintiles	Average return	7-factor stock alpha	4-factor bond alpha	11-factor alpha
Low	0.94	0.97	0.36	0.34
	(4.89)	(3.93)	(2.96)	(3.35)
2	0.43	0.39	0.13	0.21
	(3.56)	(2.81)	(1.58)	(2.23)
3	0.33	0.25	0.06	0.10
	(3.01)	(2.22)	(0.33)	(0.50)
4	0.31	0.23	-0.04	-0.07
	(2.96)	(2.15)	(-0.73)	(-0.85)
High	0.41	0.42	-0.12	-0.09
	(4.75)	(3.70)	(-0.49)	(-0.95)
High - Low	-0.53***	-0.55***	-0.47**	-0.43***
Return/Alpha diff.	(-3.38)	(-3.18)	(-2.52)	(-2.78)

Table A.5: Firm-level Univariate Portfolios of Corporate Bonds Sorted by LTR

This table reports the firm-level univariate portfolios of corporate bonds sorted by LTR. To control for bonds issued by the same firm, for each month in our sample, we pick one bond with the median size (Panel A) or the most liquid bond (Panel B) as the representative for the firm. The portfolios are value-weighted using amount outstanding as weights. Table reports the average excess return and the 11-factor alpha for each quintile. The 11-factor model combines 7 stock market factors and 4 bond market factors. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Using the median size bond		Panel B: Using the most liquid bond	
	Average return	11-factor alpha	Average return	11-factor alpha
Low LTR	0.96	0.87	0.98	0.83
	(5.26)	(5.11)	(5.28)	(5.03)
2	0.44	0.25	0.44	0.25
	(3.73)	(1.28)	(3.74)	(1.32)
3	0.33	0.12	0.33	0.12
	(3.17)	(0.33)	(3.19)	(0.38)
4	0.32	-0.08	0.33	-0.09
	(3.17)	(-0.75)	(3.23)	(-0.82)
High LTR	0.55	0.32	0.55	0.31
	(5.27)	(1.65)	(5.34)	(1.61)
High − Low	-0.41***	-0.55***	-0.43***	-0.52***
Return/Alpha diff.	(-3.32)	(-3.50)	(-3.47)	(-3.62)

Table A.6: Firm-level Fama-MacBeth Cross-Sectional Regressions

This table reports the average intercept and slope coefficients from the firm-level Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the long-term reversal (LTR), with and without controls. To control for bonds issued by the same firm, for each month in our sample, we pick one bond with the median size (Panel A) or the most liquid bond (Panel B) as the representative for the firm. Bond characteristics include time-to-maturity (years) and amount outstanding (size, in \$billion). Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. β^{Bond} is the individual bond exposure to the aggregate bond market portfolio, proxied by the Merrill Lynch U.S. Aggregate Bond Index. β^{DEF} is the default beta and β^{TERM} is the term beta. ILLIQ is the Roll's measure of bond-level illiquidity. STR is the short-term reversal proxied by previous month return. MOM is the bond momentum, defined as the past 11-month cumulative returns from $t-12$ to $t-2$, skipping month $t-1$. The Fama and MacBeth regressions are run each month for the period from January 1977 to December 2017. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last column reports the average adjusted R^2 values. Numbers in bold denote statistical significance at the 5% level or below.

Panel A: Using the median size bond

	Intercept	LTR	STR	MOM	β^{Bond}	β^{DEF}	β^{TERM}	Rating	Maturity	Size	ILLIQ	Adj. R^2
(1)	0.725	**-0.007**										0.017
	(4.35)	(-2.52)										
(2)	0.269	**-0.011**			-0.107	-0.004	-0.040	**0.034**	0.008	-0.407	**0.067**	0.227
	(1.01)	(-3.03)			(-1.37)	(-0.06)	(-0.61)	(3.55)	(1.27)	(-1.46)	(3.39)	
(3)	0.490	**-0.009**	**0.026**	**0.014**								0.156
	(1.85)	(-2.67)	(-3.24)	(2.04)								
(4)	-0.039	**-0.035**	**-0.100**	0.030	0.354	-0.234	0.165	0.049	-0.067	-1.881	**0.334**	0.323
	(-0.05)	(-2.91)	(-4.05)	(0.85)	(0.48)	(-0.83)	(0.46)	(1.37)	(-1.34)	(-1.87)	(2.62)	

Panel B: Using the most liquid bond

	Intercept	LTR	STR	MOM	β^{Bond}	β^{DEF}	β^{TERM}	Rating	Maturity	Size	ILLIQ	Adj. R^2
(1)	0.730	**-0.007**										0.018
	(3.21)	(-2.72)										
(2)	0.326	**-0.010**			-0.131	-0.029	-0.019	**0.032**	0.007	-0.717	**0.086**	0.229
	(1.04)	(-3.14)			(-1.68)	(-0.49)	(-0.32)	(3.38)	(1.21)	(-1.49)	(3.52)	
(3)	0.490	**-0.009**	**-0.024**	**0.014**								0.148
	(1.71)	(-2.55)	(-2.65)	(2.01)								
(4)	-0.983	**-0.019**	**-0.041**	0.188	0.381	-0.232	0.161	0.044	-0.077	-1.489	**0.329**	0.323
	(-0.52)	(-2.62)	(-2.62)	(0.88)	(0.52)	(-0.83)	(0.45)	(1.21)	(-1.49)	(-1.64)	(2.61)	

Table A.7: Univariate Portfolios of Stocks Associated With Non-Investment-Grade Bonds Sorted by Stock Long-term Reversal

This table shows that stocks associated with the non-investment-grade bonds do not exhibit long-term reversal during the same period as corporate bonds. We identify stocks associated with the non-investment-grade bonds and form quintile portfolios by sorting individual stocks based on their past 36-month cumulative returns (LTR^{Stock}) from $t-48$ to $t-13$, skipping the 12-month momentum and short-term reversal month. Quintile 1 is the portfolio with the lowest LTR^{Stock}, and quintile 5 is the portfolio with the highest LTR^{Stock}. The portfolios are held for 36-months and then rebalance. Table reports the next-month average excess return, the 5-factor alpha from the Fama-French (2015) factors, and the Q-factor alpha from Hou, Xue, and Zhang (2015). Average returns and alphas are defined in monthly percentage terms. The sample period is from January 1977 to December 2017. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average return	FF 5-factor alpha	Q-factor alpha
Low LTR^{Stock}	0.64	0.68	0.66
	(4.07)	(4.06)	(4.07)
2	0.71	0.78	0.77
	(4.01)	(4.03)	(4.13)
3	0.70	0.76	0.72
	(3.23)	(3.35)	(3.11)
4	0.70	0.86	0.78
	(2.67)	(3.31)	(2.72)
High LTR^{Stock}	0.45	0.58	0.52
	(1.13)	(1.65)	(1.26)
High − Low	-0.19	-0.10	-0.15
	(-0.84)	(-0.35)	(-0.39)

Table A.8: Do the Existing Stock and Bond Market Factors Explain the Long-term Reversal Factor?

This table reports the intercepts (α) and their t-statistics from time-series regressions of the long-term reversal factor on the commonly used stock and bond market factors. LTR^{Bond} covers the period from January 1977 to December 2017. Panel A reports the results for the full sample and Panel B reports the results after removing Januaries from the sample to address a potential concern about seasonality.

Model 1: Stock market factors + Bond market factors

Stock market factors include MKT^{Stock}, SMB, HML, RMW, CMA, LIQ^{Stock}, STR^{Stock}, MOM^{Stock}, and LTR^{Stock} factors. Bond market factors include MKT^{Bond}, DEF, and TERM.

Model 2: Stock market factors + Bond market factors + MOM^{Bond} + STR^{Bond}

Stock and bond market factors with the bond momentum and short-term reversal factor.

Model 3: Stock market factors + Bond market factors + DRF + CRF + LRF

Stock and bond market factors with downside, credit, and liquidity risk factors.

Model 4: Stock market factors + Bond market factors + DRF + CRF + LRF + MOM^{Bond} + STR^{Bond}

All stock and bond market factors combined.

Panel A: Full sample, Dep. Var = LTR^{Bond}

	Model 1	Model 2	Model 3	Model 4
Alpha	**0.49**	**0.44**	**0.37**	**0.35**
t-stat	(5.28)	(4.79)	(4.52)	(4.40)
Adj. R^2 (%)	17.41	19.09	25.48	26.86

Panel B: Removing Januaries from the full sample, Dep. Var = LTR^{Bond}

	Model 1	Model 2	Model 3	Model 4
Alpha	**0.49**	**0.45**	**0.34**	**0.34**
t-stat	(4.87)	(4.33)	(4.29)	(4.29)
Adj. R^2 (%)	19.97	20.36	31.27	31.29

Table A.9: Time-series Regression of the Long-term Reversal Factor on the Bond Market Factors and the Consumption-to-Wealth Ratio (CAY)

This table reports the intercepts (α), factor loadings, and their t-statistics from time-series regressions of the long-term reversal factor on the bond market factor (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF) in Bai, Bali, and Wen (2017). Since CAY is measured quarterly, the time-series regression are conducted using quarterly data and factors. Numbers in bold indicate significance at the 5% or below. LTR^{Bond} covers the period from January 1977 to December 2017.

	Alpha	β^{Bond}	β^{DRF}	β^{CRF}	β^{LRF}	β^{CAY}	Adj. R^2
LTR^{Bond}	**0.47**						
t-stat	(6.12)						
Coef.	**0.43**	0.15					1.93
t-stat	(5.19)	(1.54)					
Coef.	**0.20**	0.02	**0.30**	**0.62**	**1.58**		56.72
t-stat	(2.54)	(0.02)	(2.58)	(4.56)	(4.76)		
Coef.	**0.19**	0.01	**0.29**	**0.62**	**1.58**	-4.92	57.72
t-stat	(2.86)	(0.01)	(2.58)	(4.51)	(4.67)	(-1.57)	