Long-Term Reversals in the Corporate Bond Market*

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Abstract

Long-term reversals in corporate bonds are economically and statistically significant in a comprehensive sample spanning the period 1977 to 2017. Such reversals are stronger for bonds with high credit risk and more binding regulatory, capital, and funding liquidity constraints. Bond long-term reversal is not a manifestation of the equity counterpart and is mainly driven by long-term losers. A long-term reversal factor carries a sizable premium and is not explained by long-established equity and bond market factors. Thus, past returns capture investors' ex-ante risk assessment and the degree of institutional constraints they face, 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 reversals 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 values. As investors and analysts extrapolate past information too far into the future, some assets that experience recent

[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.

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 (see, e.g., Chordia et al., 2017; Bai, Bali, and Wen, 2019; 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 (REV) 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.

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

[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, e.g., 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 4.1.

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 (REV_F^{Bond}). We find that the factor generates significantly positive return premia, with particularly higher magnitudes during economic downturns and periods of high default risk and high regulatory, intermediary capital, and funding liquidity constraints. Further, long-established stock and bond market factors do not materially explain long-term reversals (REV) in corporate bonds.

We next explore rationales for REV in corporate bonds. First, reversal of long-term return performance could mean correction of overreaction. While models of overreaction in equities (see, e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999) suggest that momentum should be followed by reversals, 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 in the bond market 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. Thus, the balance of the evidence points away from behavioral rationales for REV in corporate bonds.

Alternatively, reversals could imply increases in required returns after a decline in prices (due to an increase in risk). The losing bonds that drive long-term reversals do indeed 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.[5] Notably, although REV 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.

Institutional constraints can also cause long-term reversals (Duffie, 2010). This is because inter-

[5]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.

mediaries demand greater required returns on bonds that are more subject to regulatory restrictions and/or are more sensitive to fluctuations in aggregate constraints. If such bonds happen to be losing bonds, then expected returns would be higher for such bonds, contributing to REV. Accordingly, we consider the roles of regulatory constraints, intermediary capital, and funding liquidity. We find that LTR-losers are held by institutions that face higher regulatory constraints and are more sensitive to aggregate measures of institutional constraints. Long-term reversals are stronger in bonds which are held by insurance companies with greater regulatory constraints, and in bonds that are more sensitive to intermediary capital constraints. Further, the time-series of returns on LTR-losers load significantly on aggregate constraints. Thus, our results support Ellul, Jotikasthira, and Lundblad (2011), He, Kelly, and Manela (2017), and Frazzini and Pedersen (2014) who provide arguments for why assets that are held by investors facing disproportionally high institutional constraints should experience greater reversals.

Finally, we jointly consider the extent to which factors related to institutional constraints and bond market risk factors (Bai, Bali, and Wen, 2019) explain long-term reversals. We find that these sets of factors play complementary roles in attenuating abnormal returns on LTR-sorted portfolios. Specifically, each set attenuates REV alphas, and both sets together attenuate these alphas to a greater degree than each set in isolation. Thus, the evidence supports the notion that institutional constraints and risk both contribute to long-term reversals in corporate bonds.

This paper proceeds as follows. Section 2 describes the data and variables used in our empirical analyses. Section 3 examines the significance of long-term reversals in the cross-section of corporate bonds. Section 4 investigates alternative explanations of long-term reversals in the bond market based on the overreaction, risk, and institutional constraints hypotheses. Section 5 concludes the paper.

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 (2019) 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.[6] 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 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.

[6] 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 construction. Our results remain similar and thus we follow the Cici, Gibson, and Moussawi (2017) approach throughout the paper for defaulting bond returns.

Panel A of Table 1 reports the time-series average of the bond long-term return (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 return (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.[7] 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 return 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 return, 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 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

[7] Similar to Jegadeesh (1990), we measure the short-term return (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 $t-1$.

the bond's outstanding dollar values as weights.

Moving from quintile 1 to quintile 5, the average excess return on the LTR-sorted 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 return 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 (REV) 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 as well.

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 (REV^{Stock}) to investigate whether these equity market factors can explain our findings.[8] The third column of Table 2 shows

[8]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 REV^{Stock} (long-term-loser minus long-term-winner) are obtained from Kenneth French's online data library:

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 (2019), 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.[9] Following Bai, Bali, and Wen (2019), 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.[10] The credit risk factor (CRF) is the value-weighted 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.

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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.

[9]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.

[10]Following Roll (1984), bond-level illiquidity is calculated as the autocovariance of the price changes. The aggregate illiquidity of the corporate bond market is proxied by the value-weighted average illiquidity of individual corporate bonds.

In addition to the 4-factor model of Bai, Bali, and Wen (2019), 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.[11] 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 (2019), 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 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 (2019) 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

[11] 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.

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 (presented in the last five columns of Table 2).

Fig.1 presents the cumulative monthly post-formation returns of the corporate bonds sorted by long-term return (LTR). Following DeBondt and Thaler (1985), in Fig.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 (2019) with the aggregate corporate bond market (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF). Fig.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. 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 seven 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. Fama-MacBeth regressions

We have so far tested the significance of long-term reversal (REV) 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 short-term reversal (STR), bond momentum (MOM), bond market beta (β^{Bond}), default beta (β^{DEF}), term beta (β^{TERM}), credit rating, year-to-maturity (MAT), bond amount outstanding (SIZE), and bond-level illiquidity (ILLIQ). 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 4 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-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).[12]

Regression specification (2) in Table 4 shows that after we control for STR^{Bond}, MOM^{Bond}, β^{Bond}, β^{DEF}, β^{TERM}, credit rating, maturity, size, and illiquidity, 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 (2019) 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 REV 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}, credit rating, maturity, size, and illiquidity. 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 else.[13] 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.

[12]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 REV^{Bond} 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).

[13]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 (2019).

3.4. A Long-term reversal factor for corporate bonds

In this section, we first introduce a novel long-term reversal factor for corporate bonds, REV_F^{Bond}, and investigate the economic and statistical significance of the factor. Then, we test whether the factor is explained by well-established stock and bond market factors.

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 REV_F^{Bond} 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 (REV_F^{Bond}) is constructed using $3\times3\times3$ trivariate conditional sorts of credit rating, time-to-maturity, and LTR. REV_F^{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 REV_F^{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 REV_F^{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* REV factor from Kenneth French's online data library, REV_F^{Stock}, is 0.36. The correlation between the REV_F^{Bond} and the REV_F^{Stock} is modest, at 0.18. The mean return on REV_F^{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 REV_F^{Stock} is positive and significant, at 0.46% per month (t-stat. = 2.32). Hence, the *stock* REV 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.[14] One may therefore think that the long-term reversal in bonds is simply an artifact 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.4 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 REV factor for corporate bonds. We conduct a formal test using the following time-series regressions:

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

where $\mathrm{REV}_{F,t}^{Bond}$ 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.5 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.[15]

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

[14] 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).

[15] To address a potential concern about seasonality in corporate bond returns (George and Hwang, 2007), we construct the REV_F^{Bond} factor using only non-January months. Panel B of Table A.5 in the online appendix shows that the alpha of the REV_F^{Bond} factor remains highly significant, both economically and statistically, after removing Januaries from the sample.

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. Fig.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 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.6 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.7 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.8 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.

3.5.5. Subsample analyses

We examine whether the long-term reversal effect is robust across different datasets. Specifically, we investigate the long-term reversal effect for the quote-based database and the transaction-based database separately. Table A.9 of the online appendix shows that the effect is stronger for transaction-based database; the average return and alpha spreads between the Low- and High-LTR portfolios are, respectively, −0.78% per month (t-stat. = −2.89) and −0.67% per month (t-stat. = −2.99) for the transaction-based TRACE database. The long-term reversal effect has a weaker economic significance for the quote-based database but remains statistically significant.[16]

We further investigate the long-term reversal effect for the three subperiods in TRACE based on a five-year interval: (i) the first pre-crisis subperiod from July 2002 to July 2007, (ii) the second subperiod including crisis and recovery periods from August 2007 to December 2012, and (iii) the third most recent subperiod from January 2013 to December 2017. The last three rows of Table A.9 show that the long-term reversal effect is strongest during the second subperiod from August 2007 to

[16]Bonds in the transaction database on average are more volatilie than those in the quotes database. For example, the time-series average of the cross-sectional long-term return standard deviation is 0.28% in the TRACE sample, whereas it is 0.15% in the Lehman database. Although the percentage of non-investment-grade bonds in the quoted database is similar to that in the TRACE sample (28% vs. 25%), the average credit rating of bonds in TRACE is higher than that in the Lehman database; 8.34 vs. 7.67, indicating higher credit risk of bonds in the former dataset. We interpret the results as consistent with higher risk associated with bonds in the transaction database which contributes to the stronger long-term reversal effect in this database. Section 4 addresses the link between risk and long-term reversal in more detail.

December 2012 (including the crisis and the post-crisis/recovery periods), but remains economically and statistically significant for the other subperiods.

Edwards, Harris, and Piwowar (2007) show that the corporate bond market is becoming increasingly transparent with higher liquidity since the introduction of the TRACE bond price reporting system. On the other hand, there is an explosion in poorer rated issues as an overall fraction in more recent years, which corresponds to the composition change of the bond market. Both of these effects should influence the strength of long-term reversals, as in previous sections we find that the REV premium is stronger among bonds with lower liquidity and higher credit risk. Fig. A.1 of the online appendix presents the monthly time-series of the aggregate corporate bond market illiquidity (ILLIQ) and credit risk (Rating) in the TRACE sample from July 2002 to December 2017. Fig. A.1 shows an increasing pattern of market liquidity and an increasing pattern of credit risk over time, consistent with the liquidity and changes in composition effects identified by earlier studies.

We further investigate the relation between the long-term reversal and aggregate bond market illiquidity and credit risk in Table A.10 of the online appendix. Using the REV premia (i.e., the return spread between the low- and high-LTR quintiles) as the dependent variable, Table A.10 shows that the coefficients on ILLIQ and Rating are positive and statistically significant, indicating a significantly positive relation between the REV premia and aggregate illiquidity and credit risk. Consistent with LTR-losers as the main driver of the REV premia, the second row of Table A.10 shows similar results when using the returns on the LTR losers (i.e., the low-LTR quintile) as the dependent variable, confirming the role of the REV premia between the low- and high-LTR quintiles. Overall, these results provide evidence that the attenuation in long-term reversal in the most recent subperiod is related to improving liquidity, whose effect dominates the changes in composition effect.

4. Why does the REV factor command a premium?

Why does REV^{Bond} command a premium? One possible hypothesis is that bond prices overreact, followed by corrections. An alternative hypothesis is that losers experience increases in conventional measures of risk, so that the higher returns of losers represent increases in required returns. A third hypothesis is that institutional restrictions/constraints bind for certain bonds, thus implying reversals (see, e.g., Duffie, 2010; Ellul, Jotikasthira, and Lundblad, 2011).

We term the overreaction, conventional risk, and constraint hypotheses OH, RH, and CH, 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 REV^{Bond} for convenience):

H1. The OH by itself does not predict asymmetry in REV, 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. The behavioral models of overreaction (see, e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999) indicate that momentum should be followed by reversals. If REV is driven by these forces, we expect to see bond momentum portfolios experience reversals in the long-run. Such evidence would support OH.

H3. 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 REV.

H4. A predominant source of risk for bonds is downside risk, viz. Bai, Bali, and Wen (2019), so we expect REV to be more prevalent in losers under RH. CH makes a similar prediction, because losing bonds represent a loss of collateral value, making them more prone to fire sales and reversals (Ellul, Jotikasthira, and Lundblad, 2011).

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. Under RH, REV returns should load positively on factors that command a positive premium in bond markets, and REV hedge portfolio profits (alphas) should attenuate when we control for bond risk factors.

H7. Under CH, we would expect REV to be more pronounced for bonds held by institutions with higher levels of regulatory restrictions and facing greater exposure to aggregate measures of institutional constraints.

4.1. Tests of the overreaction hypothesis

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 H4 above rather than H1. We now test H2 and H3 in further detail.

As mentioned in H2, 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 5 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 5 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 $t+60$.[17] These results collectively suggest that momentum and long-term reversal in corporate 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.

[17]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 insignificant for four years after portfolio formation.

We next examine H3 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.[18] 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 H3, 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 and the long-term return (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 6 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. Thus, the evidence in Table 6 is at odds with H3.

[18]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.

4.2. Long-term reversal, ratings downgrade, and changes in financial distress

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 (H5). 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 7, long-term losers indeed experience significant increases in credit risk (or ratings downgrade) 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 7, Panel A, the average differences in rating 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.[19]

Panel B of Table 7 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 7 using two proxies of financial distress: the failure probability measure of Campbell, Hilscher, and Szilagyi (2008) and the O-score measure of

[19] 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.

Ohlson (1980). Confirming our findings from credit ratings, Table 8 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.

4.3. Long-term reversal and default risk

We now test H6. We first 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 risk. For each month in our sample, we simultaneously estimate individual bond exposures to the change in default 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 1.34, whereas the average market beta of LTR-winners is lower at 0.31. Similarly, the average exposure to aggregate default risk decreases from 3.51 to 0.38, when moving from the LTR-loser to the LTR-winner quintile. That LTR losers have greater exposures to the market and default risk factors accords with H6, 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 β^{DEF} quintile (bonds with lowest default risk), whereas the alpha spreads are significant and monotonically increase in absolute magnitude when moving from the first to the fifth β^{DEF} quintile (bonds with highest default risk). Another noteworthy point in Panel B is that the alpha spread between LTR-winners and LTR-losers is largest in the highest β^{DEF}

quintile; −0.80% per month with a t-statistic of −3.60, implying that the long-term reversal effect is strongest in the sample of bonds with the highest exposure to aggregate default risk. Moreover, Panel C of Table 9 provides similar evidence when we replace β^{DEF} with β^{MKT} in the construction of bivariate portfolios, i.e., the alpha spreads between LTR-winners and LTR-losers are insignificant (significant) in the lowest two (highest three) quintiles of β^{MKT}. Overall, Table 9 shows that the long-term reversal effect is confined to the sample of bonds with high credit risk, high market risk, and high default beta. This result again supports H5 and H6, and hence, RH.

Next, we test whether the REV effect is explained by downside risk, credit risk, and liquidity risk collectively. Table A.11 of the online appendix shows that the average return on the REV_F^{Bond} 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 last row of Table A.11 shows that controlling for the downside risk (DRF), credit risk (CRF), and liquidity risk (LRF) factors of Bai, Bali, and Wen (2019) 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 H6), 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 REV premium unexplained. To the extent that the bond factor model attenuates REV, and REV profits are related to factor loadings, our tests support RH (based on H6 above).

4.4. Do institutional constraints explain REV?

In this subsection, we test H7 using various proxies for institutional restrictions and constraints. First, we investigate whether the degree of regulatory constraints can be a potential explanation of the long-term reversal effect in corporate bonds. In Section 4.2, we find evidence that long-term losers experience an increase in credit risk (i.e., credit ratings downgrade and elevated financial distress) which results in an immediate negative price response, followed by higher future returns. These results highlight the role of regulatory constraints and restrictions placed on bond holders. For example, Ellul, Jotikasthira, and Lundblad (2011) show that corporate bonds subject to a high probability of regulatory-induced selling exhibit price declines and subsequent reversal, which appear larger during periods when the insurance industry is relatively distressed and other potential buyers' capital is scarce.[20] Following Ellul, Jotikasthira, and Lundblad (2011), we use the risk-based capital ratio (RBC) (total capital divided by the risk-based capital requirement) of insurance companies as a proxy for regulatory constraints.[21] The denominator of RBC represents the minimum capital the insurance companies must maintain given their level of riskiness, so higher RBC ratios represent less-constrained insurance companies. We calculate the value-weighted average RBC of each bond in LTR-sorted portfolios, and then average across the bonds. In the first column of Table 10, Panel A, we document that the average RBC of LTR-losers is 5.21, whereas the average RBC of LTR-winners is much higher at 38.75. That LTR-losers have a much lower RBC ratio accords with the view that regulatory constraints influence REV.[22]

We conduct additional tests to examine regulatory constraints and the long-term reversal effect. Specifically, we investigate two separate bond samples. The first subsample of bonds forms the "fallen angels" group which pierce a critical ratings threshold and are downgraded from investment-grade to non-investment-grade. As shown by Ellul, Jotikasthira, and Lundblad (2011), fire sales of such downgraded corporate bonds induced by regulatory constraints imposed on insurance companies lead to price pressure and the subsequent return reversal. The second subsample is the group of bonds either with no change in ratings or with rating changes that do not pierce regulatory thresholds from investment-grade to non-investment-grade. Table A.12 of the online appendix shows that the long-term reversal effect is much stronger in the fallen angels group. In contrast, the long-term reversal

[20] Examples of other studies on how asset fire sales may deviate transaction prices from fundamental values include Shleifer and Vishny (1992), Schultz (2001), Coval and Stafford (2007), Mitchell, Pedersen, and Pulvino (2007), Pulvino (1998), and Campbell, Giglio, and Pathak (2011), among others.

[21] Data Source: National Association of Insurance Commissioners, by permission. The NAIC does not endorse any analysis or conclusions based upon the use of its data.

[22] We also calculate the change in institutional ownership (ΔINST) by insurance companies during months $t-12$ to $t-1$ for the LTR quintile portfolios, and find that ΔINST is negative with an average of -23.18% for the LTR-losers (quintile 1), compared to the average of 11.20% for the LTR-winners (quintile 5), which indicates the collective sales of LTR-losers from insurance companies with more binding regulatory constraints.

effect is economically weak in the group of bonds that excludes fallen angels, confirming the role of regulatory constraints in explaining the long-term reversal effect. Moreover, we investigate portfolios of long-term reversal and *changes* in ownership within the two separate bond samples. Table A.13 of the online appendix shows that the long-term reversal effect is stronger within the fallen angels group when institutions have a strong tendency of sales (e.g., the ΔINST,1 and ΔINST,2 quintiles). In contrast, the long-term reversal effect is much weaker and insignificant within the group of bonds that excludes fallen angels, even within the ΔINST,1 and ΔINST,2 quintiles. Overall, Tables A.12 and A.13 confirm that regulatory restrictions and constraints are an important driver of the long-term reversal effect, which is stronger among institutions with collective sales of bonds.

Second, we test whether intermediary capital constraints can be a potential explanation of the long-term reversal effect. He, Kelly, and Manela (2017) show that changes in the aggregate capital ratio of financial intermediaries (defined as equity capital over total capital) possesses significant explanatory power for cross-sectional variation in expected returns for many asset classes. Specifically, assets with low sensitivities to intermediary capital shocks form a valuable hedge and have lower expected returns and vice versa. In the corporate bond market, more than 95% of bonds are traded via dealers (intermediaries) in over-the-counter markets. Edwards, Harris, and Piwowar (2007) show that only 2% of bond trades in TRACE result from retail investors, suggesting that intermediaries may be important for pricing corporate bonds. Our first proxy for intermediary constraints is generic: it is simply the illiquidity levels of individual bonds. Illiquid bonds represent higher trading costs, and should influence required returns of intermediaries. Our measure of illiquidity, ILLIQ, is calculated for each bond as per Bao, Pan, and Wang (2011). We present the average levels of ILLIQ for the five LTR portfolios in the third column of Table 10, Panel A. As can be seen, the extreme losers are more than three times more illiquid than the extreme winners. Next, following He, Kelly, and Manela (2017), we estimate corporate bond exposure to the change in aggregate intermediary capital ratio (ICR), which is defined as the aggregate value of market equity divided by aggregate market equity plus aggregate book debt of primary dealers.[23] Panel B of Table 10 shows that LTR-losers are held by institutions with a greater exposure to changes in intermediary capital constraints (as

[23]The monthly data on the aggregate intermediary capital ratio (ICR) constructed by He, Kelly, and Manela (2017) are obtained from Asaf Manela's online data library: http://apps.olin.wustl.edu/faculty/manela/data.html.

well as to changes in the value-weighted aggregate levels of ILLIQ and RBC).

Finally, we investigate if the long-term reversal effect in corporate bonds is related to funding liquidity constraints of institutional investors, who are the primary holders of corporate bonds. In accordance with Brunnermeier (2009) and Frazzini and Pedersen (2014), we consider the change in TED spread, defined as the difference between the three-month Treasury bill and the three-month LIBOR, as a proxy for aggregate funding liquidity constraints. Analogous to the argument above for ICR, the idea here is that bonds with lower sensitivity to funding liquidity constraints are worth more in times of greater funding constraints and therefore require lower returns going forward. Indeed, Panel B of Table 10 shows that LTR-losers have a higher sensitivity to aggregate funding liquidity than LTR-winners.

In sum, LTR-losers, that contribute the most to REV, are more illiquid, are held by institutions that face greater levels of regulatory constraints, and are more sensitive to fluctuations in intermediaries' aggregate constraints than other bonds. In addition, the losing bonds have greater sensitivity to fluctuations in intermediary capital and funding liquidity. The latter finding indicates that when constraints are more binding, the return on losing bonds is more adversely affected than that of other bonds. This is consistent with intuition which suggests that losing bonds (with low credit quality) would be more likely to be sold in times of greater constraints. In an additional test, Table 11 shows that long-term reversals are stronger in bonds held by institutions with higher regulatory constraints, and in bonds that are more sensitive to intermediary capital ratios and aggregate funding liquidity, which supports H7 and hence CH. Thus, overall, the findings so far accord with the idea that REV is influenced by institutional constraints. Sections 4.4.1 and 4.4.2 further explore this notion.

4.4.1. REV premia over time

Do REV premia vary in the time series with proxies for risk and institutional constraints? We now explore this issue. Table 12 reports the average return spreads and the corresponding t-statistics from the value-weighted quintile portfolios of LTR across different sample periods. We first examine the return premia on the LTR-sorted portfolios of corporate bonds during high and low bond market states. Panel A of Table 12 shows that the value-weighted average return spread between LTR-losers and LTR-winners is higher at 0.56% per month (t-stat. = 3.67) during low market states ($\text{MKT}^{Bond} \leq Median$), whereas it is lower at 0.37% per month (t-stat. = 2.87) during high market states ($\text{MKT}^{Bond} > Median$). We also test the significance of return premia conditioning on aggregate default risk, and find that the REV premia are significantly high during periods of high default risk ($\Delta\text{DEF} > 0$), but lower during periods of low default risk ($\Delta\text{DEF} \leq 0$); 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.

Second, we investigate the significance of return premia conditioning on aggregate regulatory constraints in Panel B, and find that the REV premia are higher during periods of high regulatory constraints (RBC $\leq$ Median), compared to periods of low regulatory constraints (RBC $>$ Median);[24] 0.92% per month (t-stat. = 4.46) during periods of RBC $\leq$ Median, whereas much lower at 0.23% per month (t-stat. = 3.02) during periods of RBC $>$ Median.

Third, we examine the significance of return premia conditioning on aggregate intermediary capital constraints in Panel C, and show that the long-term reversal effect is stronger during periods of high capital constraints (ICR $\leq$ Median), compared to periods of low capital constraints (ICR $>$ Median); 0.82% per month (t-stat. = 4.03) during periods of ICR $\leq$ Median, whereas much lower at 0.12% per month (t-stat. = 2.54) during periods of ICR $>$ Median. The results are similar in Panel C when we use the aggregate bond market illiquidity as another proxy for an aggregate capital constraint, replacing the aggregate intermediary capital ratio.

Finally, we examine the significance of return premia conditioning on aggregate funding liquidity constraints in Panel D, and find that the REV premia are again higher during periods of high funding liquidity constraints (TED $>$ Median), compared to periods of low funding liquidity constraints (TED $\leq$ Median); 0.85% per month (t-stat. = 3.55) during periods of TED $>$ Median, whereas much lower but still significant at 0.23% per month (t-stat. = 2.84) during periods of TED $\leq$ Median.[25]

[24] Aggregate regulatory constraint is proxied by the value-weighted average of the firm-level risk-based-capital ratio (RBC).

[25] An issue that arises from the analysis is whether REV obtains only in the period of the financial crisis. So 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. =

Electronic copy available at: https://ssrn.com/abstract=2978861

4.4.2. A joint test of the risk vs. constraints hypotheses

In this section, we compare the economic magnitudes of the REV premia explained by the risk vs. constraint hypotheses in a common estimation framework. As discussed in Section 3.1, we use the Bai, Bali, and Wen (2019) (BBW) factors related to downside risk (DRF), credit risk (CRF), and liquidity risk (LRF). Following Ellul, Jotikasthira, and Lundblad (2011), He, Kelly, and Manela (2017), and Frazzini and Pedersen (2014), we assume that the comprehensive role of regulatory, capital, and funding liquidity constraints placed on bond holders is quantified by the risk-based capital ratio (RBC), the intermediary capital ratio (ICR), and the TED spread (TED).

The first column in Panel A of Table 13 shows that the average return on the REV_F^{Bond} factor is economically large and highly significant at 0.82% per month with a t-statistic of 5.53 for the sample period from July 2002 to December 2017.[26] As reported in the second column of Table 13, Panel A, the average return on the REV_F^{Bond} factor reduces from 0.82% to 0.76% per month (t-stat. = 3.89) controlling for the aggregate bond market portfolio (i.e., the CAPM alpha), implying that the bond market risk explains only 6 basis points per month of the original LTR loser-minus-winner premium.

Next, we estimate the economic magnitude of the REV premia explained by the BBW factors. The third column in Panel A of Table 13 shows that controlling for the downside risk (DRF), credit risk (CRF), and liquidity risk (LRF) factors of Bai, Bali, and Wen (2019) reduces the CAPM alpha of 0.76% to 0.33% per month (t-stat. = 2.51), indicating that the BBW factors as a group explain an additional 43 bps per month.

Then, we measure the size of the REV premia explained by the regulatory, capital, and funding liquidity constraints jointly. The fourth column in Panel A of Table 13 demonstrates that controlling for the RBC, ICR, and TED factors reduces the alpha from 0.76% to 0.53% per month (t-stat. = 3.44), implying that the institutional restrictions and constraints simultaneously explain 23 bps per month of the original REV premium.

Finally, we test the extent to which REV is explained by the institutional constraints and risk factors collectively. As presented in the last column of Table 13, Panel A, controlling for the market,

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.

[26]Since the RBC data are available for the sample period from 2001, the joint test of the risk vs. constraint hypotheses in a common estimation framework is conducted for the TRACE sample from 2002 to 2017.

downside, credit, and liquidity risk factors as well as for the proxies of regulatory, capital, and funding liquidity constraints reduces the alpha from 0.76% to 0.16% per month. More importantly, this economically small alpha also becomes statistically insignificant with a t-statistic of 0.94, indicating that the risk and constraint-related factors jointly explain an economically large 60 basis points per month of the original REV premium. We also test whether the slope coefficients on the RBC, ICR, and TED factors are jointly zero. As presented in the last column of Table 13, Panel A, the joint F-statistic is highly significant, indicating that the constraints as a group contribute significantly to the explanation of REV, even after controlling for the conventional risk factors.

In Panel B of Table 13, we consider the economic magnitudes of the LTR-loser returns explained by the risk vs. constraint hypotheses, since LTR-losers are the principal contributors to long-term reversals. The first column of Panel B in Table 13 shows that the unconditional alpha for loser bonds is 0.90% per month and highly significant. We see that including the BBW factors reduces the alpha on LTR-losers to 0.42% per month. The last column in Panel B of Table 13 shows that when all three constraint-related factors are included along with the BBW factors, the alpha is approximately halved relative to the case where only the BBW factors are included. The alpha also drops to insignificance when RBC, ICR, and TED are included along with the BBW factors. Accordingly, the F-statistic from testing whether the slope coefficients on the RBC, ICR, and TED factors are jointly zero is highly significant, showing that the constraints significantly contribute to the explanation of loser bond returns, even after controlling for all three risk factors. Thus, the BBW risk factors and the three factors related to institutional constraints are able to capture LTR-loser returns, which accords with an analogous result in the last column of Panel A in Table 13 for the long-short (loser-minus-winner) returns.

In Table A.14, we explore the loadings on the various factors in more detail for LTR losers. We see that the loser bonds' returns load positively and significantly on the BBW risk factors. The two factors representing regulatory constraints and intermediary capital are significant at the 5% level, while the TED factor is only marginally significant,[27] when the factors are included one-at-a-time in

[27]Frazzini and Pedersen (2014) (FP) show that since many institutional investors are constrained in the leverage that they can take, they overweight risky securities instead of using leverage. This behavior of tilting toward high-beta assets suggests that risky high-beta assets require lower risk-adjusted returns than low-beta assets. As discussed in Section 3.1, we find that LTR-losers have a higher market beta compared to LTR-winners. In FP's setting, the spread between low- and high-beta portfolio returns is negatively related to the

the presence of the BBW factors.

In Table A.15, we explore the alphas and loadings on the various factors separately for two subsamples of LTR losers; (i) the "fallen angels" group with RBC ratio below the median (i.e., high regulatory constraints) and (ii) the group of bonds which do not pierce the junk-bond threshold and which have RBC ratio above the median (i.e., have low regulatory constraints). Panel A shows that the BBW risk factors reduce the CAPM alpha of LTR-losers from 0.96% to 0.61% per month for the fallen angels group with high regulatory constraints, whereas the constraint-related factors reduce this number further down to 0.49% per month. Taking together, both the risk and constraint-related factors are able to reduce the abnormal return on the long-term loser portfolio to an insignificant 0.21% per month, indicating that the two sources (risk and constraints) reinforce each other in terms of their contribution to the long-term reversal effect in corporate bonds. In sharp contrast, Panel B shows that for the group with low institutional constraints that excludes fallen angels, the abnormal return on long-term losers is not material, and the LTR-loser portfolio does not load significantly on the factors.

As discussed earlier, Panel A of Table 11 shows that the long-term reversal effect is stronger in bonds held by institutions with higher regulatory constraints (proxied by low RBC), while the REV effect is small and not significant in bonds with high RBC. To further investigate the degree of complementarity between the risk and constraints hypotheses, we first form 5×5 value-weighted bivariate portfolios of credit rating and long-term return (LTR) and show that a similar result is obtained when the REV effect is conditioned on the credit quality of corporate bonds. Table A.16 of the online appendix shows that the long-term reversal effect is stronger (weaker) in bonds with high (low) credit risk. Thus, our results indicate that institutional investors' ex-ante required returns are higher in more risky bonds and in bonds where investors face a higher degree of regulatory constraints.

Finally, we test how the long-term reversal effect manifests itself in the sample of bonds which have low credit quality *and* also are held by low-RBC investors. Specifically, we form trivariate portfolios of credit rating, RBC, and LTR. Corporate bonds are first sorted by credit rating into

TED spread because greater funding illiquidity implies taking leverage is more difficult, thus making high beta stocks more desirable. Our finding of a positive loading on TED indicates that the betting-against-beta phenomenon applies more in the equity market.

three portfolios and within each rating portfolio, bonds are further sorted by the risk-based-capital ratio (RBC) into three portfolios. Finally, with each 3×3 rating and RBC sorted portfolio, bonds are further sorted based on the long-term return (LTR) into losers and winners and the difference in their returns (losers-minus-winners) is calculated. Table 14 shows that the long-term reversal effect is indeed largest and most statistically significant for bonds with low credit quality and held by low-RBC investors; the 11-factor alpha spread is -0.92% per month with a t-statistic of -3.20 for this group of bonds. The REV effect disappears in the sample of bonds with high credit quality and held by high-RBC investors. Also, within each RBC-sorted portfolio, the REV effect increases in statistical and economic significance as we move from the low to the high credit risk portfolio. Similarly, within each rating-sorted portfolio, the REV effect becomes gradually stronger when moving from the high to the low RBC portfolio. Thus, we find that each effect (risk vs. constraints) independently contributes to long-term reversals in corporate bonds. But, these two effects (risk and constraints) also augment each other in the sense that long-term reversals are strongest for riskier bonds held by investors with higher institutional and regulatory constraints. Overall, these results suggest that institutional investors' ex-ante required returns are influenced not only by standard bond risk factors, but also by the degree of regulatory and capital constraints they face.

5. 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.

Why do long-term reversals (REV) arise in corporate bonds? We make progress on this issue via a series of tests. We explore three rationales for REV that are based on overreaction, risk compensation, and institutional constraints. First, the overreaction hypothesis indicates that corporate bonds are mispriced and REV is subject to arbitrage forces. This suggests that under short-selling constraints, we would expect greater profits for winners rather than losers, since arbitrageurs would face costs in shorting winners. But we find that 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. In addition, 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. These pieces of evidence point away from overreaction driving REV.

We show that the losing bonds that drive REV 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. Further, although REV is driven by a subset of bonds, the role of the REV factor in pricing the cross-section of bonds is pervasive. Overall, these tests indicate 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.

We also investigate whether institutional restrictions and constraints cause long-term reversals in corporate bonds. We find that losing bonds are more sensitive to aggregate regulatory, capital, and funding liquidity constraints, consistent with the hypothesis that these constraints influence investors' required returns in the cross-section of corporate bonds. Long-term reversals are stronger in bonds that are held by insurance companies with greater regulatory constraints, and in bonds more sensitive to aggregate intermediary capital. Joint tests reveal that the increased required returns for losers are driven by previously-developed bond risk factors, as well as factors representing institutional constraints.

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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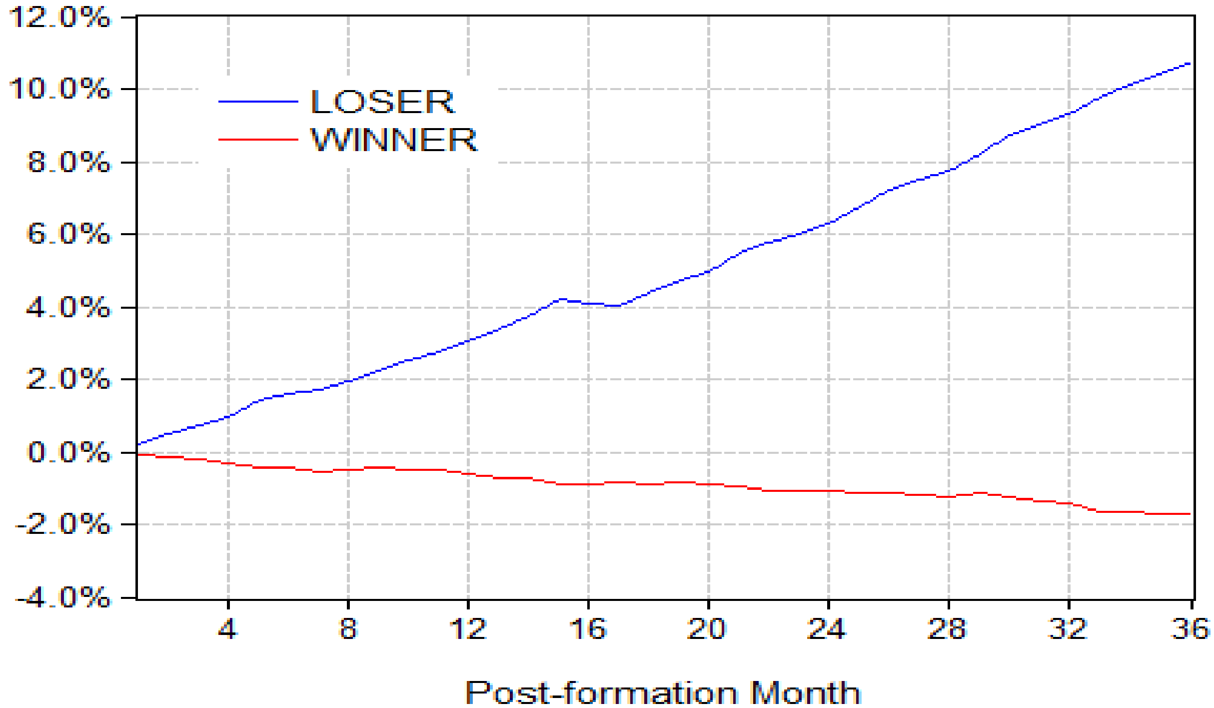


Fig.1. Post-formation Cumulative Return for the LTR-sorted Portfolios. This figure presents the cumulative monthly post-formation returns of the corporate bonds sorted by long-term return (LTR). Following DeBondt and Thaler (1985), we use non-overlapping three-year periods for portfolio formation, and 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), the credit risk factor (CRF), and the liquidity risk factor (LRF). 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 return

Quintile portfolios are formed every month from January 1977 to December 2017 by sorting corporate bonds based on their long-term return (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. The 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 stock short-term reversal factor (STR^{Stock}), and the stock long-term reversal factor (REV^{Stock}). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF). 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	-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	6.94	12.85	0.26
		(5.16)	(4.10)	(0.29)	(0.44)					
High − Low Return/Alpha diff.		-0.47***	-0.60***	-0.43***	-0.44***					
		(-3.27)	(-3.31)	(-3.59)	(-3.76)					

Table 3

Bivariate portfolios of corporate bonds sorted by long-term return 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 return (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
	(1.82)	(2.01)	(1.72)	(1.61)	(1.75)	(0.02)	(0.11)
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

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 return (LTR), with and without controls. Bond characteristics include credit rating, 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 bond short-term reversal proxied by previous month bond 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 5

Longer horizon 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 6

Bivariate portfolios of long-term return 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 return (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. The table reports the 11-factor alpha 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 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)	

Table 7

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 return (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 8

Long-term reversal and changes in financial distress

Quintile portfolios are formed every month by sorting corporate bonds based on their long-term return (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 of 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 9

Bivariate portfolios of long-term return and bond market beta and default beta

Panel A reports the univariate LTR portfolios' exposure to the bond market and the changes in default spread: MKT^{Bond} and ΔDEF,

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{DEF} \cdot \Delta DEF_t + \beta_{i,t}^{MKT} \cdot MKT_t^{Bond} + \epsilon_{i,t},$$

In Panels B and C, quintile portfolios are formed every month from January 1977 to December 2017 by first sorting corporate bonds into quintiles based on the factor exposure (β^{DEF} in Panel B and β^{MKT} in Panel C), then within each quitile portfolio, corporate bonds are further sorted into sub-quintiles based on their LTR. Panels B and C report the 11-factor alpha 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^{MKT}	β^{DEF}
Low LTR	1.34	3.51
2	0.74	2.08
3	0.33	1.32
4	0.27	0.35
High LTR	0.31	0.38

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}	0.27	0.09	-0.01	-0.01	0.12	-0.14
	(4.76)	(1.81)	(-0.33)	(-0.31)	(1.09)	(-1.54)
2	0.27	0.09	-0.01	-0.01	0.12	-0.15*
	(4.76)	(1.81)	(-0.33)	(-0.31)	(1.59)	(-1.94)
3	0.30	0.07	0.05	0.03	0.13	-0.17**
	(4.72)	(1.57)	(0.88)	(0.77)	(1.57)	(-2.41)
4	0.41	0.06	0.11	0.08	0.08	-0.32***
	(5.01)	(1.18)	(2.16)	(1.86)	(0.56)	(-2.95)
High β^{DEF}	1.28	0.22	0.13	0.21	0.48	-0.80***
	(7.78)	(2.27)	(2.12)	(3.19)	(4.81)	(-3.60)

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

	Low LTR	2	3	4	High LTR	High − Low
Low β^{MKT}	0.06	0.03	0.00	0.00	0.04	-0.02
	(1.03)	(0.68)	(0.00)	(0.05)	(0.83)	(-0.45)
2	0.15	0.05	-0.00	-0.00	0.07	-0.07
	(2.58)	(1.01)	(-0.09)	(-0.06)	(1.43)	(-1.25)
3	0.26	0.12	0.09	0.12	0.05	-0.21**
	(2.62)	(1.61)	(1.25)	(1.84)	(1.81)	(-2.02)
4	0.71	0.20	0.12	0.09	0.36	-0.35**
	(4.94)	(3.03)	(2.28)	(1.80)	(4.94)	(-2.29)
High β^{MKT}	1.81	0.65	0.52	0.64	0.90	-0.92***
	(7.00)	(3.11)	(2.85)	(2.84)	(5.24)	(-5.42)

Table 10

Average institutional constraints of LTR-sorted portfolios

Univariate portfolios are formed every month from January 2001 to December 2017 by sorting corporate bonds into quintiles based on the long-term return (LTR). Panel A reports the univariate LTR portfolios' average risk-based capital ratio (RBC) and illiquidity (ILLIQ), which is calculated following Bao, Pan, and Wang (2011). Panel B reports the univariate LTR portfolios' exposure to changes in aggregate regulatory, illiquidity, intermediary capital, and funding liquidity constraints, controlling for the bond market factor (MKT^{Bond}):

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{RBC} \cdot \Delta RBC_t + \beta_{i,t}^{MKT} \cdot MKT_t^{Bond} + \epsilon_{i,t},$$

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{ILLIQ} \cdot \Delta ILLIQ_t + \beta_{i,t}^{MKT} \cdot MKT_t^{Bond} + \epsilon_{i,t},$$

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{ICR} \cdot \Delta ICR_t + \beta_{i,t}^{MKT} \cdot MKT_t^{Bond} + \epsilon_{i,t},$$

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{TED} \cdot \Delta TED_t + \beta_{i,t}^{MKT} \cdot MKT_t^{Bond} + \epsilon_{i,t}.$$

The proxy for regulatory constraints (β^{RBC}) is the bond exposure to changes in aggregate regulatory pressure (i.e., a value-weighted average of firm-level risk-based capital ratio (RBC)). The proxy for intermediary capital constraint β^{ICR} is the bond exposure to changes in aggregate intermediary capital ratio (i.e., a value-weighted average of dealer's capital ratio (ΔICR)). The proxy for funding liquidity constraint (β^{TED}) is the exposure to changes in funding liquidity constraints, defined as the monthly change in TED spread (ΔTED).

Panel A: Long-term return portfolios' RBC and ILLIQ

	RBC	ILLIQ
Low LTR	5.21	17.43
2	8.68	5.18
3	14.08	3.24
4	21.05	3.21
High LTR	38.75	4.86

Panel B: Long-term return portfolio exposures to changes in aggregate constraints

	β^{RBC}	β^{ILLIQ}	β^{ICR}	β^{TED}
Low LTR	3.24	2.43	4.33	0.26
2	2.05	0.95	1.60	0.28
3	1.61	0.78	0.72	0.06
4	0.84	0.41	0.33	-0.12
High LTR	0.32	0.55	0.40	-1.08

Table 11

Bivariate portfolios of long-term return and regulatory, intermediary capital, and funding liquidity constraints

Panel A reports bivariate portfolios of long-term return and regulatory constraints (RBC), defined as the ratio of total adjusted capital to NAIC risk-based capital. Higher RBC ratios are considered better capitalized and lower RBC ratios are indicative of financial struggles. Panel B reports bivariate portfolios of long-term return and the bond exposure to changes in intermediary capital constraints. The proxy for intermediary capital constraints is the changes in aggregate intermediary capital ratio (i.e., a value-weighted average of dealer's capital ratio (ΔICR)). Panel C reports bivariate portfolios of long-term return and exposure to changes in funding liquidity constraints, defined as the changes in the TED spread in a month (ΔTED). The table reports the 11-factor alpha 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: First sort on RBC then on LTR, 11-factor alpha

	Low LTR	2	3	4	High LTR	High − Low
Low RBC	2.31	0.89	0.81	0.89	1.68	-0.63***
	(8.21)	(3.69)	(4.21)	(4.17)	(6.52)	(-3.30)
2	0.34	0.19	0.16	0.08	0.01	-0.34***
	(3.13)	(2.75)	(2.67)	(1.22)	(1.51)	(-3.29)
3	0.08	0.04	0.01	0.03	-0.11	-0.18*
	(1.01)	(0.76)	(0.17)	(0.57)	(-0.21)	(-1.92)
4	0.14	0.12	0.08	0.06	0.08	-0.06
	(2.33)	(2.07)	(1.46)	(1.42)	(1.82)	(-1.21)
High RBC	0.01	0.01	0.03	0.07	0.04	0.03
	(0.16)	(0.17)	(0.59)	(1.20)	(0.74)	(0.57)

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

	Low LTR	2	3	4	High LTR	High − Low
Low β^{ICR}	0.10	0.10	0.03	0.02	0.08	-0.01
	(1.77)	(1.60)	(0.52)	(0.48)	(1.86)	(-0.34)
2	0.12	0.04	0.01	0.01	0.07	-0.05
	(2.20)	(0.85)	(0.20)	(0.19)	(1.63)	(-1.11)
3	0.28	0.15	0.14	0.07	0.14	-0.14**
	(2.98)	(1.96)	(1.82)	(1.31)	(1.49)	(-2.00)
4	0.95	0.15	0.13	0.19	0.45	-0.50***
	(5.44)	(1.73)	(1.58)	(1.78)	(4.67)	(-2.82)
High β^{ICR}	1.51	0.60	0.46	0.57	0.81	-0.71***
	(6.88)	(3.70)	(3.17)	(3.01)	(5.14)	(-4.54)

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

	Low LTR	2	3	4	High LTR	High − Low
Low β^{TED}	0.31	0.20	0.16	0.10	0.15	-0.15
	(2.99)	(2.95)	(2.42)	(1.61)	(1.39)	(-1.24)
2	0.25	0.12	0.03	0.06	0.07	-0.18
	(3.81)	(2.92)	(0.86)	(1.62)	(1.27)	(-1.56)
3	0.37	0.11	0.06	0.04	0.11	-0.26*
	(4.24)	(3.22)	(1.86)	(1.23)	(2.12)	(-1.93)
4	1.74	0.72	0.55	0.63	1.34	-0.40**
	(7.11)	(3.58)	(3.24)	(2.74)	(4.86)	(-2.61)
High β^{TED}	1.22	0.33	0.18	0.15	0.38	-0.84***
	(6.28)	(3.65)	(1.99)	(2.33)	(4.67)	(-4.91)

Table 12

Long-term reversal 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 market and default risk, regulatory constraints, intermediary capital constraints, and funding liquidity constraints. The REV^{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. The proxy for regulatory constraints is the aggregate regulatory pressure (i.e., a value-weighted average of firm-level risk-based capital ratio (RBC)). The proxies for intermediary capital constraints is the aggregate intermediary capital ratio (i.e., a value-weighted average of dealer's capital ratio (ICR)) and aggregate bond illiquidity (ILLIQ), which is calculated the value-weighted average of the (negative of the) autocovariance of the price changes. The proxy for funding liquidity constraints is the TED spread (TED), defined as the difference between the three-month Treasury bill and the three-month LIBOR.

	REV^{premia}	
	Mean	t-stat
Panel A: Market risk and default risk (Jan 1977 to Dec 2017)		
Low market return ($\text{MKT}^{Bond} \leq$ Median)	0.56	3.67
High market return ($\text{MKT}^{Bond} >$ Median)	0.37	2.87
Aggregate default risk decreases ($\Delta\text{DEF} \leq 0$)	0.49	3.37
Aggregate default risk increases ($\Delta\text{DEF} > 0$)	0.66	2.49
Panel B: Regulatory constraints (Jan 2001 to Dec 2017)		
Low regulatory constraint (RBC > Median)	0.23	3.02
High regulatory constraint (RBC ≤ Median)	0.92	4.46
Panel C: Intermediary capital constraints (Jan 1977 to Dec 2017)		
Low intermediary capital risk (ICR > Median)	0.12	2.54
High intermediary capital risk (ICR ≤ Median)	0.82	4.03
Aggregate illiquidity decreases ($\Delta\text{ILLIQ} \leq 0$)	0.21	2.60
Aggregate illiquidity increases ($\Delta\text{ILLIQ} > 0$)	0.78	3.71
Panel D: Funding liquidity constraints (Jan 1986 to Dec 2017)		
Low funding liquidity risk (TED ≤ Median)	0.23	2.84
High funding liquidity risk (TED > Median)	0.85	3.55

Table 13

Time-series regressions of the long-term reversal factor and long-term loser returns on the bond market factors and institutional constraints

This table reports the intercepts (α) and their t-statistics from time-series regressions of the long-term reversal factor (REV_F^{Bond} in Panel A) and long-term loser returns (LTR^{Loser}, the low-LTR quintile, in Panel B) on the bond market risk factors and the proxies for institutional constraints. REV_F^{Bond} and LTR^{Loser} cover the TRACE sample period from July 2002 to December 2017. The DRF, CRF, and LRF factors are the downside risk factor, credit risk factor, and liquidity risk factors. The proxy for regulatory constraints is the changes in aggregate regulatory pressure (i.e., a value-weighted average of firm-level risk-based capital ratio (ΔRBC)). The proxy for intermediary capital constraints is the changes in aggregate intermediary capital ratio (i.e., a value-weighted average of dealer's capital ratio (ΔICR)). The proxy for funding liquidity constraints is the changes in aggregate funding liquidity constraints, defined as the monthly change in TED spread (ΔTED). p (F-stat.) is the p-value of the F-statistic from testing whether the slope coefficients on institutional constraints are jointly zero. Numbers in bold denote statistical significance at the 5% level or below.

Model 1: Bond market return MKT^{Bond}

Model 2: Bond market return MKT^{Bond} + DRF + CRF + LRF

Bond market factor plus the downside, credit and liquidity risk factors.

Model 3: Bond market return MKT^{Bond} + ΔRBC + ΔICR + ΔTED

Bond market factor plus the changes in aggregate regulatory constraints, intermediary capital constraints, and funding liquidity constraints.

Model 4: Bond market return MKT^{Bond} + DRF + CRF + LRF + ΔRBC + ΔICR + ΔTED

All factors combined.

Panel A: Dep. var = REV_F^{Bond}

	REV_F^{Bond}	Model 1	Model 2	Model 3	Model 4
Average return/alpha	**0.82**	**0.76**	**0.33**	**0.53**	0.16
t-stat	(5.53)	(3.89)	(2.51)	(3.44)	(0.94)
Adj. R^2 (%)	–	0.66	37.76	27.32	43.03
					p (F-stat.) < 0.01

Panel B: Dep. var = LTR^{Loser}

	LTR^{Loser}	Model 1	Model 2	Model 3	Model 4
Average return/alpha	**0.90**	**0.58**	**0.42**	**0.45**	0.22
t-stat	(5.63)	(4.67)	(4.06)	(3.12)	(1.06)
Adj. R^2 (%)	-	19.39	55.50	42.62	63.95
					p (F-stat.) < 0.01

Table 14

Trivariate portfolios of corporate bonds sorted by credit rating, RBC ratio, and long-term return

This table reports the results for trivariate portfolios of corporate bonds. The bonds are first sorted by credit rating into three portfolios and within each rating portfolio, bonds are further sorted by the risk-based-capital ratio (RBC) into three portfolios. Finally, within each 3×3 rating- and RBC-based portfolio, bonds are further sorted based on the long-term return (LTR), and the difference in returns between the losers and winners is calculated. The table reports the 11-factor alpha of the loser-minus-winner portfolio for each of the nine portfolios within each rating and RBC portfolio. 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.

	Low credit risk		
	Low RBC (high constraint)	Medium RBC	High RBC (low constraint)
High LTR − Low LTR	-0.32**	0.02	0.10
	(-2.08)	(0.34)	(0.85)

	Medium credit risk		
	Low RBC (high constraint)	Medium RBC	High RBC (low constraint)
High LTR − Low LTR	-0.38**	-0.29	-0.26
	(-2.51)	(-1.54)	(-1.41)

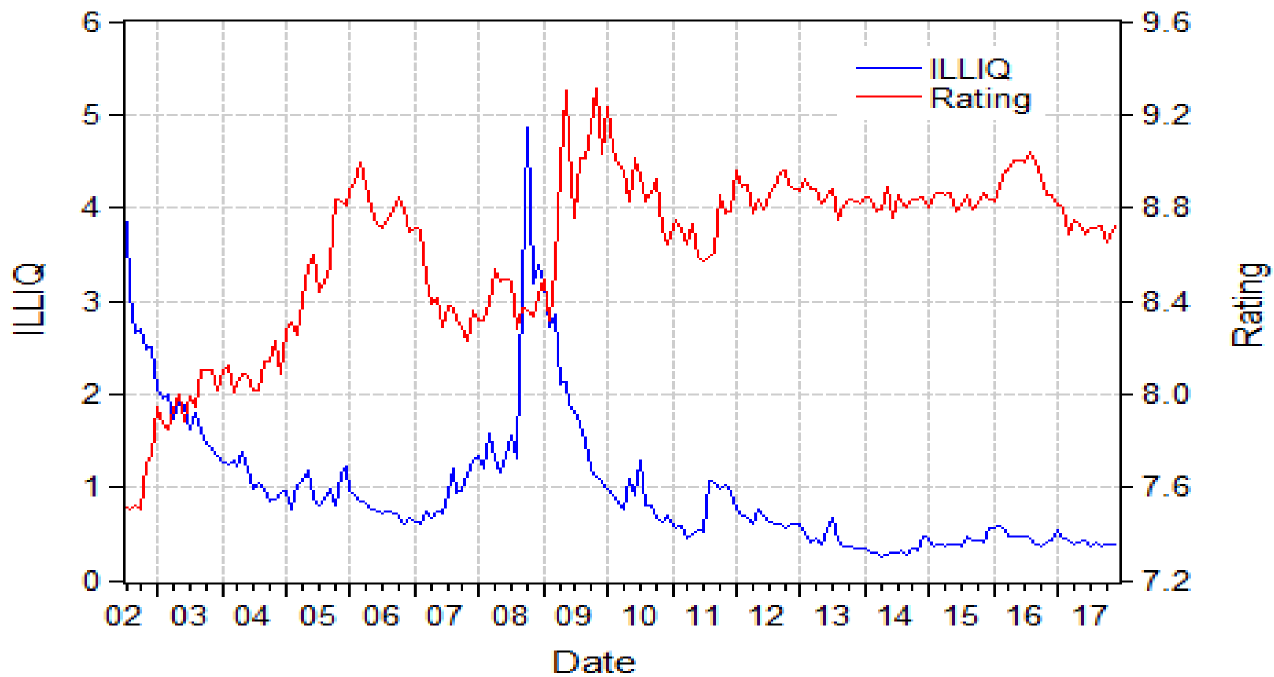
	High credit risk		
	Low RBC (high constraint)	Medium RBC	High RBC (low constraint)
High LTR − Low LTR	-0.92**	-0.56**	-0.30*
	(-3.20)	(-2.76)	(-1.98)

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. Fig. A.1 plots the monthly time-series of the aggregate corporate bond market illiquidity (ILLIQ) and credit risk (Rating) in the TRACE sample. 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 shows that stocks associated with non-investment-grade bonds do not exhibit long-term reversal during the same period as corporate bonds. Table A.5 shows that commonly used stock and bond market factors do not explain the long-term reversal factor return. Table A.6 presents results of the long-term reversal effect using alternative measures of defaulting bond returns. Table A.7 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.8 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.9 reports the quintile portfolios of corporate bonds sorted by their long-term return (LTR) for the subsamples and subperiods. Table A.10 reports the time-series regressions of the long-term reversal return premia on the bond market factor (MKT^{Bond}), aggregate bond market illiquidity (ILLIQ), and credit risk. Table A.11 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). Table A.12 reports the quintile portfolios of corporate bonds sorted by their long-term return (LTR) for two subsamples of bonds (i) the "fallen angel" group which pierce a credit ratings threshold and are downgraded from investment-grade to non-investment-grade, and (ii) the group of bonds with no change in ratings or those with rating changes that do not piece regulatory thresholds from investment-grade to non-investment-grade. Table A.13 reports bivariate portfolios of long-term return and changes in institutional ownership for the subsample of bonds. Table A.14 reports the intercepts (α), slope coefficients, and their t-statistics from time-series regressions of the long-term loser returns (LTR^{Loser}, the low-LTR quintile) on the bond market risk factors and the proxies for institutional constraints. Table A.15 reports the time-series regressions of long-term loser subsample returns on bond market factors and institutional constraints. Table A.16 presents the bivariate portfolios of long-term reversal controlling for credit risk.

Fig. A.1: Aggregate Corporate Bond Market Illiquidity and Credit Risk



This figure plots the monthly time-series of the aggregate corporate bond market illiquidity (ILLIQ) and credit risk (Rating) in the TRACE sample from July 2002 to December 2017. ILLIQ is the equal-weighted average of the bond-level illiquidity following Bao, Pan, and Wang (2011), defined as the autocovariance of the daily price changes which aims to extract the transitory component from bond price. Rating is the equal-weighted average of the bond-level credit rating, where higher numeric value of rating is associated with higher credit risk.

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

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 stock short-term reversal factor (STR^{Stock}), and the stock 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), the credit risk factor (CRF), and the liquidity risk factor (LRF). 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 Return 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 stock short-term reversal factor (STR^{Stock}), and the stock 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), the credit risk factor (CRF), and the liquidity risk factor (LRF). 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	-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 Return 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: Univariate Portfolios of Stocks Associated With Non-Investment-Grade Bonds Sorted by Stock Long-term Return

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.5: 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. REV_F^{Bond} covers the period from January 1977 to December 2017. Panel A reports the results for the full sample and Panel B report-s 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 = REV_F^{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 = REV_F^{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.6: 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.7: 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.8: 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 return (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 credit rating, 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 bond short-term reversal proxied by previous month bond 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.9: Long-term Reversal Subsample and Subperiod Analyses

This table reports the LTR return premia (i.e., the return spread between the low- and high-LTR quintiles) for two subsamples (i) the quote-based database, and (ii) the transaction-based database (TRACE). For the transaction-based database, we further divide the whole sample into three subperiods based on a 5-year interval (i) the first subperiod pre-crisis from July 2002 to July 2007, (ii) the second subperiod including crisis from August 2007 to December 2012, and (iii) the third most recent subperiod from January 2013 to December 2017. 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 month. "Low LTR" is the portfolio with the lowest LTR and "High LTR" is the portfolio with the highest LTR. Table reports the next-month average excess return and the 11-factor alpha for the high minus low portfolio. 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.

	High − Low Average return	High − Low 11-factor alpha
Quote-based database	-0.30**	-0.28**
	(-2.54)	(-2.30)
Transaction-based database (July 2002 - Dec 2017)	-0.78***	-0.67***
	(-2.89)	(-2.99)
Transaction-based database (July 2002 - July 2007)	-0.42**	-0.32**
	(-2.58)	(-2.36)
Transaction-based database (August 2007 - Dec 2012)	-1.04**	-0.89**
	(-2.44)	(-2.16)
Transaction-based database (January 2013 - Dec 2017)	-0.31**	-0.26**
	(-2.22)	(-2.03)

Table A.10: Time-series Regression of the Long-term Reversal Return Premia on Aggregate Bond Market Illiquidity and Credit Risk

This table reports the loadings and their t-statistics from time-series regressions of the long-term reversal return premia on the bond market factor (MKT^{Bond}), aggregate bond market illiquidity (ILLIQ), and credit risk (Rating). ILLIQ is the equal-weighted average of the bond-level illiquidity following Bao, Pan, and Wang (2011). Rating is the equal-weighted average of the bond-level credit rating. Higher numeric value of rating is associated with higher credit risk. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	MKT^{Bond}	ILLIQ	Rating	Adj.R^2
Dep. = LTR return premia between Low and High LTR	0.003	0.039***	0.054***	51.30
	(1.63)	(4.95)	(4.37)	
Dep. = Return premia on Low LTR	0.011***	0.050***	0.069***	60.05
	(4.34)	(4.95)	(4.95)	

Table A.11: Time-series Regression of the Long-term Reversal Factor on the Bond Market Factors

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). 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}	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)	

Table A.12: Long-term Reversal Subsample Analysis

This table reports the quintile portfolios of corporate bonds sorted by their long-term return (LTR) for two subsamples of bonds (i) the "fallen angels" group which pierce a credit ratings threshold and are downgraded from investment-grade to non-investment-grade, and (ii) the group of bonds either with no change in ratings or with rating changes that do not piece regulatory thresholds from investment-grade to non-investment-grade. 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 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 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.

	Within the fallen angels group		Within the group that excludes fallen angels	
Quintiles	Average return	11-factor alpha	Average return	11-factor alpha
Low LTR	1.37	1.07	0.72	0.23
	(5.23)	(4.87)	(3.91)	(2.70)
2	0.95	0.73	0.29	0.08
	(4.19)	(3.84)	(2.90)	(0.92)
3	0.47	0.30	0.26	0.06
	(2.71)	(1.90)	(2.59)	(0.85)
4	0.37	0.32	0.26	-0.04
	(2.46)	(1.27)	(2.62)	(-0.91)
High LTR	0.48	0.38	0.36	0.12
	(3.31)	(1.46)	(3.59)	(1.03)
High − Low	-0.88***	-0.69***	-0.37*	-0.11
Return/Alpha diff.	(-4.44)	(-3.88)	(-1.94)	(-0.94)

Table A.13: Bivariate Portfolios of Long-term Return and Changes in Institutional Ownership: Subsample Analyses

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 changes in their institutional ownership (ΔINST) and long-term return (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. ΔINST is the change in institutional ownership, defined as the total percentage of amount outstanding held by all investors during the formation period. ΔINST,1 (ΔINST,5) represents strong sell (buy). Panels A and B respectively consider two subsamples of bonds (i) the "fallen angels" group which pierce a credit ratings threshold and are downgraded from investment-grade to non-investment-grade, and (ii) the group of bonds either with no change in ratings or with rating changes that do not piece regulatory thresholds from investment-grade to non-investment-grade. The table reports the 11-factor alpha 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 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.

Panel A: Within the fallen angels group

	Low LTR	2	3	4	High LTR	High − Low
ΔINST, 1	1.44	0.79	0.24	0.88	0.38	-0.86***
	(2.64)	(2.72)	(1.10)	(2.75)	(0.96)	(-3.23)
ΔINST, 2	1.32	0.53	0.57	0.59	0.71	-0.67**
	(2.89)	(3.20)	(2.71)	(1.04)	(1.42)	(-2.67)
ΔINST, 3	1.15	0.58	0.47	0.94	0.60	-0.43*
	(2.94)	(1.91)	(2.31)	(1.67)	(1.51)	(-1.98)
ΔINST, 4	0.81	0.12	0.46	0.42	0.41	-0.30
	(1.80)	(0.44)	(1.93)	(1.91)	(1.41)	(-0.51)
ΔINST, 5	1.07	0.92	0.61	0.33	0.87	-0.24
	(3.02)	(3.51)	(2.15)	(1.14)	(2.54)	(-0.55)

Panel B: Within the group that excludes fallen angels

	Low LTR	2	3	4	High LTR	High − Low
ΔINST, 1	0.42	0.21	0.21	0.36	0.27	-0.14
	(5.84)	(3.71)	(2.89)	(1.60)	(1.31)	(-1.16)
ΔINST, 2	0.22	0.26	0.16	0.40	0.11	-0.11
	(3.93)	(4.16)	(3.29)	(2.35)	(1.13)	(-1.02)
ΔINST, 3	(3.57)	(5.13)	(3.92)	(2.71)	(3.04)	(-0.34)
	0.27	0.25	0.18	0.31	0.21	-0.05
ΔINST, 4	(4.98)	(5.06)	(3.75)	(3.37)	(2.87)	(-0.59)
	0.36	0.24	0.24	0.25	0.28	-0.08
ΔINST, 5	(4.02)	(3.70)	(3.50)	(2.58)	(3.06)	(-0.65)

Table A.14: Time-series Regressions of Long-term Loser Returns on Bond Market Factors and Institutional Constraints

This table reports the intercepts (α), slope coefficients, and their t-statistics from time-series regressions of the long-term loser returns (LTR^{Loser}, the low-LTR quintile) on the bond market risk factors and the proxies of institutional constraints. The first row reports the average LTR^{Loser} return covering the TRACE sample period from July 2002 to December 2017. The DRF, CRF, and LRF are the downside risk, credit risk, and liquidity risk factors. The proxy for regulatory constraints is the changes in aggregate regulatory pressure (i.e., a value-weighted average of firm-level risk-based capital ratio (ΔRBC)). The proxy for intermediary capital constraints is the changes in aggregate intermediary capital ratio (i.e., a value-weighted average of dealer's capital ratio (ΔICR)). The proxy for funding liquidity constraints is the changes in aggregate funding liquidity constraints, defined as the monthly change in TED spread (ΔTED). Numbers in bold denote statistical significance at the 10% level or below.

	Intercept	MKT^{Bond}	DRF	CRF	LRF	ΔRBC	ΔICR	ΔTED	Adj. R^2 (%)
LTR^{Loser}	**0.90**								–
	(5.63)								
(1)	**0.58**	**0.86**							19.39
	(4.67)	(6.78)							
(2)	**0.42**	**0.66**	**0.09**	**0.28**	**0.34**				55.50
	(4.06)	(6.78)	(2.33)	(2.76)	(4.93)				
(3)	**0.36**	**0.62**	-0.17	**0.30**	**0.29**	**0.24**			60.72
	(3.43)	(7.59)	(-1.24)	(2.38)	(4.16)	(2.64)			
(4)	**0.33**	**0.67**	-0.09	**0.25**	**0.32**		**0.58**		59.25
	(3.20)	(7.71)	(-1.19)	(2.05)	(3.92)		(2.39)		
(5)	**0.41**	**0.67**	-0.09	**0.29**	**0.34**			**0.75**	57.60
	(3.32)	(7.26)	(-1.06)	(2.03)	(4.35)			(1.88)	
(6)	**0.45**	**0.78**				**0.16**	**0.87**	-0.51	42.62
	(3.12)	(6.90)				(3.33)	(4.25)	(-0.89)	
(7)	0.22	**0.65**	-0.18	**0.30**	**0.28**	**0.22**	**0.46**	0.40	63.95
	(1.06)	(6.01)	(-1.28)	(1.82)	(3.97)	(2.18)	(1.90)	(0.43)	

Table A.15: Time-series Regressions of Long-term Loser Subsample Returns on Bond Market Factors and Institutional Constraints

This table separates long term losers into two subsamples of bonds (i) the "fallen angels" group with RBC ratio below the median (i.e., high regulatory constraints) and (ii) the group of bonds either with no change in ratings (or those with rating changes that do not piece regulatory thresholds from investment-grade to investment-grade), and with RBC ratio above the median (i.e., low regulatory constraints). Table reports the intercepts (α), slope coefficients, and their t-statistics from time-series regressions of the long-term loser returns (LTR^{Loser}) of each subsample on the bond market risk factors and the proxies of institutional constraints. The DRF, CRF, and LRF are the downside risk, credit risk, and liquidity risk factors. The proxy for regulatory constraints is the changes in aggregate regulatory pressure (i.e., a value-weighted average of firm-level risk-based capital ratio (ΔRBC)). The proxy for intermediary capital constraints is the changes in aggregate intermediary capital ratio (i.e., a value-weighted average of dealer's capital ratio (ΔICR)). The proxy for funding liquidity constraints is the changes in aggregate funding liquidity constraints, defined as the monthly change in TED spread (ΔTED). Numbers in bold denote statistical significance at the 10% level or below.

Panel A: Within the fallen angels group with RBC below the median

	Intercept	MKT^{Bond}	DRF	CRF	LRF	ΔRBC	ΔICR	ΔTED	Adj. R^2 (%)
(1)	**0.96**	**0.95**							34.99
	(5.36)	(5.66)							
(2)	**0.61**	**0.65**	**0.20**	**0.42**	**0.59**				61.20
	(5.21)	(5.24)	(2.43)	(2.72)	(5.12)				
(3)	**0.49**	**0.83**				**0.11**	**2.60**	-1.16	63.68
	(5.50)	(4.90)				(2.74)	(4.47)	(-1.33)	
(4)	0.21	**0.66**	-0.28	**0.34**	**0.48**	**0.21**	**1.06**	0.06	73.85
	(1.37)	(4.72)	(-1.65)	(1.51)	(5.48)	(3.33)	(3.78)	(0.06)	

Panel B: Within the group that excludes fallen angels and has an above-median RBC

	Intercept	MKT^{Bond}	DRF	CRF	LRF	ΔRBC	ΔICR	ΔTED	Adj. R^2 (%)
(1)	0.34	**0.76**							40.49
	(1.65)	(8.33)							
(2)	0.24	**0.68**	0.06	0.03	0.16				50.12
	(1.27)	(4.42)	(0.88)	(0.27)	(1.08)				
(3)	0.23	**0.70**				0.26	-0.44	0.24	47.26
	(1.23)	(6.87)				(1.20)	(-1.20)	(0.59)	
(4)	0.18	**0.65**	-0.06	0.10	0.12	0.26	-0.59	0.54	63.85
	(1.06)	(4.70)	(-0.57)	(0.92)	(1.14)	(1.22)	(1.80)	(0.80)	

Table A.16: Bivariate Portfolios of Long-term Reversal Controlling for Credit Risk

Quintile portfolios are formed every month from January 1977 to December 2017 by first sorting corporate bonds based on their credit rating into quintile portfolios, then within each rating portfolio, corporate bonds are sorted into sub-quintiles based on their LTR. Table reports the 11-factor alpha 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.

	Low LTR	2	3	4	High LTR	High − Low
Low credit risk	0.05	0.03	0.06	0.07	0.03	-0.02
	(0.75)	(0.59)	(0.99)	(1.28)	(0.61)	(-0.40)
2	0.07	0.03	-0.00	0.02	0.01	-0.06
	(0.94)	(0.65)	(-0.02)	(0.34)	(0.30)	(-0.90)
3	0.25	0.12	0.07	-0.05	0.07	-0.18**
	(2.47)	(1.90)	(1.18)	(-1.12)	(1.47)	(-2.08)
4	0.43	0.18	0.13	-0.05	0.11	-0.32**
	(2.52)	(2.45)	(1.96)	(-0.85)	(1.60)	(-2.51)
High credit risk	1.96	0.98	0.91	0.82	1.10	-0.86***
	(6.72)	(3.20)	(3.51)	(3.77)	(5.74)	(-5.85)