

Sources of Momentum in Bonds[☆]

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Abstract

This paper documents that momentum profits in corporate bonds emerge during weakening aggregate credit conditions. We find that a conditional default factor explains the returns of corporate bond portfolios sorted by past performance. We develop a bond pricing model in which firms with more intangible capital generate higher returns but also have higher liquidation costs, hence lower recovery values. Momentum can exist during adverse credit shocks because bonds with better past performance require higher recovery premiums. Empirical results strongly support this. Time-varying aggregate credit shocks and firm characteristics associated with growth and liquidation are the main sources of momentum in bonds.

JEL Codes: G11, G12

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1. Introduction

Does momentum exist in bond markets? Following [Jegadeesh and Titman \(1993\)](#), a sizable body of literature concerning the momentum in equity returns has been developed. However, there is little evidence on momentum in bond markets, and the existing literature provides equivocal answers to this question for corporate bonds. For instance, [Khang and King \(2004\)](#) and [Gebhardt et al. \(2005b\)](#) do not find statistically significant momentum in corporate bond returns, yet [Jostova et al. \(2013\)](#) document its existence, which is mainly driven by low rated bonds.¹

In this paper, we study bond markets to verify the existence of momentum returns, and identify systematic factors that determine the momentum in bond returns. In particular, we consider aggregate credit conditions as the main source of risk to affect the cross-sectional bond returns. Why aggregate credit conditions? We hypothesize that firms with more intangible capital have high growth potential, but they are also subjected to higher liquidation costs, hence lower recovery values. Momentum can exist in these firms' bonds during periods of adverse credit shocks. While their bonds perform well when credit markets are good, these bonds' return contain a higher risk premium reflecting smaller recovery value in the event of default triggered by aggregate credit shocks.

To empirically test this hypothesis, we measure time-varying aggregate credit conditions by using innovations in aggregate credit spread and refer to worsening (improving) aggregate credit conditions as *high (low) default shocks*. Controlling for changes in aggregate credit risk, we follow a standard methodology ([Jegadeesh and Titman, 1993](#)) to examine momentum in the corporate bond market. By constructing a data set that covers the whole U.S. corporate bond market, we find that momentum does in fact exist in bond returns, but it is concentrated in the periods of high aggregate default shocks. In our sample, the momentum strategy produces 28 basis points profit per month with a t-statistic of 1.86 (i.e., statistically significant at 10%). However after conditioning on high aggregate default shocks, momen-

¹[Avramov et al. \(2007\)](#) also document that equity momentum is generated by firms with low credit ratings (speculative grade bonds).

tum profit increases to 70 basis points per month with much stronger statistical significance (t-statistic of 4.30). In contrast, it is -17 basis points during low aggregate default shocks. Robustness checks with alternative measures of aggregate credit shocks confirm that bond momentum is indeed conditional on these default shocks.

This result is consistent with our hypothesis and motivates us to propose a conditional factor pricing model in which the sensitivity of corporate bond prices to aggregate default shocks fluctuates over time. In particular, we augment an empirical factor pricing model that incorporates the market and term premiums, with default shock and *conditional* default shock factors (conditional on high default shock). According to the results, the conditional default betas of bond winners (losers) are positive (negative) implying that they have relatively higher (lower) risk and expected returns. Moreover, the conditional default factor is priced in the cross section of momentum bond portfolio returns and explains a large portion of the *anomalous* performance.

To account for this finding, we develop a theory of “default-risky” bonds and related firm behaviors. In the model, expected bond returns depend on default risk and the ability of bondholders to recover firm value in financial distress. The model predicts that bondholders’ ability to recover value can become more important than a default premium in periods of high aggregate default shocks. We call this the *recovery premium*, a new premium related to recovery risk in the event of bankruptcy. We assume that firms with more (less) intangible and firm-specific assets have higher productivity on average, yet they are more costly to liquidate and have lower recovery value. The first part of the assumption above is inferred from the literature on endogenous economic growth.² It suggests that economic growth results mainly from the intangible forms of capital, especially those related to human capital. However, this source of growth comes with a cost: If bankruptcy occurs, the value of this type of asset can be hard to recoup, so has lower recovery value.³

²See Barro and Sala-i-Martin (2003), Lucas (1988), Lucas (1993), or Romer (1994) for an excellent survey.

³Garlappi et al. (2008) uses a similar argument to study relations between shareholder bargaining power and equity returns. A related, but more broad line of literature studies risk-return characteristics of growth options. For more details, see Berk et al. (1999), Berk et al. (2004) and references therein.

Incorporating these features, we theoretically show that corporate bond winners (losers) become more (less) risky when high default shocks arise because of lower (higher) bondholder recovery. Since the recovery value matters more during high aggregate default shocks, the model also predicts that the recovery premium of winners is higher than the default premium of losers in this state. Therefore, momentum profits will exist mainly in periods of worsening default conditions. In normal times, the recovery premium is very small and the default premium dominates, implying that momentum is hard to observe. In addition, our theory implies that low rated bonds are more likely to display momentum because those low rated issuers will be heavily affected by aggregate default shocks. This model provides a risk-based explanation for momentum in bond returns consistent with empirical evidence, and provides a link between firm characteristics and corporate bond returns.

We empirically assess the link between bondholder recovery and bond returns. To this end, we employ two characteristics that capture bondholder recovery, following [Garlappi et al. \(2008\)](#): a firm’s tangibility of assets and industry Herfindahl index.⁴ Our model predicts that bondholders of low recovery firms face higher risk in periods of high default shocks, and require higher returns. Using these measures of bondholder recovery, we test this prediction empirically and show that bonds in the “loser” (“winner”) portfolio indeed have relatively higher (lower) recovery potential. Therefore, the “loser” (“winner”) portfolio can have lower (higher) risk. Further, we present evidence that the recovery premium is greater in high default states, whereas the default premium is higher during low default states.

Consistent with the theory that no momentum prevails in a market with (nearly) zero default risk, we find virtually no momentum in the U.S. government bonds. On the other hand, sovereign bonds display positive momentum in times of high aggregate credit shocks and negative momentum during low shocks.⁵ Overall, all these results support our proposition that

⁴Tangibility is the ratio of the recoverable fraction of inventory, equipment, receivables, and cash to the total book value of assets and captures the expected liquidation value of the firm. Bondholders of firms with mostly intangible assets expect lower liquidation value in default, and, thus, face higher risk during worsening credit conditions. The industry Herfindahl index (the concentration of industry sales) represents the specificity of the firm’s assets. The higher (lower) the index, the higher (lower) the asset specificity, and hence lower (higher) recovery.

⁵Many sovereign bonds have potential default concerns. The Russian government defaulted on its obli-

time variations in aggregate default risk play a central role in driving the momentum anomaly in the bond market and recovery in high default states significantly affect the momentum effect.⁶

Our work touches upon a large literature on momentum, pioneered by [Jegadeesh and Titman \(1993\)](#). While the majority of subsequent studies focus on equity momentum, few examine momentum in corporate bonds. The latter focus on discerning the existence of momentum in the bond market, and as discussed earlier, obtain mixed results. While we analyze this issue as well, we extend the literature in two important dimensions.

First, our main emphasis is on discovering the economic factors generating momentum in bonds. We obtain evidence that momentum in corporate bonds does exist, and depends critically on the nature of economy-wide default shocks. We then scrutinize characteristics associated with the growth and liquidation of firms to provide a theoretical model and to empirically confirm that these variables indeed matter in explaining momentum profits. Second, despite a litany of empirical evidence, commonly accepted empirical asset-pricing models generally fail to explain the momentum puzzle.⁷ To the best of our knowledge, no other work has provided a risk-based explanation to this puzzle in the bond market consistent with rational expectations, empirically or theoretically.⁸

The rest of the paper proceeds as follows. Section 2 presents the basic empirical results. Section 3 introduces a theoretical model explaining our findings and derives the relation

gations in 1998, and Greece and Cyprus are more recent examples.

⁶Recently [Garlappi and Yan \(2011\)](#) argue that the default likelihood of a firm changes the relation between shareholder recovery and the riskiness of equity. They claim that equity momentum profits tend to increase for firms with high default likelihood via the channel of shareholder recovery. However, their story is largely cross-sectional and deals with only the stock market, based on shareholder bargaining power. We emphasize the time-series aspect of aggregate default risk in determining the cross section of bond returns through firm characteristics affecting both growth options and liquidation value. In particular, we attempt to disentangle a bond risk premium into a conventional market premium, a default premium, and a *conditional* recovery premium.

⁷[Fama and French \(1996\)](#) show that the market, SMB and HML factors cannot capture momentum profitability. [Griffin et al. \(2003\)](#), testing the model of [Chen et al. \(1986\)](#), incorporate innovations in macroeconomic variables and show that this model also cannot explain momentum.

⁸For the equity momentum, [Johnson \(2002\)](#) and [Lewellen \(2002\)](#) suggest explanations based on rational expectation. [Choi and Kim \(2013\)](#) develop an equilibrium model with rational expectation and quantitatively explain the equity momentum.

between financial distress, bondholder recovery, and momentum. Section 4 empirically analyzes the testable implications of the model. Section 5 provides a number of robustness checks and additional discussions. Section 6 concludes the paper.

2. Corporate Bond Momentum and Aggregate Default Shocks

2.1. Data and Portfolio Construction

We merged information from Bloomberg, DataStream and TRACE (Trade Reporting and Compliance Engine) databases to obtain our samples. We exclude bonds with unusual coupons such as: convertible, auction, exchanged, variable, flat trading, funged, pay-in-kind, step, and zero as well as defaulted bonds and asset-backed securities. We start by obtaining bond prices, coupons, and the number of bonds in an issue from DataStream following the procedure described above. We include all U.S. corporate bonds traded in the U.S. market which have all necessary information available in DataStream. Because of thin coverage of the bond market in the early 1990s, we start the sample period in January of 1995 and include all data through December of 2010.

From Bloomberg we then collect information about ratings, first coupon date, maturity, coupon frequency (assume semi-annual if missing) and type. If the first coupon date is not available, we assume that a coupon starts accruing from the issuance date using 30/360 convention. We also obtain prices and all necessary information to calculate bond returns from January 1995 and December 2004.

Finally, we match our data with the TRACE database that includes trade-based information. TRACE was initially introduced in 2002 and was implemented in stages. It covered 99% of the U.S. corporate bond market by 2005. Based on SEC rules, all FINRA members are supposed to report all transactions in corporate bonds to TRACE. We collect bond prices from the inception of TRACE in 2002 up to December of 2012. Since TRACE is a trade-based database, we use stale prices (the price from the last available transaction) for the months when bonds were not traded.

After applying all the filters and merging information from all three databases, we obtain

the final sample that contains information on 37,703 individual corporate bonds. The coverage starts with about 100 bonds per month and finishes in December of 2012 with about 15,000 bonds. To estimate measures of bondholder recovery, we match our bond sample with financial statements data from Compustat.

To estimate corporate bond returns we follow [Gebhardt et al. \(2005a\)](#):

$$r_{i,t} = \frac{(D_{i,t} + AC_{i,t} + C_{i,t}) - (D_{i,t-1} + AC_{i,t-1})}{D_{i,t-1} + AC_{i,t-1}}, \quad (1)$$

where $r_{i,t}$ is the monthly return on bond i at time t ; $D_{i,t}$ is the price of bond i at time t ; $AC_{i,t}$ is the accrued interest on bond i at the end of the month t ; and $C_{i,t}$ represents any coupon payments on bond i made between t and $t - 1$. To correct for potential data errors and to make sure that the results are not driven by outliers, we exclude observations with returns above 100% per month following [Jostova et al. \(2013\)](#).

To create bond momentum portfolios, we follow [Jegadeesh and Titman \(1993\)](#) and sort bonds into deciles based on the cumulative performance over the formation period ($t - 6$ to $t - 1$). The bonds are equally weighted within each decile. The top decile is comprised of recent winners and the bottom decile contains recent losers. We skip a month after the formation period to avoid short-term reversals. The momentum strategy entails buying recent winners and selling recent losers. The portfolios are rebalanced every month and then held for 6 months (we refer to this as 6-1-6 strategy).

[Table 1](#) presents simple summary statistics for the portfolios from January 1995 to December 2012. The first impression from the data is that the bond momentum strategy is only marginally profitable (the return to the bond momentum strategy is 28 basis points per month and statistically significant at 10%). We also find that the return distributions of the bond portfolios do not differ substantially. The standard deviation of losers is higher than that of winners (2.49% vs. 1.34%, respectively).

[Insert [Table 1](#) here]

Consistent with the information in [Table 1](#), existing empirical evidence on bond momen-

tum is mixed. [Khang and King \(2004\)](#) do not find statistically significant momentum in corporate bonds returns. [Gebhardt et al. \(2005b\)](#) report that past winners tend to underperform past losers in the corporate bond market, but also find that equity momentum spills over to bonds, suggesting that corporate bond momentum may be security specific. On the other hand, [Jostova et al. \(2013\)](#) show that the momentum anomaly exists in corporate bonds during the period 1973 to 2008. However, the effect is observed mainly in speculative grade (low credit rating) bonds, and it is insignificant in the earlier subsample from 1973 to 1990. Therefore, prior literature suggests either no momentum or a time-varying relation between bond momentum and credit risk. We attempt to reconcile these results by exploring the profitability of the momentum strategy in bonds conditional on shocks to economy-wide default risk. In particular, we hypothesize that bond momentum profits are state-dependent.

2.2. Aggregate Default Shocks: Measurement and Interpretations

To capture time-series innovations in aggregate credit conditions, we compose a measure that records shocks in aggregate credit spread. We refer to worsening (improving) aggregate credit conditions as *high (low) default shocks*. Specifically, we define the aggregate default spread (DEF_t) as the yield difference between CCC corporate bond index and the 10-year U.S. Treasury bond. CCC bonds are non-investment grade and regarded as *extremely speculative*. Most of the previous studies use credit spread associated with investment grade bonds. However, the conventional credit spread is limited in capturing aggregate credit risk because it encompasses only a subset of bonds that have very small historical default rate. The conventional credit spread is actually known to capture business cycle fluctuations. For details, see [Vassalou and Xing \(2004\)](#). We construct the CCC index using the Lehman Brothers-Barclays Bond Indices available from Ibbotson and Datastream. We then estimate default shocks as the residuals of the following AR(2) model:

$$DEF_t = \alpha_0 + \alpha_1 DEF_{t-1} + \alpha_2 DEF_{t-2} + \xi_t. \quad (2)$$

Aggregate default shocks are captured by ξ_t . An increase (decrease) in the residuals (ξ_t) corresponds to higher (lower) shocks to aggregate default. We use the median of ξ_t to demarcate high and low shock periods. Also, to avoid the potential look-ahead bias, we estimate equation (2) using a recursive cumulative procedure as well. Specifically, we initially estimate the model using the pre-sample period (from January 1954 to December 1959). We then add one monthly observation to the sample and re-estimate the model using the updated time series. We repeat this procedure (keep adding one observation) until we obtain the estimates for every observation in the sample. Therefore, the residual at any time t is conditional on the data from January 1954 to $t - 1$.⁹

Another important interpretation of ξ_t is that the *minus* default shock ($-\xi_t$) can be used to approximate *holding period return* on a long CCC bond and a short U.S. Treasury bond portfolio. Appendix A shows that the *minus* default shock times the maturity of the bond ($-\xi_t \times \text{maturity}$) approximates the bond returns, provided that bond returns are persistent.¹⁰ Figure A.1 in Appendix A shows comparisons between actual returns and the approximate returns using our aggregate default shock measure. The figure displays an impressive fit between the two measures. Correlation between our measure of aggregate credit shock and actual bond returns is over 92 percent. Thus, $-\xi_t$ has the same sign as the *credit risk premium* obtained from holding CCC rated bonds. This facilitates providing a risk-based explanation based on our empirical results.

2.3. Bond Momentum Conditional on Shocks to Aggregate Default

Using this definition of aggregate default shocks, we document momentum in corporate bonds during periods of high and low default shocks.¹¹ Table 2 presents the performance of bond momentum conditional on high and low default states of the world. Panel A documents

⁹We also control for lagged liquidity and market volatility using Amihud (2002) and French et al. (1987) in equation (2). The results obtained from all these procedures are very similar to those reported here.

¹⁰ DEF_t is indeed highly persistent: The estimated α_1 and α_2 using the whole sample are 1.13 and -0.15 with Newey-West corrected t -statistics of 9.11 and -1.28 respectively. If AR(1) model is applied, the persistence coefficient is 0.98 with a Newey-West corrected t -statistic of 43.6.

¹¹For the relation between default shocks and equity returns, see Mahajan et al. (2012). The paper documents that the conditional default factor affects equity momentum as well, giving further credence to our story.

the returns of winners and losers for the entire sample period (1995-2012). Panels B and C present the results obtained from the earlier (1995-2002) and later (2003-2012) subperiods. Our total sample has 216 monthly observations - 113 periods are classified as high default shocks and 103 as low default shocks.¹²

Panel A of [Table 2](#) shows that the momentum strategy (W - L) produces 28 basis points of profit with a marginal statistical significance. For the period of 1995-2002, the momentum profit is significant both economically and statistically. Then, it disappears during the period of 2003-2012. Since the data set virtually covers the universe of traded corporate bonds, it is unlikely that the reported temporal nature of the bond momentum results from sample selection. [Jostova et al. \(2013\)](#) also document this temporal nature, finding that the momentum does not exist between 1973 and 1990, but it is statistically significant during the period of 1991-2008. It is interesting to note over first sub-period, 1995-2002, during which we document positive momentum overlaps with [Jostova et al. \(2013\)](#) 1995-2002 period for which it reports similar results. By extending their sample period by four years to 2012, momentum again becomes unobservable during the 2003-2012 period. To shed light on the sources of the time varying nature of momentum profits, we condition bond returns on high and low default states of the economy. Positive momentum returns increase during high default shocks (70 basis points with a t -statistic of 4.30), and almost identical performance of losers and winners in low default states (the difference is -17 basis points with a t -statistic of -0.68).

[Insert [Table 2](#) here]

One might suspect that this result is primarily driven by the early period of the sample when temporary mispricing is more likely to occur. However, if bond momentum is a result of mispricing or market inefficiency, it should decline and become insignificant over time. We test whether momentum profits in high default states become smaller and insignificant over

¹²The high and the low default shock periods are unequal because of the look-ahead bias adjustment procedure that categorizes the sample in high and low default shocks by using only historical data that available at time t .

the subsample periods of 1995-2002 and 2003-2012. As shown in Panels B and C of [Table 2](#), momentum returns (86 and 55 basis points) are significant in both periods. Even though the magnitude of the momentum profits in the later part of our sample appears smaller, it turns out that the difference between the two subsamples is not statistically significant (t -statistic is 0.98). The result suggests that momentum in bonds is closely related to aggregate default shocks and not likely to be a product of temporary mispricing or inefficiency.

To make sure that the results are robust to alternative measures of aggregate default shocks, we repeat our sorting procedure using the Senior Loan Officer survey provided by the Federal Reserve Board and aggregate modified Altman’s Z-score¹³. Specifically, we characterize high default shock periods if there is an increase in the number officers who tighten standards for loans for large and medium firms.¹⁴ The results in Panel (a) of [Figure 1](#) show that momentum is only observed during periods when loan officers tighten credit standards. In particular, we observe bond momentum profits of 64 basis points per month during these tight credit or high default shock periods and 0 otherwise. We also repeat our analysis using the aggregate modified Altman’s Z-score to identify default shock periods. We define such a period if a change in the Z-score is negative. Panel (b) of [Figure 1](#) presents the results of this analysis. Consistent with all our previous results, bond momentum is positive only when the aggregate modified Z-score decreases. Overall, our results strongly suggest that momentum exists in corporate bond returns - but its profitability varies and critically depends on aggregate-level default shocks.

[Insert Figure 1 here]

¹³Following [Graham et al. \(1998\)](#) and calculate this measure for every firm in the sample. To obtain the aggregate modified Z-score we take equally-weighted average of the firm-level measures for every point in time using the whole Comptustat sample.

$$z = \frac{1.2 \times wcap + 1.48 \times re + 3.3 \times pi + sale}{at},$$

where $wcap$, re , pi , and $sale$ represent working capital, retained earnings, earnings before interest and taxes, and sales, respectively. ta stands for the book value of total assets.

¹⁴As a robustness check, we also use the same measures for small firms and for large, medium, and small firms. The results are similar to the findings reported in the paper.

Chordia and Shivakumar (2002) and Stivers and Sun (2010) argue that equity momentum tends to prevail during “good times.”¹⁵ We further investigate the relation between the profitability of bond momentum and general economic conditions by using a double sorting procedure on both business cycles and aggregate default shocks. Figure 2 documents the results of this analysis. We find that the majority of the momentum profits are observed when specific economic conditions prevail, namely, at the intersection of recessions and high default shocks. The momentum profit during these periods is 0.81% per month. Note that momentum is also positive and significant in periods of high default shocks and expansions (0.64% per month). Finally, when low default shocks occur during expansions (recession) momentum profits decrease to 0.23% (-1.26%).

[Insert Figure 2 here]

To better illustrate this relation, Figure 3 presents profitability of the momentum strategy and high default shocks (shaded area). We observe that momentum is consistently positive during worsening aggregate credit conditions. One notable event period in this figure is 2008-2009. On the verge of financial crisis that lead to the Great Recession, bond momentum profits jump to 8% per month in 2008 during periods of high default shocks. However, a large *drop* in momentum profits is observed in 2009 when adverse aggregate credit conditions had receded. These results provide further evidence that momentum is strongly correlated with high default shocks in the time series.

[Insert Figure 3 here]

This state-dependent nature of momentum profits raises the possibility that these observed profits may actually be a compensation for bearing risk associated with the state of high aggregate default risk. If so, the conditional aggregate default risk should be priced in the cross section, and the returns of winners and losers should have different sensitivities to this conditional risk factor. We verify this in the following sections.

¹⁵Chordia and Shivakumar (2002) define the periods of expansion (as defined by the National Bureau of Economic Research) as “good times.” Stivers and Sun (2010) suggest that low cross-sectional dispersion in stock returns corresponds to “good times.”

2.4. Pricing the Conditional Default Risk Factor

In this section, we estimate the exposure of winners and losers to unexpected default shocks in the corporate bond market. To this end, we utilize empirical asset-pricing models that incorporate the commonly accepted factors of asset returns and factors representing unexpected default shocks. [Fama and French \(1993\)](#) argue that besides the standard market, size (SMB), and book to market (HML) factors, the default (DEF) and term (UTS) premiums capture the cross-sectional variation of bond returns. [Gebhardt et al. \(2005a\)](#) suggest that default and term spreads are major determinants of bond returns and should be examined separately. In addition, the recent literature studying bond returns includes macroeconomic variables capturing inflation and real activity. We follow [Ang and Piazzesi \(2003\)](#), [Chen et al. \(1986\)](#), [Kim and Moon \(2005\)](#) and [Ludvigson and Ng \(2009\)](#) and use unemployment rate (UNMP) and unanticipated inflation (UI) in our analysis.¹⁶

$$R_t^e = \beta_0 + \beta^{MKT} MKT_t + \beta^{UTS} UTS_t + \beta^{DEF} DEF_t \quad (3)$$

$$+ \beta^{SMB} SMB_t + \beta^{HML} HML_t + \beta^{UI} UI_t + \beta^{UNMP} UNMP_t + \epsilon_t,$$

where R_t^e corresponds to the excess return ($R - r_f$) at time t . Because our hypothesis is based on the assumption that the bond momentum portfolios are sensitive to shocks to aggregate default rather than the simple default spread, we substitute shocks to default ξ_t (as defined in equation (2)) into the model in place of DEF .

The majority of the recent empirical literature on bonds focuses on unconditional models. However, the results from [Table 2](#), and [Figure 1](#) to [Figure 3](#) clearly show that momentum profit in corporate bonds is conditional on high unexpected default risk. This leads us to a conditional default factor ($C\xi_t$) that allows the default betas to be time-dependent in the

¹⁶ $UI_t = I_t - E[I(t)|t-1]$. I_t is the first difference in log of consumer price index, obtained from the Federal Reserve Bank of St. Louis (FRBS). $E[I(t)|t-1]$ is expected inflation and obtained from the Federal Reserve Bank of Cleveland and UNMP from the FRBS. We define UTS as the spread between the 10-year and 1-year U.S. government bond yields.

following fashion:

$$C\xi_t = I_t\xi_t, \quad (4)$$

where ξ_t represents the shock to aggregate default in month t as defined in equation (2), and I_t is an indicator that takes a value of 1 during high default shocks and 0 otherwise. The conditional default factor captures the additional default exposure when the economy is in a high default state. Rewriting (3) yields our main empirical model as follows:

$$R_t^e = \beta_0 + \beta^{MKT}MKT_t + \beta^{UTS}UTS_t + \beta^{DEF}\xi_t + \beta^{CDEF}C\xi_t \\ + \beta^{SMB}SMB_t + \beta^{HML}HML_t + \beta^{UI}UI_t + \beta^{UNMP}UNMP_t + \epsilon_t. \quad (5)$$

The estimated time-series beta loading spreads (winners - losers) are presented in [Table 3](#) for various specifications. Model (a) corresponds to equation (5), and models (b) to (f) tabulate results with subsets of the factors in equation (5).¹⁷ In all the specifications, the difference in the market loadings (β^{MKT}) of winner and loser portfolios is negative and statistically significant. This implies that corporate bond losers are more sensitive to the market and riskier, which makes the reversal anomaly rather than the momentum anomaly a more likely result. Size and book-to-market factors do not show any significance in explaining bond momentum returns, similar to equity momentum returns. The spread in term loadings of losers and winners is also not significant.¹⁸

For the macroeconomic factors, both inflation and real activity variables are statistically significant and negative, similar to the equity market return factor (MKT), reinforcing the belief that the returns of the loser portfolio are subject to more aggregate risks and business cycle fluctuations. We can infer that both the financial asset market factors and the macro factors matter in explaining corporate bond returns, and incorporating the macroeconomic variables are important to identify the effect from the financial factors. However, cross-

¹⁷We tried other variables such as monthly growth of industrial production in our analysis as well. These were statistically insignificant and not reported to conserve space.

¹⁸For individual portfolio returns, consistent with [Acharya et al. \(2013\)](#), we do observe a positive and significant β^{UTS} .

sectional variations in returns from the momentum strategies are not fully explained by these conventional factors in light of the risk-return trade-off.

We now turn to the default factors. As discussed in section 2.3 and Appendix A, to interpret the default betas in a consistent manner with the market betas, we report $-\beta^{DEF}$ and $-\beta^{CDEF}$. The results on $-\beta^{DEF}$ imply that winners (losers) are less (more) sensitive to the aggregate default shock, similar to other risk factors. However, when the economy experiences high default shocks ($-\beta^{CDEF}$), default risk affects these portfolios in the opposite directions, and winners become relatively riskier than losers in that the sum of betas ($-(\beta^{DEF} + \beta^{CDEF})$) are positive in our main model. In fact, as long as the macroeconomic risk, in particular, inflation factor (UI) is included, the same result prevails.¹⁹

These results imply that corporate bond losers are riskier on average, as suggested by the market, macro, and unconditional default betas, yet losers (winners) become relatively safer (riskier) than before in high default states, and consequently have lower (higher) expected returns. Therefore, the observation of bond momentum depends on the existence of aggregate default shocks. This finding helps explain the previous literature's mixed results on corporate bond momentum.

Next we estimate factor premiums in the cross section. We follow the procedure by Fama and MacBeth (1973) and use 30 momentum-based portfolios to get consistent estimates. To control for the errors-in-variables problem, we apply the correction for standard errors proposed by Shanken (1992). The base asset-pricing model that we test becomes:

$$E[r_i] = \gamma_0 + \gamma^{MKT} \beta_i^{MKT} + \gamma^{UTS} \beta_i^{UTS} + \gamma^{DEF} (-\beta_i^{DEF}) + \gamma^{CDEF} (-\beta_i^{CDEF}) \quad (6)$$

$$+ \gamma^{SMB} \beta^{SMB} + \gamma^{HML} \beta^{HML} + \gamma^{UI} \beta^{UI} + \gamma^{UNMP} \beta^{UNMP},$$

where $E[r_i]$ is the expected excess return on asset i and the gammas are prices of risks.

¹⁹It turns out that the DEF factor still captures macro or other systematic risks to some extent as well as the default risk, and therefore, the conditional default risk is correctly estimated in models with both inflation and the real activity factors.

Table 4 reports the time-series mean value of the premiums (gammas). Even though the MKT premium is positive and significant in Model (b), the adjusted R^2 is low (0.28), suggesting that some factors are missing in the model. Augmenting the model with the term and default factors improves R^2 . However, our previous results in Table 3 show that the term loadings of winners and losers cannot explain momentum profits. Macro variables marginally improve R^2 . Finally, we look at the conditional default factor (Model (a)), the conditional default premium (γ^{CDEF}) is positive and significant (0.0129 with a t-statistic of 2.69).

[Insert Table 4 here]

We interpret the reported results as follows: winners do not necessarily outperform losers. Winners become riskier during high default states of the world, and, therefore, investors require higher returns. In addition, the conditional default factor can explain a large portion of momentum profits in periods of high default shocks. The $-\beta^{CDEF}$ beta spread between losers and winners ($-(\beta_W^{CDEF} - \beta_L^{CDEF}) = 1.435$, see Table 3) multiplied by the premium ($\gamma^{CDEF} = 0.0129$, see Table 4) can generate up to 1.85% of momentum profits. Of course, this is the partial effect without considering the conventional default risk premium. Roughly, from the estimates of $-\beta^{DEF} = -1.306$ and $\gamma^{DEF} = 0.0077$ reported in Tables 3 and 4, DEF affects the momentum profit by -1% , and summing the two components produces around 85 basis points of momentum profit during the high default state. This is close to the momentum profits during high default states reported in Table 2, ranging from 55 to 86 basis points. Indeed, our empirical model can explain the cross section of corporate bond momentum returns fairly well.

3. Sources of Momentum in Bonds

The empirical results in the previous section show that bond winners are relatively safer on average, while losers become safer in high default states of the world. Can we make sense of this finding and provide an economic explanation? We begin with developing a theoretical model of corporate bond prices and firm behavior.

3.1. Model

Time is discrete, and uncertainty is described by a probability space (Ω, \mathcal{F}, P) with its filtration $\mathbb{F} = \{\mathcal{F}_0, \dots, \mathcal{F}_T\}$. Denote the price of a zero-coupon corporate bond with maturity n and the face value of one unit good at time t by $D_t^{(n)}$. M_{t+1} is the stochastic discount factor at $t+1$, $(1 - \phi_{t,t+1})$ is the risk-neutral conditional probability of default at $t+1$ given that this firm has not filed for bankruptcy before t ($0 \leq \phi_{t,t+1} \leq 1$), and X_{t+1} is the recovery value if default (or an event of financial distress) occurs.²⁰ $\phi_{t,t+1}$ is assumed to be adapted at t . Under the no arbitrage condition, the pricing formula of $D_t^{(n)}$ is given as

$$D_t^{(n)} = \phi_{t,t+1} E_t \left[M_{t+1} D_{t+1}^{(n-1)} \right] + (1 - \phi_{t,t+1}) E_t [M_{t+1} X_{t+1}], \quad (7)$$

where the notation for issuer is suppressed for the time being. Assume that the recovery value X is a fraction η of total firm value (denoted as V), in particular, $X_{t+1} = \eta_t V_{t+1}$ following the existing literature such as [Duffie and Singleton \(1999\)](#). We will explain more details about η and V when we model corporate behavior in the next subsection. Then (7) can be expressed as

$$0 = \log E_t \left[M_{t+1} \Pi_{t+1}^{(n)} \frac{D_{t+1}^{(n-1)}}{D_t^{(n)}} \right], \quad (8)$$

where

$$\Pi_{t+1}^{(n)} \equiv \phi_{t,t+1} + (1 - \phi_{t,t+1}) \frac{\eta_t V_{t+1}}{D_{t+1}^{(n-1)}}. \quad (9)$$

Note that $\Pi_{t+1}^{(n)} \in [0, 1]$ and measures a conditional expectation of bondholder recovery ratio. Thus, corporate bond returns will depend on the default-related factor (9) as well as the conventional discount factor M_{t+1} . For tractability, assume that $D_t^{(n)} = D_t/N$, where D_t is the total amount of debt and $n = 1, \dots, N$. Now we define $\log D_{t+1}^{(n-1)}/D_t^{(n)}$ as the holding

²⁰This follows from [Duffie and Singleton \(1999\)](#). Alternative procedures to price default risky assets exist. For example [Garlappi and Yan \(2011\)](#) provide a theoretical framework for stock returns in this context, extending previous studies on the relationship between costly bankruptcy and asset valuation, such as [Anderson and Sundaresan \(1996\)](#), [Broadie et al. \(2007\)](#), [Fan and Sundaresan \(2000\)](#), [Galai et al. \(2003\)](#), and [Mella-Barral and Perraudin \(1997\)](#).

period return $(r_{t+1}^{(n)})$ on this corporate bond and express equation (8) as follows:

$$\begin{aligned} E_t(r_{t+1}^{(n)} - r_t^f) + \frac{Var_t(r_{t+1}^{(n)}) + Var_t(\pi_{t+1}^{(n)})}{2} \\ = -E_t(\pi_{t+1}^{(n)}) - Cov_t(m_{t+1}, \pi_{t+1}^{(n)}) - Cov_t(r_{t+1}^{(n)}, m_{t+1}) - Cov_t(r_{t+1}^{(n)}, \pi_{t+1}^{(n)}), \end{aligned} \quad (10)$$

where r_t^f is the risk-free rate at time t , m and π are the logarithms of M and Π respectively.²¹ Equation (10) is a return-beta representation for corporate bonds, and the right hand side represents bond risk premium for holding default-risky bonds. The following proposition characterizes the terms related to bond risk premium. We first define the stochastic discount factor and explicitly state our assumptions.

Definition 1 The logarithm of the stochastic discount factor M_{t+1} , denoted as m_{t+1} is given as

$$m_{t+1} = -r_t^f - \delta \epsilon_{t+1}^m - \frac{1}{2} \sigma_\epsilon^2 \delta^2, \quad (11)$$

where ϵ_{t+1}^m measures the innovations in the growth rate of aggregate wealth following $N(0, \sigma_\epsilon^2)$, and δ measures risk aversion.

Assumption 1 A bond issuer's firm value-to-debt ratio is uncorrelated with the changes in aggregate wealth (i.e., $Cov_t(\epsilon_{t+1}^m, \frac{V_{t+1}}{D_{t+1}}) = 0$).

Assumption 2 When the firm value (V) is close to debt (D), the conditional default likelihood $(1 - \phi)$ approaches one, and vice versa.

The functional form of equation (11) is common in the term structure models and well justified with economic models. For instance, if the utility function of the representative investor over her consumption plan $\{C_t\}_{t=0}^\infty$ is given as $\sum_{t=0}^\infty \rho^t C_t^{1-\delta}$, it is easy to show that (11) holds. Roughly, assumption 1 states that shocks to the fundamental macro factors

²¹Given our focus on the default premium rather than term premium, we abstract from the superscript (n) indicating maturity, where possible, for expositional purpose.

affecting the stochastic discount factor (ϵ_{t+1}^m) are not correlated with the bond issuer's value-to-debt ratio. Admittedly, this assumption is strong and mainly for tractability. However, given our empirical results that conventional factors that proxy for the discount factor do not account for momentum portfolio returns, this assumption is reasonable to use for our purpose.²² assumption 2 stipulates that default likelihood (ϕ), debt amount (D), and firm value (V) are associated with each other in the limit.

Proposition 1. Define $\Lambda_{\phi,t}$ as

$$\Lambda_{\phi,t} \equiv \frac{(1 - \phi_{t,t+1}) \eta_t}{\phi_{t,t+1} + (1 - \phi_{t,t+1}) \eta_t \frac{V_t N}{D_t}}. \quad (12)$$

Then $\Lambda_{\phi,t}^i$ is decreasing in $\phi_{t,t+1}$ and $\frac{V_t}{D_t}$, but increasing in η_t . Under assumption 1, the corporate bond risk premium is due to

i) the negative conditional expectation of risk-adjusted average bondholder recovery ratio

$$-E_t(\pi_{t+1}) = -E_t \left(\ln \left[\phi_{t,t+1} + (1 - \phi_{t,t+1}) \eta_t N \frac{V_{t+1}}{D_{t+1}} \right] \right) \geq 0, \quad (13)$$

ii) the conventional risk premium for holding a risky asset

$$-Cov_t(r_{t+1}, m_{t+1}) = \delta Cov_t(r_{t+1}, \epsilon_{t+1}^m), \quad (14)$$

iii) co-variation between bond returns and firm value-to-debt ratio

$$-Cov_t(r_{t+1}, \pi_{t+1}) = -\Lambda_{\phi,t} Cov_t \left(r_{t+1}, \frac{V_{t+1}}{D_{t+1}} \right). \quad (15)$$

Proof. See [Appendix B](#). □

Equation (13) is greater than or equal to zero because $0 \leq \Pi \leq 1$, and represents the first-order effect of firm-level default risk. If default is unlikely ($\phi_{t,t+1}$ is close to 1), then this

²²We can relax this assumption and impose more realistic assumptions like financing constraints on firms to derive this covariance. This is an interesting extension, but beyond the scope of our paper.

value is close to zero, and if the distance to default is short ($\phi_{t,t+1}$ is small), equation (13) gets closer to $-\eta_t N$. Thus, bondholder recovery becomes a key determinant of bond risk premium when the probability of default is non-trivial. Equation (14) describes the premium of risky assets in general (see Cochrane (2005) for an extensive review.) Corporate bonds will have a positive risk premium if ϵ_{t+1}^m positively co-varies with contemporaneous returns (r_{t+1}). In fact, this is consistent with our empirical results depicted in Table 3. Asset market factors and macroeconomic factors that proxy for variations in aggregate wealth returns affect portfolio returns of corporate bonds.

Equation (15) consists of two terms: $\Lambda_{\phi,t}$ and the covariance between corporate bond returns (r_{t+1}) and the enterprise value-to-debt ratio (V_{t+1}/D_{t+1}). Since $\Lambda_{\phi,t}$ is decreasing in ϕ , a higher default risk renders more weight on this term. In addition, bonds with higher bondholder recovery (i.e., higher value of η) will have a higher value $\Lambda_{\phi,t}$ than those with lower η . Again, in a regime with low default risk, equation (15) will converge to zero as $\Lambda_{\phi,t}$ approaches zero, hence (15) will not matter. Taken together, if the covariance term in (15) is positive, when high default shocks occur (i.e., high values of $\Lambda_{\phi,t}$), bonds with the higher recovery value will have lower risk premium according to the equations (13) and (15), and this effect disappears when there is no default risk. With multiple sources of corporate bond risk premiums given by ((13), (14) and (15)), a natural question is how shocks to the default risk factor (ϕ) as well as the discount factor (ϵ^m) determine the cross section of corporate bond returns. To answer the question, we propose an economic model determining firm value (V), recovery (η), and corporate bond risk premium.

3.2. Default, Recovery, and Asset Returns

Suppose that a firm produces goods (Y) using two types of inputs, tangible capital (k) and intangible capital (h) and has the following production function:

$$Y = A(H)f(K), \tag{16}$$

$$H = h + \epsilon,$$

$$K = h + k$$

in which ϵ is an *i.i.d.* productivity shock following a normal distribution $N(0, \sigma_\epsilon^2)$, and the following assumption describes the properties of (16).

Assumption 3 For (16), $A > 0$, $\frac{dA}{dH} > 0$, $\frac{d^2A}{dH^2} < 0$, $f > 0$, $\frac{df}{dK} > 0$, and $\frac{d^2f}{dK^2} < 0$ hold.

In addition, there exists $\bar{H} > 0$ such that $\frac{dA}{dH}|_{H=\bar{H}} = 0$ and $\frac{dA}{dH}|_{H=0} = \infty$ to prevent explosive dynamics.

The production function states that both tangible and intangible capital are used to produce Y but intangible capital increases the total factor productivity A in a decreasing fashion. This is reminiscent of production functions used in economic growth and development literature (e.g., Barro and Sala-i-Martin (2003), Lucas (1988), Lucas (1993), Romer (1994)). Production is costly, represented by the cost function $C(K)$ with the usual property that $C > 0$, $\frac{dC}{dK} > 0$, and $\frac{d^2C}{dK^2} > 0$ hold. Following the setup from the previous section, the firm can be shut down with the conditional, risk-neutral probability $(1 - \phi_{t,t+1})$. For the recovery value of the firm, we have the following assumption.

Assumption 4 When a bankruptcy occurs at $t + 1$, the value of the firm is given as λk_{t+1} , where $\lambda > 0$ is the price of the scrapped tangible capital.

While it is easy to relax assumption 4 to include intangible capital with a lower weight than tangible capital, we believe it is important to highlight the key difference between the two types of capital. Managers after observing the productivity shock, the current levels of capital and the conditional likelihood of default, maximize firm value V by selecting the inputs (h_{t+1}, k_{t+1}) to be used in period $t + 1$ as follows:

$$V_t = F(h_t, k_t, \epsilon_t) + \left\{ \phi_{t,t+1} E_t [M_{t+1} V_{t+1}] + (1 - \phi_{t,t+1}) e^{-r_t^f} \lambda k_{t+1} \right\}, \quad (17)$$

$$F(h_t, k_t, \epsilon_t) \equiv A(h_t + \epsilon_t) f(k_t + h_t) - C(k_t + h_t),$$

$$(h_{t+1}, k_{t+1}) \in \Gamma(k_t, h_t, \epsilon_t, \phi_{t,t+1})$$

where $V_t \equiv V(k_t, h_t, \epsilon_t, \phi_{t,t+1})$, $F(h_t, k_t, \epsilon_t)$ is the earnings function at t , and $\Gamma(k_t, h_t, \epsilon_t, \phi_{t,t+1})$ refers to the feasibility set in selecting (h_{t+1}, k_{t+1}) . Note that characterizing $\Gamma(\cdot, \cdot, \cdot, \cdot)$ is about constraints imposed on raising capital.

Assumption 5 F is concave, and Γ is a convex set.

Under assumption 5, the solution of the Bellman equation (17) exists. In this paper, we only analyze the case with no constraints on capital adjustment for analytical tractability. While this is restrictive, it turns out that this frictionless version can give many useful insights regarding the problem.

Recalling $H = h + \epsilon$ and $K = k + h$, the first-order conditions of this problem with the interior solution are

$$\begin{aligned} \phi_{t,t+1} E_t \left[M_{t+1} \frac{\partial V(k_{t+1}, h_{t+1}, \epsilon_{t+1}, \phi_{t,t+1})}{\partial k_{t+1}} \right] + (1 - \phi_{t,t+1}) \lambda e^{-r_t^f} &= 0, \\ \phi_{t,t+1} E_t \left[M_{t+1} \frac{\partial V(k_{t+1}, h_{t+1}, \epsilon_{t+1}, \phi_{t,t+1})}{\partial h_{t+1}} \right] &= 0, \end{aligned}$$

and the envelope conditions are

$$\frac{\partial V(k_t, h_t, \epsilon_t, \phi_{t,t+1})}{\partial k_t} = A(H_t) \frac{df(K_t)}{dK_t} - \frac{dC(K_t)}{dK_t}, \quad (18)$$

$$\frac{\partial V(k_t, h_t, \epsilon_t, \phi_{t,t+1})}{\partial h_t} = \frac{dA(H_t)}{dH_t} f(K_t) + \alpha A(H_t) \frac{df(K_t)}{dK_t} - \frac{dC(K_t)}{dK_t}. \quad (19)$$

Combining them with the fact that ϵ_{t+1} is not observable when k_{t+1} and h_{t+1} are determined at t , we obtain

$$E_t \left[M_{t+1} \alpha A(H_{t+1}) \right] \frac{df(K_{t+1})}{dK_{t+1}} = \left[\frac{dC(K_{t+1})}{dK_{t+1}} - \left(\frac{1 - \phi_{t,t+1}}{\phi_{t,t+1}} \right) \right] \lambda e^{-r_t^f}, \quad (20)$$

$$E_t \left[M_{t+1} \frac{dA(H_{t+1})}{dH_{t+1}} \right] f(K_{t+1}) = \left(\frac{1 - \phi_{t,t+1}}{\phi_{t,t+1}} \right) \lambda e^{-r_t^f}. \quad (21)$$

Equations (20) and (21) describe the optimality conditions of the firm. The left hand side of (20) is the expected marginal productivity of tangible capital, and the right hand side

refers to the marginal cost. The term $(1 - \phi_{t,t+1}) \phi_{t,t+1}^{-1} \lambda$ represents the additional benefits of investing in tangible capital because of the increase in recovery value. As the default likelihood $(1 - \phi_{t,t+1})$ increases, the size of this benefit increases. Given high substitutability between tangible and intangible capital in this setup, the difference of the two types of capital entirely comes from the recovery in case of default shocks and the ability of intangible capital to boost the total factor productivity. This is recorded in equation (21). For a low $\phi_{t,t+1}$ (high default likelihood), there is an incentive to reduce the intangible capital (h_{t+1}) and to increase the tangible capital (k_{t+1}). Put differently, as long as the default likelihood is low (high $\phi_{t,t+1}$), more intangible capital is preferred, for it spurs the growth of firms and produces higher earnings. The next proposition summarizes this result.

Proposition 2. *Suppose that $\phi_{t+i,t+i+1}$ is close to 1 for $i = 0, 1, \dots, T^*$, and there are two firms (1 and 2) with the same amount of K_t , yet $h_{t+j}^1 > h_{t+j}^2$ and $k_{t+j}^1 < k_{t+j}^2$, where $j = 0, 1$. If T^* is sufficiently large, the value of firm 1 is greater than that of firm 2 ($V_t^1 > V_t^2$) at t .*

Proof. See [Appendix C](#). □

The main intuition of this proposition is simple. Intangible capital increases total factor productivity (A) at the expense of lower recovery value. When the default probability is close to zero, recovery value is not relevant the latter effect disappears. Thus, if there are two firms with similar characteristics except for the tangibility of their assets in the past, the one with more intangible assets is likely to be the past winner for its higher productivity, provided that default possibility is low. Note, however, that historical high returns of firms with more intangible capital do not necessarily lead to higher future performances, because the marginal productivity of intangible capital is decreasing as stipulated in Assumption 3. In addition, we need to analyze the expected future returns of these firms to better assess the possibility of performance persistence.

For this purpose, we probe the risk return relations of the bonds issued by these firms in the model. There are two sources of risk, the productivity shock and the default shock, and Proposition 1 shows that the three terms (13), (14), and (15) compose the bond risk premium for bearing these risks. The following proposition determines the signs of these

terms so that the model offers theoretical links between firm characteristics and their future asset returns.

Proposition 3. *Under assumptions 1 to 5, the following properties hold approximately:*

$$Cov_t(r_{t+1}, \epsilon_{t+1}) > 0, \quad (22)$$

$$Cov_t\left(r_{t+1}, \frac{V_{t+1}}{D_{t+1}}\right) > 0. \quad (23)$$

In addition, for the two firms (1 and 2) with $h_t^1 > h_t^2$, $k_t^1 < k_t^2$, and $K_t^1 = K_t^2$,

$$Cov_t(r_{t+1}^2, \epsilon_{t+1}) > Cov_t(r_{t+1}^1, \epsilon_{t+1}). \quad (24)$$

Proof. See [Appendix D](#). □

3.3. Momentum in Bonds

We now analyze the momentum portfolios of corporate bonds. Suppose that there are two bond issuers of same asset size, W and L , with the property that L has more tangible assets than W , or W has more intangible capital than L . That is, the recovery value of L is greater than that of W ($\eta_t^L > \eta_t^W$). Proposition 2 indicates that W has shown a superior performance than L given low default risk, therefore, $r_t^W > r_t^L$. Based on performance, we form a long-short strategy to consider $E_t(r_{t+1}^W - r_{t+1}^L)$ and apply Proposition 1 to obtain

$$\begin{aligned} E_t(r_{t+1}^W - r_{t+1}^L) &\propto \quad (25) \\ &\Lambda'_{m,t} [Cov_t(\epsilon_{t+1}^m, r_{t+1}^W) - Cov_t(\epsilon_{t+1}^m, r_{t+1}^L)] + E_t(\pi_{t+1}^L - \pi_{t+1}^W) \\ &+ \left[\Lambda_{\phi,t}^L Cov_t\left(r_{t+1}^L, \frac{V_{t+1}^L}{D_{t+1}^L}\right) - \Lambda_{\phi,t}^W Cov_t\left(r_{t+1}^W, \frac{V_{t+1}^W}{D_{t+1}^W}\right) \right]. \end{aligned}$$

Then, we can show that momentum can prevail in states of high aggregate default shocks.

Proposition 4. *Assumptions 1 to 5 hold. In addition, suppose that productivity shock ϵ equals shocks to stochastic discount factor, ϵ^m . When aggregate default risk is small (both $\phi_{t,t+1}^W$ and $\phi_{t,t+1}^L$ are close to 1), momentum is unlikely to occur. However, positive momentum*

profits can arise when $\phi_{t,t+1}$ is sufficiently low (i.e., if the default likelihood is high) for both issuers.

Proof. See [Appendix E](#). □

If default is a serious concern for both issuers, the second and the third terms in the right hand side of equation (25) become significant and positive, because recovery in the event of default becomes a highly probable outcome. Given the assumption that bond winners (losers) have lower (higher) recovery in case of default, this produces a positive risk premium from the momentum strategy as a firm gets closer to default. However, the sign of equation (25) during periods of low default shocks is ambiguous, hence the momentum strategy does not generate significantly positive profits during the regime of low aggregate default shocks.

Our theory predicts momentum in corporate bonds, consistent with the empirical results reported in [Tables 2 to 4](#). In addition, our theory provides several other testable predictions. First, expected bond returns contain a recovery component. Second, there is a risk premium for securities with low bondholder recovery in high default states, and the recovery premium should be mainly observed in high default states. Third, this recovery premium should be closely and positively related to the momentum in bonds. Fourth, the conventional default risk premium is small in the default states. Thus, under the regime of high aggregate default risk, the recovery premium becomes more important than the conventional default risk premium, and vice versa. Finally and consequently, the momentum phenomenon should be hard to observe, or the reversal is more likely in bonds with small or no default risk.

4. Empirical Results on Bondholder Recovery and Momentum

4.1. Bondholder Recovery

Based on the theoretical predictions, this section uncovers fundamental characteristics of bond issuing firms that can explain the difference in the expected returns of losers and winners in periods of high default shocks to the economy. In particular, we test whether bondholder recovery drives the difference in exposure to the conditional default factor between winners and losers. Our theory implies that the ability to recover value in default

plays an instrumental role in determining the risk of bonds and can explain conditional momentum in bonds. To proxy for this recovery capacity, we use two firm characteristics, asset tangibility and asset specificity.²³

The tangibility measure of bondholder recovery is based on the expected liquidation value of the firm. Bondholders of firms with high asset tangibility recover a relatively larger portion of value in case of default. Therefore, they face relatively lower risk in high default states of the world, and, as a result, require lower expected returns. Bondholders of firms with low tangibility recover less and, therefore, bear more risk during high default periods. We measure tangibility using the proxies of recovery per dollar from the previous empirical literature. [Berger et al. \(1996\)](#) argue that more general assets produce higher liquidation value. In particular, they find that claim holders will recover 71.5 cents on the dollar from receivables, 54.7 cents per dollar of inventory, and 53.5 cents per dollar of property plant and equipment. Additionally, claim holders should recover 100% of cash holdings. We calculate tangibility as

$$tng = \frac{(0.715 \times rect + 0.547 \times invt + 0.535 \times ppent + che)}{at}. \quad (26)$$

where *rect*, *invt*, *ppent*, and *che* represent receivables, inventory, net property plant and equipment and cash, respectively. All else equal, bondholders' ability to recover value in default will be high if the tangibility of the firm's assets is high.

The other proxy of bondholder recovery is based on the specificity of the firm's assets. [Shleifer and Vishny \(1992\)](#) argue that redeployable assets should have higher liquidation value because they can be successfully used for production in other industries.²⁴ This is especially important during periods of high default shocks when firms are likely to experience more problems leading to asset sales below their potential value. Other things being equal, assets

²³[Garlappi et al. \(2008\)](#), [Garlappi and Yan \(2011\)](#), [Favara et al. \(2012\)](#) and [Mahajan et al. \(2012\)](#) adopt these measures to examine the relation between bankruptcy risk and expected equity returns conditional on shareholder bargaining power.

²⁴In the context of this paper, redeployable assets can have other alternative usage that is not specific to a particular industry. [Garlappi et al. \(2008\)](#) and [Mahajan et al. \(2012\)](#) also use Herfindahl index for the same purpose.

are more readily redeployed when there are numerous firms in the same industry that could make use of the assets. In other words, firms in highly concentrated industries should have a smaller market in which to sell their assets during liquidation (more specific assets) and, hence, should have higher liquidation costs and lower liquidation value in bankruptcy. We measure the specificity of assets using the firm's two-digit SIC industry Herfindahl index based on sales. This is calculated as:

$$HI_{j,t} = \sum_{i=1}^{N_{j,t}} s_{i,t}^2, \quad (27)$$

where $s_{i,t}$ represents sales of firm i at time t as a proportion of total sales of its industry j . Firms with a high (low) Herfindahl index should have relatively higher (lower) asset specificity and, therefore, have higher (lower) liquidation costs and lower (higher) bondholder recovery.

To make sure that financial statement information is incorporated by the market, we allow for 6 month lag, while matching financial data with bond returns data. The results of this analysis are presented in [Table 5](#). For each measure of bondholder recovery, we find that winners have relatively lower bondholder recovery potential. Note that the average tangibility of winners is lower than the tangibility of losers (44.15% versus 46.31% for winners and losers, respectively), and the difference is statistically significant (with a t -statistic of -5.38). Therefore, losers (winners) have higher (lower) recovery potential in default. We also observe that losers are more likely to be found in less concentrated industries, suggesting that these firms have more redeployable assets and, as a result, lower liquidation costs and higher recovery in default. On the other hand, winners are more likely to belong to high concentration industries, implying more specific assets and lower liquidation value. Again, we find the difference in Herfindahl's index between winners and losers is significant (0.30% with a t -statistic of 2.16). Overall, both measures of bondholder recovery unequivocally report that higher asset specificity and lower expected liquidation value characterize winners. In either case, bondholders of winners are adversely affected by lower expected recovery and require higher returns. These concerns are especially relevant in states of high aggregate

default.

[Insert Table 5 here]

We further test how performance of the corporate bond momentum varies with recovery in distress. In particular, we present a double sorting procedure of bonds based on their historical performance and recovery potential. Each month, we sort bonds independently into terciles based on recovery measures (we use tangibility (*tng*) and Herfindahl index (*HI*) based on sales as proxies for bondholder recovery) and into deciles based on past six-month returns. We report raw average monthly raw return (%) of winners, losers, and momentum profits (W - L) for top and bottom recovery terciles conditional on high and low default shocks. Since the coverage is shallow at the beginning of the sample and to ensure that we have at least 15 bonds per one portfolio we exclude years 1995 and 1996 from the sample. The results of this analysis are presented in Panel B of Table 5. We document that for bonds with higher recovery on average winners outperform losers in high default states. In particular, we observe that firms in the top tangibility tercile (high bondholder recovery) winners outperform losers during high default shocks by 41 basis points with a *t*-statistic of 2.14. Similarly, we show that momentum among firms in the bottom *HI* tercile (high bondholder recovery) equals to 33 basis points with a *t*-statistic of 1.84.

4.2. Default and Recovery Premiums by State

A key implication of our model is that the recovery premium is higher during high default shocks because recovery concerns are higher during these periods.²⁵ Related, our model also predicts that the conventional default premium should be lower in high default states. To test these predictions, we sort bonds in our sample in 10 portfolios based on bondholder recovery as measured by tangibility and described in (26). Similarly, we independently sort the sample in 10 portfolios based on firm-level distress as measured by credit ratings.²⁶ We

²⁵For more details and discussion see our testable predictions 1 and 2 on page 24.

²⁶The domestic issue credit ratings of bonds are obtained from Bloomberg and DataStream. Higher numerical values represent low credit rating. For example, AAA equals to 1 and D corresponds to 22.

then estimate the recovery premium as the difference between the returns on low (p1) and high tangibility (p10) portfolios for every month of the test period. We follow a similar procedure to estimate the default premium as the return difference between low and high credit rating portfolios.

The results of this analysis are presented in [Table 6](#). According to Panel A of the table, there is almost no difference between performance of low and high tangibility (recovery) bonds during low default states (-0.09% and not statistically different from zero). However, when the economy experiences unexpected increases in aggregate default, low tangibility bond returns contain a higher recovery premium, hence, they outperform high tangibility bonds. The difference is 26 basis points with a t -statistic of 2.18, confirming our theoretical proposition that holders of low tangibility bonds face higher risk during adverse economic conditions due to lower potential recovery in case of liquidation. On the other hand, in periods of low aggregate default, the “recovery effect” is less important because of low likelihood of unexpected liquidation. Thus, there is no difference in returns of low and high tangibility portfolios. Moreover, we document that the difference in the recovery premium between high and low default states is positive and significant. In particular, we show that the recovery is 35 basis points higher during periods of high default with a t -statistic of 1.99. This is consistent with our theoretical predictions that suggest that recovery is more important when default is high.

[Insert [Table 6](#) here]

Similarly, Panel B of [Table 6](#) documents the conditional default premium. We find that in this case, the performance of low and high rated bonds is not statistically different during periods of high default shocks. However, during low default shocks, low rated bonds outperform high rated bonds by 87 basis points per month with a t -statistic of 4.52. Thus, both Panels A and B of [Table 5](#) and [Table 6](#) provide strong support to our conditional model of corporate bond prices and help explain momentum in the corporate bond market.

5. More Results and Discussions

This section presents results of robustness checks and additional tests. First, we associate bond momentum with firm-level and aggregate-level default. We expect that firm-level default risk is a necessary but not a sufficient condition for momentum. According to the theory, the subsample of low credit rated bonds should not generate momentum profits unless there are aggregate default shocks. We verify this using bonds with different credit ratings. In so doing, we also test if our results are driven by seasonality. Second, we examine whether the difference in the conditional default loadings between winners and losers remain significant for different credit risk groups. Third, we extend our analysis to the sovereign bond and the U.S. government bond markets. Since U.S. government default risk is often assumed to approach zero (at least in theory) and sovereign bonds of some countries are likely to contain a default component, we do not expect to find momentum in U.S. government bonds; however we expect some weak evidence of momentum among sovereign bonds. Finally, we examine if there is a momentum reversal in corporate bond market.

5.1. Bond Momentum and Conditional Default Shocks by Credit Risk Groups

According to our theory, the significance of momentum in the corporate bond market will depend on the frequency of high default shocks and the fraction of firms susceptible to these shocks. We test one implication of this result by estimating the performance of the momentum strategy conditional on default shocks for subsample of bonds with different credit risks. We follow [Avramov et al. \(2007\)](#) and assign numeric values to each credit rating²⁷ (1 represents AAA rating and 22 corresponds to D). We first drop bonds with C and lower ratings from the total sample. Next, we form a subsample by excluding bonds with ratings below CCC+ and, finally, we create another subsample by excluding all bonds rated below BBB.

The results are presented in [Table 7](#). The returns of the momentum strategy (6-1-6) are estimated conditionally on default shocks (as defined by residuals of equation (2)). Panel A

²⁷The domestic issue credit ratings of bonds are obtained from Bloomberg and DataStream.

of [Table 7](#) presents the results for the subsample of bonds with credit ratings from AAA to C. Consistent with our previous results, momentum in the corporate bond market is significant only in periods of high default shocks (53 basis points with a t -statistic of 3.16). Furthermore, after excluding bonds with ratings below CCC+, momentum performance remains the same. Finally, in Panel C, we exclude all bonds with ratings below BBB, and the returns to the bond momentum strategy become insignificant during high default shocks (0.10 with a t -statistics of 0.87) and negative during low default shock periods (-0.47 with a t -statistic of -0.41).

Another important finding in Panel C of [Table 7](#) is that losers outperform winners during low default shocks, as bonds with lower ratings are excluded. Recall from our theory that recovery premium is small in periods of low default shocks. Thus, firms that have good credit ratings and performed better in the past will be less risky during periods of low credit shocks. This implies that expected returns will be lower (higher) for winners (losers). The negative momentum result, therefore, is not altogether surprising.

[Insert [Table 7](#) here]

Overall, [Table 7](#) strongly confirms our theory and documents that high aggregate default shocks are critical for positive momentum; Panel A of [Table 7](#) shows that even including high credit risk bonds in the sample does not generate positive momentum during periods of low default shocks.

We further test whether momentum in corporate bond returns exhibits seasonality properties. [Jegadeesh and Titman \(1993, 2001\)](#) observe seasonal changes in equity momentum strategies. Specifically, they document that momentum generates negative or zero profits in January. [Figure 4](#) presents corporate bond momentum profits for every month. We do not find the “January effect” in bonds momentum; instead we observe that majority of momentum profits are concentrated in the second half of the year (July-December). Therefore, as a robustness check we repeat our sorting procedure after excluding data from January to June. The results of this analysis are presented in Panel D of [Table 7](#). Consistently with our previous findings, even after concentrating on the second half of the year, when momentum

profits are higher, the profitability of corporate bond momentum remains conditional on high default shocks. Momentum profits in high default states are 87 basis points with a t -statistic of 4.12 and essentially zero otherwise.

[Insert [Figure 4](#) here]

5.2. Conditional Default Shock Loadings by Credit Risk Groups

This section continues the analysis for different credit risk groups. Given our results above, we postulate that the spread of $-\beta^{CDEF}$ loadings should disappear for the subsample of low credit risk (i.e., high rated) bonds because they are less sensitive to unexpected changes in aggregate default.

Panel A of [Table 8](#) presents the results. First, we estimate model (5) for the subsample of bonds with ratings C and higher. The conditional default shock loadings ($-\beta_{AAA-C}^{CDEF}$) of winners and losers are 0.094 and -1.156, respectively. More importantly, the difference in the $-\beta^{CDEF}$ loadings between winners and losers is significant (1.25 with a t -statistic of 2.80). We then repeat this analysis for the subsample of bonds with credit ratings CCC+ and higher. In this case, the $-\beta^{CDEF}$ spread between winners and losers decreases and becomes smaller (1.151 with a t -statistic of 2.68). Finally, we exclude from the sample bonds rated below BBB, and the spread becomes even smaller (0.834 with a t -statistic of 2.30). We also estimate the price of conditional default risk using the [Fama and MacBeth \(1973\)](#) procedure and the [Shanken \(1992\)](#) adjustment. The results reported in Panel B of [Table 8](#) confirm our prediction that after excluding low rated bonds from the sample, the price of conditional default risk is no longer significant.

[Insert [Table 8](#) here]

We want to stress that momentum is not profitable during periods of low aggregate default shocks, irrespective of the credit ratings of bonds. [Avramov et al. \(2007\)](#), [Jostova et al. \(2013\)](#) and others find that stocks and bonds from low rated issuers are associated with positive momentum. Our results extend this literature by showing that this effect

arises only when high aggregate default shocks prevail. Furthermore, unlike for the high credit risk sample, there is no difference between the $-\beta^{CDEF}$ loadings of losers and winners among low credit risk bonds. Time-variations in aggregate credit risk drive the momentum phenomenon.

5.3. Momentum in U.S. Government Bonds and Sovereign Bonds

[Asness et al. \(2012\)](#) find that the momentum anomaly exists in different types of securities, such as sovereign bonds, futures, and commodities. In most of the empirical literature, the U.S. government bond returns serve as a proxy for the risk-free rate. Assuming that default risk of the U.S. government bonds is negligible, our theory implies that there will be no difference between the $-\beta^{CDEF}$ loadings of winners and losers, no difference in their expected returns, and no momentum in U.S. government bonds.

On the other hand, sovereign bond returns may have some default component. One of the most famous examples is the default by Russian government of its debt obligations in 1998. Similar events also unfolded in Argentina in late 2001, and more recently, are being observed in the Euro zone. There is also empirical evidence indicating that sovereign bond returns are affected by default risk. For example, [Pan and Singleton \(2008\)](#) using data from Mexico, Turkey, and Korea document that the sovereign CDS spreads reflect default risk and it is related to unpredictable future variation in credit-event arrival intensity. We therefore anticipate to find some evidence of momentum in sovereign bonds because of the default component in their returns. However, the momentum anomaly is unlikely to be large in magnitude due to their sovereign nature, and it should manifest only in periods of high default shocks.

We estimate the performance of the 6-1-6 momentum strategy for all U.S. government bonds and all sovereign bonds trading in the U.S. The data is obtained from the DataStream database. We follow our cleaning procedure described in section [2.2.1](#). The period of the sample is from 1995 to 2010. Panel A of [Table 9](#) documents the performance of the momentum strategy based on U.S. government bonds conditional on high and low default shocks. As expected, aggregate default shocks do not affect momentum returns in this case.

While losers tend to outperform winners on average, the difference is not significant (-12 basis points with a t -statistic of -1.34). Further, it appears that during periods of high default shocks, the performance of winners and losers increases; however, it increases at the same rate, and, as a result, there is no significant momentum.

[Insert [Table 9](#) here]

In Panel B of [Table 9](#), we document the returns of losers and winners among sovereign bonds traded in the U.S. market, conditional on default shocks. First, we note that the momentum anomaly does not exist for the full sample (-3 basis points with a t -statistic of -0.23). However, after conditioning on aggregate default, we document positive (negative) momentum in periods of high (low) default states of the world. The difference in performance of losers and winners is weakly significant (27 basis points with a t -statistic of 1.69).

6. Conclusion

The main finding of the paper is that bond momentum exists and it is conditional on aggregate default risk. Specifically, bond winners and losers have different exposures to unexpected changes in economy-wide default risk, and closely related, the conditional aggregate default factor is positively priced in the cross section of bond momentum portfolios. Since winners have higher loadings than losers, the results show that in periods of high default shocks, winners are relatively riskier than losers, *ceteris paribus*. Therefore, bond winners require higher returns to compensate for higher risk during these periods.

We theoretically and empirically link momentum to bondholder recovery and firm-level financial distress with an emphasis on aggregate default shocks. In particular, we show that winners have lower bondholder recovery than losers, and, therefore, become relatively riskier in high default states, while the opposite is true for losers. Results obtained from analyzing U.S. government bonds and sovereign bonds are also in line with this prediction.

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Figure 1: Conditional bond momentum

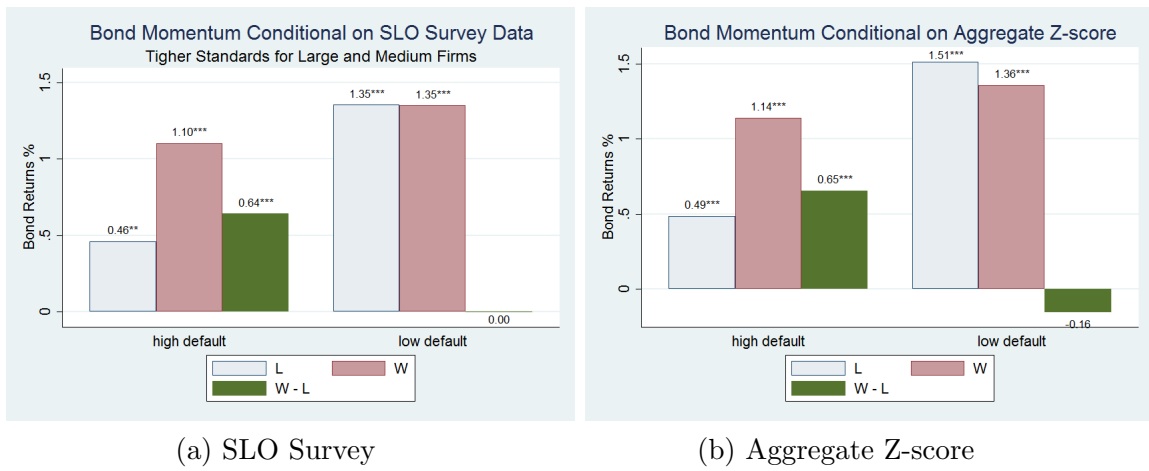


Figure 1 presents average monthly returns (%) on bond momentum portfolios conditional on aggregate default shocks. Panel (a) is based on the Senior Loan Officer (SLO) survey provided by the Federal Reserve Board over the period 1995 - 2012. Specifically, we characterize periods as high default shocks if a percentage of the officers who tighten standards for loans increases for large and medium firms. In panel (b) default shocks based on the modified Z-score over the period 1995 - 2012. Specifically, we define a period as a high default shock if a change in the aggregate Z-score is negative. The average returns followed by *, **, and *** are significantly different from zero at 10%, 5% and 1% level, respectively.

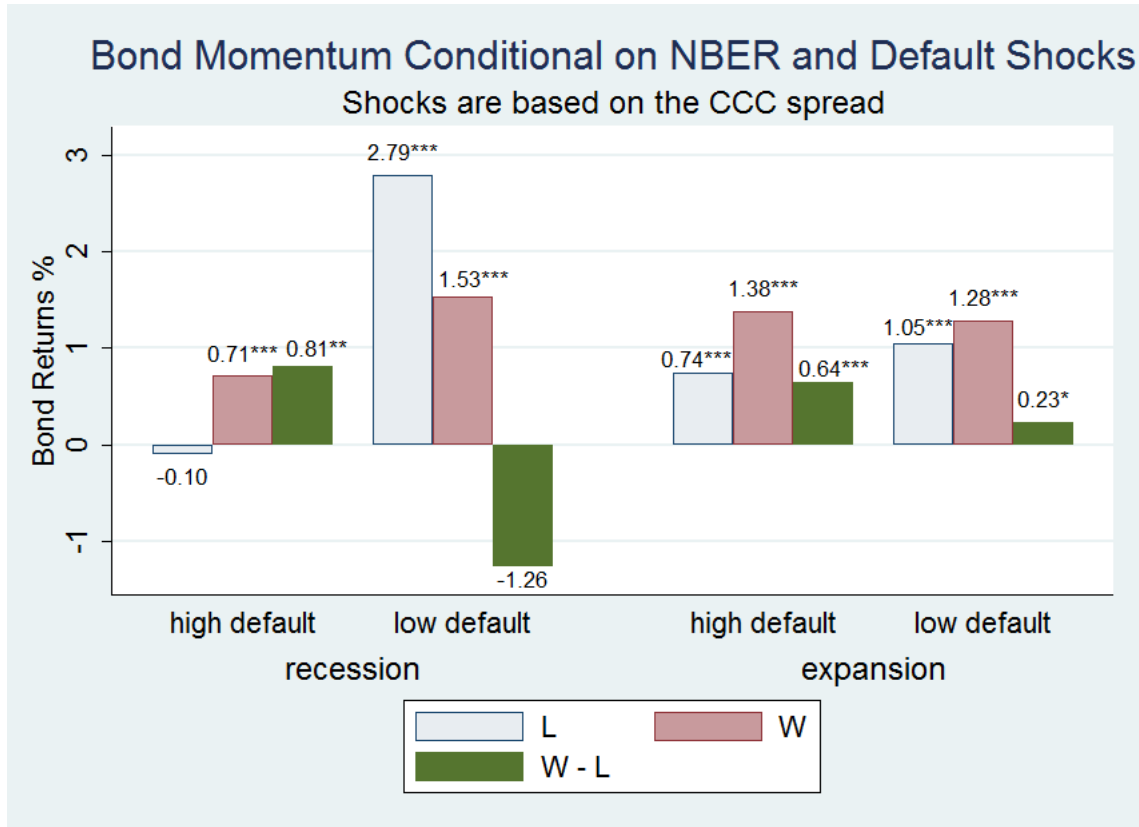


Figure 2: Bond momentum portfolio returns conditional on business cycles and default shocks

Figure 2 documents average monthly returns on bond momentum portfolios formed based upon a sorting procedure conditional on both business cycles and aggregate default shocks (residuals from equation (2)) over the period 1995 - 2012. The average returns followed by *, **, and *** are significantly different from zero at 10%, 5% and 1% level, respectively.

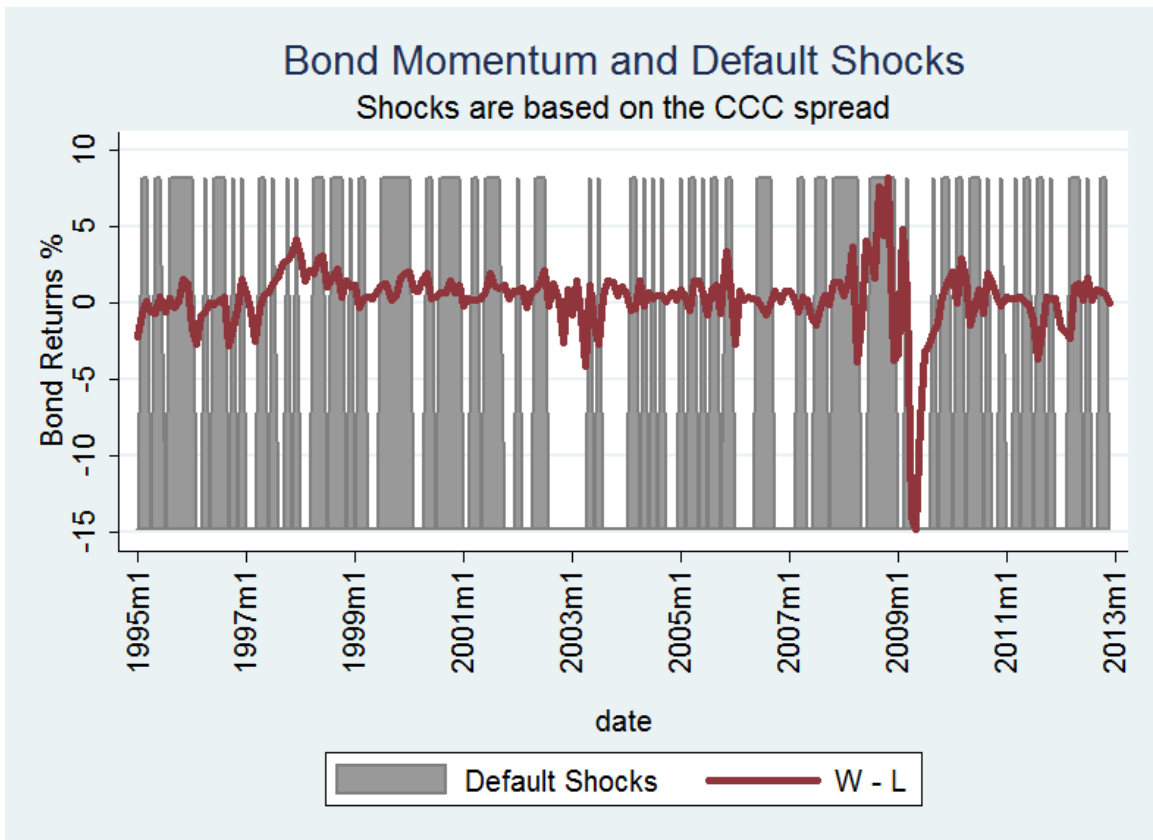


Figure 3: Profitability of momentum and default shocks

Figure 3 presents profitability of the bond momentum strategy from 1995 to 2012 on a monthly basis (m1 is January). Shaded areas of the graph correspond to periods of high default shocks as defined by residuals from equation (2).

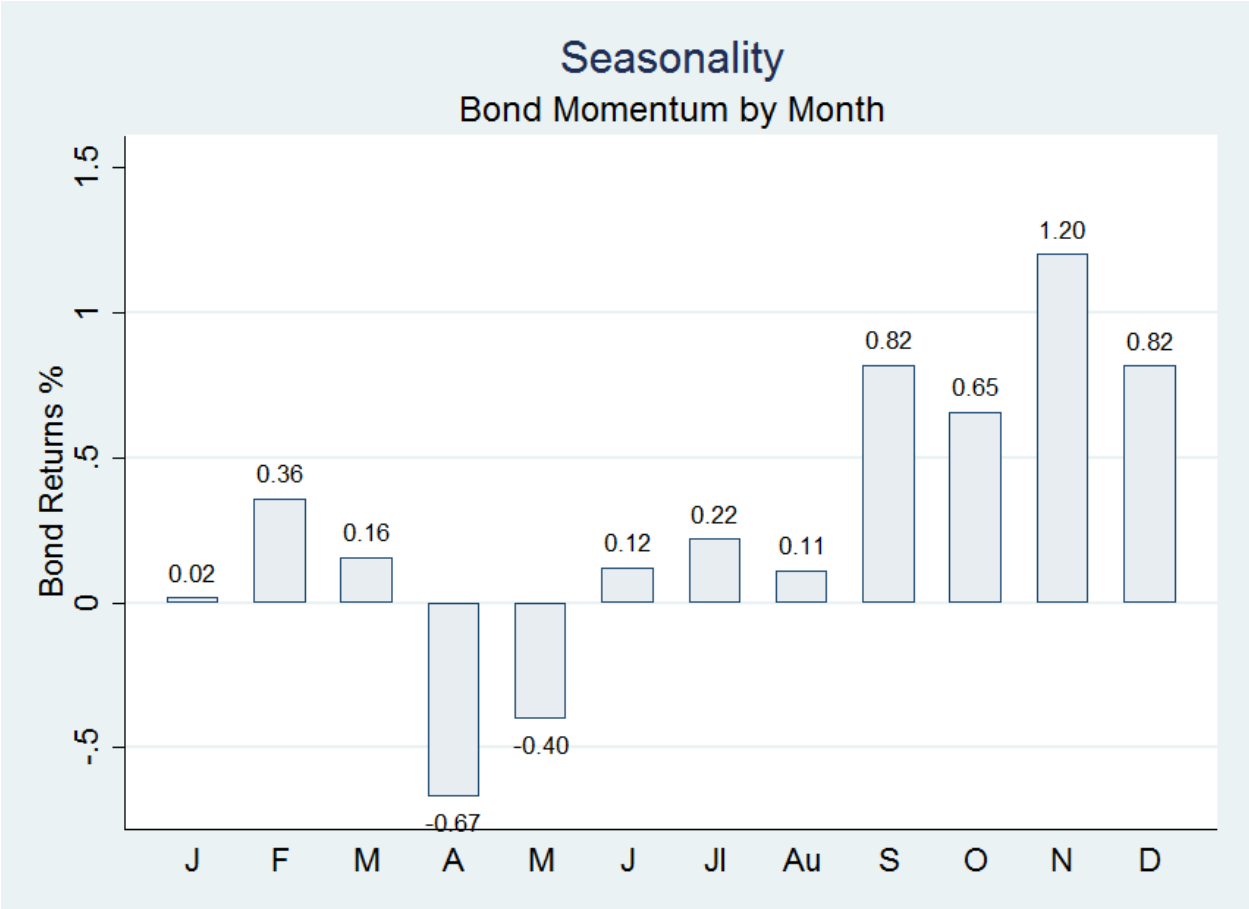


Figure 4: Seasonality of momentum

Figure 4 presents profitability of the bond momentum strategy from 1995 to 2012 for every calendar month.

Table 1: Summary statistics

Table 1 presents descriptive statistics for monthly returns (%) of equally-weighted momentum portfolios over the period 1995 to 2012. The bond momentum portfolios are based on the 6-1-6 strategy. Portfolios L and W are comprised of loser and winner bonds, respectively. Basic descriptive statistics, such as mean, median, standard deviation and percentiles are presented in the subsequent columns.

Portfolios	Mean	Std.	5%	25%	Median	75%	95%
L	0.96	2.49	-1.22	0.17	0.77	1.45	4.32
Portfolio 2	0.65	1.31	-0.57	0.22	0.55	0.90	2.95
Portfolio 3	0.62	0.99	-0.33	0.30	0.56	0.78	2.29
Portfolio 4	0.62	0.81	-0.23	0.34	0.58	0.76	2.08
Portfolio 5	0.63	0.72	-0.04	0.36	0.60	0.78	1.68
Portfolio 6	0.64	0.70	0.00	0.37	0.59	0.84	1.43
Portfolio 7	0.65	0.75	-0.31	0.37	0.59	0.90	1.65
Portfolio 8	0.69	0.90	-0.52	0.31	0.66	1.01	1.89
Portfolio 9	0.71	1.02	-0.85	0.34	0.71	1.18	2.12
W	1.24	1.34	-1.04	0.63	1.33	1.86	3.76
W - L	0.28	2.23	-2.79	-0.28	0.41	1.21	3.10

Table 2: Bond momentum portfolio returns conditional on default shocks

Table 2 documents average monthly returns (%) on the bond portfolios formed based upon a sorting procedure conditional on aggregate default shocks (residuals from equation (2)) over the period 1995 to 2012. The returns to the momentum strategy (6-1-6) based on equally-weighted portfolios are presented in the columns with t-statistics in parentheses. W and L represent portfolios of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). Panel A presents results obtained from the whole sample (1995-2012). Panel B and Panel C present results from analyzing earlier (1995-2002) and later (2003-2012) subperiods. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively.

	W	L	W - L
Panel A: Total sample			
High Default	1.14*** (8.10)	0.44** (2.20)	0.70*** (4.30)
Low Default	1.35*** (12.06)	1.52*** (5.64)	-0.17 (-0.68)
Total	1.24*** (13.63)	0.96*** (5.64)	0.28* (1.86)
Panel B: Period from 1995 to 2002			
High Default	1.70*** (11.13)	0.84*** (5.83)	0.86*** (5.74)
Low Default	1.44*** (6.98)	1.10*** (6.74)	0.34 (1.58)
Total	1.59*** (12.73)	0.95*** (8.81)	0.64*** (4.93)
Panel C: Period from 2003 to 2012			
High Default	0.62*** (2.97)	0.07 (0.21)	0.55** (2.01)
Low Default	1.29*** (10.25)	1.82*** (4.14)	-0.53 (-1.32)
Total	0.96*** (7.72)	0.96*** (3.28)	-0.00 (-0.00)

Table 3: Factor loading estimates

Table 3 presents the time-series beta spreads estimates for the monthly returns of the momentum portfolio (W - L) on the market β^{MKT} , term structure β^{UTS} , default shock $-\beta^{DEF}$, conditional default shock $-\beta^{CDEF}$, unemployment rate ($UNMP$), unanticipated inflation (UI), size (SMB) and value (HML) factors. Momentum is estimated using equally-weighted portfolios (the 6-1-6 strategy). The sample period is 1995 to 2012. The t-statistics from the regressions are based on the Newey-West standard errors with 3 lags. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively.

	(a)	(b)	(c)	(d)	(e)	(f)
β_0	0.0236*** (3.32)	0.00352* (1.81)	0.00952*** (3.34)	0.0201*** (3.03)	0.0114*** (3.67)	0.0231*** (3.85)
β^{MKT}	-0.0924** (-2.14)	-0.123** (-2.15)	-0.0793* (-1.85)	-0.0903* (-1.85)	-0.0854** (-1.84)	-0.0765* (-2.06)
$-\beta^{DEF}$	-1.306** (-2.37)		-1.318** (-2.20)	-1.388** (-2.39)	-1.372** (-2.26)	-1.281** (-2.23)
$-\beta^{CDEF}$	1.435** (2.14)		1.275* (1.82)	1.258* (1.95)	1.493** (2.02)	1.374** (2.03)
β^{UTS}	0.222 (1.41)		-0.111 (-0.82)			0.230 (1.52)
β^{UNMP}	-0.003** (-2.27)			-0.002* (-1.90)		-0.003** (-2.30)
β^{UI}	-1.263* (-1.92)				-1.153* (-1.73)	-1.250* (-1.85)
β^{SMB}	0.0118 (0.31)					
β^{HML}	-0.0685 (-1.21)					
Adj R^2	0.36	0.08	0.30	0.33	0.31	0.34

Table 4: Pricing time-varying aggregate default risk in the cross section

Table 4 presents estimated monthly risk premiums based on the Fama-MacBeth procedure and using 30 bond momentum portfolios. γ^{MKT} , γ^{UTS} , γ^{DEF} , γ^{CDEF} , γ^{UNMP} , γ^{UI} , γ^{SMB} , and γ^{HML} represent the market, term structure (defined as the spread between the 10-year and 1-year U.S. government bond yields), default shocks (measured by residuals ξ_t from equation (2)), and conditional default shocks (measured by the product of ξ_t and I , where I is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise), industrial production growth, unanticipated inflation, size, and value premiums. T-statistics based on the Shanken (1992) method are reported in parentheses below. The sample period is 1995 to 2012. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively. To be consistent with Table 3, the default shock γ^{DEF} and conditional default shock γ^{CDEF} premiums are based on $-\beta^{DEF}$ and $-\beta^{CDEF}$, respectively.

	(a)	(b)	(c)	(d)	(e)	(f)
γ_0	0.00411** (2.51)	0.00341*** (5.28)	0.00557*** (2.89)	0.00381* (1.83)	0.00379 (1.53)	0.00579*** (3.89)
γ^{MKT}	0.0550 (1.58)	0.0275*** (2.92)	0.0551** (2.34)	0.0581 (0.86)	0.108* (1.80)	0.0407 (1.58)
γ^{DEF}	0.0077 (1.51)		0.0126** (2.54)	0.0008 (1.38)	0.0102 (1.30)	0.0129*** (2.92)
γ^{CDEF}	0.0129** (2.69)		0.0170*** (3.13)	0.131** (2.52)	0.0234** (2.23)	0.0132*** (3.32)
γ^{UTS}	-0.0125 (-1.21)		-0.0167** (-2.33)			-0.0126 (-1.40)
γ^{UNMP}	-1.946** (-2.24)			-1.936* (-1.75)		-2.149** (-3.41)
γ^{UI}	0.00124 (0.46)				0.00793 (1.27)	-0.000316 (-0.13)
γ^{SMB}	-0.0324 (-0.83)					
γ^{HML}	0.0297 (0.84)					
Adj R^2	0.91	0.28	0.81	0.83	0.82	0.88

Table 5: Bondholder recovery of winners and losers

Panel A of Table 5 documents the bondholder recovery of winners (W) and losers (L). It presents the average bondholder recovery of winners and losers using the tangibility measure (*tng*) reflecting the expected liquidation value of the firm and the Herfindahl index (*HI*) based on sales (represents the specificity of the assets) based a 2-digit SIC industry code. Panel B of Table 5 presents a double sorting procedure of bonds based on their historical performance and recovery potential. Each month, we sort bonds independently into terciles based on recovery measures (we use tangibility (*tng*) and Herfindahl index (*HI*) based on sales as proxies for bondholder recovery) and into deciles based on past six-month returns. We report raw average monthly raw return (%) of winners, losers, and momentum profits (W - L) for top and bottom recovery terciles conditional on high and low default shocks. The sample period is 1997 to 2012. T-statistics are presented in parentheses below. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively.

	W	L	W - L
Panel A. Recovery			
<i>tng</i>	44.1	46.3	-2.2*** (-5.38)
<i>HI</i>	8.1	7.8%	0.3** (2.16)
Panel B. Returns			
High Default:			
<i>High tng</i>	0.78	0.37	0.41** (2.14)
<i>Low tng</i>	0.85	0.57	0.27 (1.40)
Low Default:			
<i>High tng</i>	1.21	1.79	-0.58* (-1.81)
<i>Low tng</i>	1.44	1.48%	-0.04 (-0.13)
High Default:			
<i>High HI</i>	0.67	0.46	0.21 (1.14)
<i>Low HI</i>	0.88%	0.55	0.33* (1.84)
Low Default:			
<i>High HI</i>	1.27	1.49	-0.22 (-0.74)
<i>Low HI</i>	1.17	1.72	-0.55* (-1.67)

Table 6: Conditional recovery and default premiums

Table 6 documents the average monthly returns (%) of the bondholder recovery and financial distress premiums conditional on aggregate default shocks (residuals from equation (2)) over the period 1995 to 2012. We sort bonds in 10 portfolios based on their recovery (tng) and 10 portfolios based on distress (credit rating) for every month. Panel A shows bond returns on low (p1), high (p10), and low minus high tangibility portfolios (bondholder recovery premium) for states of high and low aggregate default probabilities, which are denoted as high default and low default states, respectively. Panel B presents bond returns on low (p1), high (p10), and low minus high credit rating portfolios (default premium) for high and low states of aggregate default. The numbers in parentheses represent t-statistics. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively.

	High Default States	Low Default States	High - Low States
Panel A. Conditional Recovery premium			
Low Tng	0.76*** (5.86)	0.85*** (9.29)	-0.09 (-0.86)
High Tng	0.50*** (3.44)	0.94*** (6.71)	-0.44** (-2.15)
Low - High Tng	0.26** (2.18)	-0.09 (-1.06)	0.35** (1.99)
Panel B. Conditional Default premium			
Low Rating	0.46** (2.35)	1.47*** (6.88)	-1.01*** (-3.50)
High Rating	0.70*** (7.24)	0.60*** (6.95)	0.10 (0.73)
Low - High Rating	-0.24 (-1.28)	0.87*** (4.52)	-1.10*** (-4.12)

Table 7: Momentum in corporate bonds by credit risk groups

Table 7 presents average monthly returns (%) from momentum portfolios formed based upon a sorting procedure using aggregate default shocks (residuals from equation (2)) over the period 1995 to 2012. The returns generated using the momentum strategy (6-1-6) based on equally-weighted portfolios are presented in the three columns. W and L represent portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). Panel A, Panel B and Panel C contain results obtained from sorting based on the sample of bonds with ratings from AAA to C, AAA to CCC+, and AAA to BBB, respectively. Panel D presents a sorting procedure concentrated on the second half of the year (excluding months from January to June). The numbers in parentheses represent simple time-series t-statistics for the average monthly returns. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively.

	W	L	W - L
Panel A. AAA to C			
High Default	0.98*** (7.01)	0.45** (2.22)	0.53*** (3.16)
Low Default	1.19*** (10.71)	1.56*** (5.69)	-0.37 (-1.47)
Panel B. AAA to CCC+			
High Default	1.00*** (7.43)	0.47** (2.36)	0.53*** (3.28)
Low Default	1.15*** (10.20)	1.50*** (5.86)	-0.35 (-1.46)
Panel C. AAA to BBB			
High Default	0.75*** (6.07)	0.65*** (4.52)	0.10 (0.87)
Low Default	0.60*** (5.62)	1.01*** (5.89)	-0.41*** (-2.84)
Panel D. Seasonality			
High Default	1.16*** (6.34)	0.27 (0.95)	0.89*** (4.12)
Low Default	1.48*** (8.99)	1.38*** (4.90)	0.10 (0.39)

Table 8: Conditional default loadings by credit risk groups and price of risk

Panel A of Table 8 reports loadings for the returns of each of the 10 bond momentum portfolios on the conditional default factor (measured by the product of ξ and I , where I is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise) by credit risk groups. The equally-weighted momentum portfolios are based on the 6-1-6 momentum strategy. W and L represent the portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). The sample period is 1995 to 2012. The conditional default loadings are estimated from the main model with other risk factors X :

$$R_t^e = \beta_0 + \beta^{DEF} \xi_t + \beta^{CDEF} C \xi_t + \beta^X X_t + \epsilon_t.$$

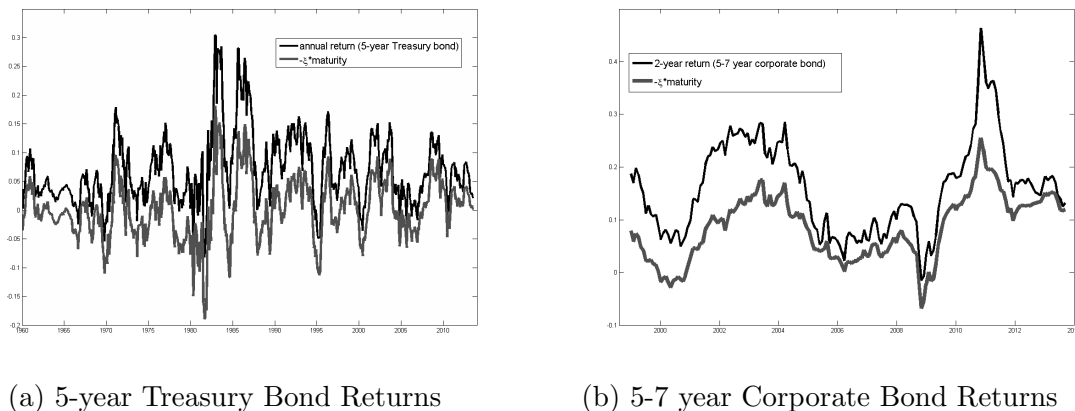
β_{AAA-C}^{CDEF} , $\beta_{AAA-CCC+}^{CDEF}$, and $\beta_{AAA-BBB}^{CDEF}$ represent the conditional default shock loadings of the momentum portfolios based on samples with different credit risks. The t-statistics from the regressions are based on the Newey-West standard errors with 3 lags. Panel B presents estimated monthly premiums of the conditional default shock factor (γ^{CDEF}) based on the Fama-MacBeth procedure and using 30 portfolios sorted on momentum. The Fama-MacBeth t-statistics are calculated using the Shanken (1992) method. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively. To be consistent with Table 3 and Table 4 the conditional default shock premium γ^{CDEF} is based on $-\beta^{CDEF}$.

Portfolio	$-\beta_{AAA-C}^{CDEF}$	t-stat	$-\beta_{AAA-CCC+}^{CDEF}$	t-stat	$-\beta_{AAA-BBB}^{CDEF}$	t-stat
Panel A: Beta loadings						
L	-1.156***	(-2.75)	-1.071***	(-2.74)	-1.025***	(-2.84)
2	-0.670***	(-2.61)	-0.653***	(-2.66)	-0.597***	(-3.09)
3	-0.464***	(-2.75)	-0.455***	(-2.80)	-0.438***	(-3.17)
4	-0.318**	(-2.42)	-0.315**	(-2.43)	-0.326***	(-2.73)
5	-0.201**	(-2.37)	-0.196**	(-2.36)	-0.193**	(-2.55)
6	-0.086	(-1.64)	-0.086*	(-1.66)	-0.107**	(-2.12)
7	-0.003	(-0.06)	-0.011	(-0.19)	-0.07	(-1.21)
8	0.006	(0.09)	-0.001	(-0.01)	-0.066	(-0.84)
9	0.010	(0.11)	0.004	(0.05)	-0.129	(-1.37)
W	0.094	(0.79)	0.080	(0.70)	-0.191	(-1.47)
W-L	1.25***	(2.80)	1.151***	(2.68)	0.834**	(2.30)
Panel B: Price of conditional default risk						
γ^{CDEF}	0.0151***	(2.85)	0.0154***	(2.69)	0.00406	(0.93)

Table 9: U.S. government and sovereign bond momentum portfolio returns conditional on default shocks
Table 9 documents average monthly returns (%) on the U.S. government and sovereign bond portfolios formed based upon a sorting procedure conditional on aggregate default shocks (residuals from equation (2)) over the period 1995 to 2010. The returns to the momentum strategy (6-1-6) based on equally-weighted portfolios are presented in the columns with t-statistics in parentheses. W and L represent portfolios of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). Panel A presents results using US government bonds. Panel B documents results for sovereign bonds that trade in the U.S. market. Coefficients that are followed by *, **, and *** are significant at the 10%, 5% and 1% levels, respectively.

	W	L	W - L
Panel A: US government bonds			
High Default	0.68** (2.72)	0.73*** (2.73)	-0.05 (-0.41)
Low Default	-0.36 (-1.29)	0.16 (-0.66)	-0.20 (-1.48)
Total	0.18 (1.06)	0.30 (1.58)	-0.12 (-1.34)
Panel B: Sovereign bonds			
High Default	0.31* (1.76)	0.04 (0.11)	0.27 (1.69)
Low Default	-0.01 (-0.06)	0.37 (1.72)	-0.38 (-1.73)
Total	0.19 (1.08)	0.22 (0.99)	-0.03 (-0.23)

Figure Appendix A.1: Aggregate Default Shocks ($-\xi \times$ maturity) as Approximate Bond Returns



The figures compare actual bond returns with the approximate bond returns using the aggregate default shock ($-\xi \times$ maturity). Panel (a) represents the annual returns for 5-year Treasury bonds during 1960 June-2013 June period, and panel (b) refers to the 2-year holding period returns for 5- to 7- year corporate bond between 1998 January and 2013 August. For Treasuries, CRSP data set is used, and St. Louis Fed data repository (FRED) is the source of corporate yields. Both data sets are monthly.

Appendix A. Approximation of Credit Risk Premium

Denote the price of a corporate bond by D_t and its corresponding yield to maturity (n) by $y_t = -\ln D_t/n$. Similarly, D^f is the price of a risk-free bond. Then DEF_t is defined as $y_t - y_t^f$, where y^f is the risk-free rate, or $-\ln D_t^f/n$. Thus, the following holds from the definition of yield to maturity

$$DEF_t = n^{-1}(-\ln D_t + \ln D_t^f) \quad (\text{A.1})$$

Suppose that equation (2) follows an AR(1) structure and the autoregressive coefficient is one. Since $\alpha_1 + \alpha_2$ is close to one in our estimation and α_2 is close to zero, this assumption is reasonable. Focusing on the time varying portion of this equation, we ignore α_0 and write equation (2) as

$$-\xi_t = -DEF_t + DEF_{t-1}. \quad (\text{A.2})$$

Substituting equation (A.1) into equation (A.2), we obtain

$$-\xi_t = n^{-1}[(\ln D_t - \ln D_{t-1}) - (\ln D_t^f - \ln D_{t-1}^f)]. \quad (\text{A.3})$$

If maturity (n) is sufficiently large, then it is reasonable to assume that $\ln D_{t-1}$ and the price of bond with the adjacent maturity ($n-1$) will be close to each other. Then, equation (A.3) implies that $-\xi_t$ will measure n^{-1} times the difference between one-period return from holding a corporate bond and a risk-free bond. Therefore, $-\xi_t$ proxies for a default risk premium.

To verify if this approximation is valid, figure Appendix A.1 displays actual returns of Treasury and corporate bonds. For the Treasury bonds, 5-year and 4-year Treasury bonds are used to compute the annual bond returns. For the corporate bonds, the effective yields of the Bank of America Merrill Lynch US Corporate Yield Index with three to seven year maturities are employed to compute the two-year holding period returns. The approximate returns are computed by $-\xi_t \times$ maturity using the formula shown above. Both figures (a) and (b) show that the aggregate default shock is quite accurate in explaining return dynamics. In both cases, the correlations are 92 percent and 97 percent, respectively.

Appendix B. Proof of Proposition 1

The property of $\Lambda_{\phi,t}$ is easy to show and hence omitted. A linear approximation of $\log \Pi_{t+1}$ in terms of V_{t+1}/D_{t+1} around V_t/D_t is given by

$$\begin{aligned}\pi_{t+1} &= \ln \left[\phi_{t,t+1} + (1 - \phi_{t,t+1}) \frac{\eta_t V_{t+1} N}{D_{t+1}} \right] \\ &\approx \ln \left[\phi_{t,t+1} + (1 - \phi_{t,t+1}) \frac{\eta_t V_t N}{D_t} \right] + \Lambda_{\phi,t} \left(\frac{V_{t+1}}{D_{t+1}} - \frac{V_t}{D_t} \right).\end{aligned}$$

We then substitute this into the conditional covariance terms in (10) together with equation (11). This proves the result.

Appendix C. Proof of Proposition 2

Fix a number $T^* > 0$ and suppose that $\phi_{t+i,t+i+1} \rightarrow 1$ for $i = 1, \dots, T^*$. Then, the value function of the firm can be written as

$$V_t = \sum_{i=0}^{T^*} E_t [M_{t,t+i} F_{t+i}] + E_t [M_{t,t+T^*+1} V_{t+T^*+1}] \quad (\text{C.1})$$

If T^* is sufficiently large, $E_t [M_{t,t+T^*+1} V_{t+T^*+1}]$ should be small and close to zero to make V finite. For two firms with the same amount of total assets (K), yet different amount of intangible capital (h) at t and $t+1$, the corresponding $F(h, k, \epsilon)$ will be higher for the firm with the higher h . Under no constraint for raising capital, both firms will choose the same (h, k) from $t+2$ onwards. Thus, the firm value V is higher for the firm with the higher intangible capital. This proves the result.

Appendix D. Proof of Proposition 3

To measure the sensitivity of firm values to risk factors (i.e., delta), the following results are derived:

$$\frac{\partial V(k_t, h_t, \epsilon_t, \phi_{t,t+1})}{\partial \epsilon_t} = A'(h_t + \epsilon_t) f(k_t + h_t), \quad (\text{D.1})$$

$$\frac{\partial V(k_t, h_t, \epsilon_t, \phi_{t,t+1})}{\partial \phi_{t,t+1}} = E_t^* [V(k_{t+1}, h_{t+1}, \epsilon_{t+1}, \phi_{t+1,t+2})] - \lambda e^{-r_t^f} k_{t+1}. \quad (\text{D.2})$$

By linearizing $V(k_{t+1}, h_{t+1}, \epsilon_{t+1}, \phi_{t+1,t+2})$ around $(k_t, h_t, \epsilon_t, \phi_{t,t+1})$, we obtain a direct implication of (D.1) on the risk-return relationship, given as

$$\text{Cov}_t \left(\frac{V_{t+1} - V_t}{V_t}, \epsilon_{t+1} \right) = \frac{\partial V(k_t, h_t, \epsilon_t, \phi_{t,t+1})}{\partial \epsilon_t} \frac{\sigma_\epsilon^2}{V_t}. \quad (\text{D.3})$$

Equation (D.3) shows that the rate of return from this firm covaries positively with the productivity shock, and (D.1) dictates the risk sensitivity. (D.2) states that delta with respect to conditional survival likelihood ($\phi_{t,t+1}$) will depend on both the expected value of the firm and the amount of tangible capital. The latter reduces the sensitivity to default risk in the next period through the channel of the higher recovery value, consistent with the optimality conditions. Since $V_{t+1} = D_{t+1} \cdot \left(\frac{V}{D}\right)_{t+1}$, linearizing V_{t+1} around D_t and $\left(\frac{V}{D}\right)_t$ yields

$$\frac{V_{t+1} - V_t}{V_t} = \frac{D_{t+1} - D_t}{D_t} + \frac{\left(\frac{V}{D}\right)_{t+1} - \left(\frac{V}{D}\right)_t}{\left(\frac{V}{D}\right)_t}. \quad (\text{D.4})$$

From assumption 1, we can compute that

$$Cov_t \left(\frac{D_{t+1} - D_t}{D_t}, \epsilon_{t+1} \right) = \frac{A'(h_t + \epsilon_t) f(k_t + h_t) \sigma_\epsilon^2}{V_t}.$$

Assumption 3 implies that $Cov_t \left(\frac{D_{t+1} - D_t}{D_t}, \epsilon_{t+1} \right)$ is positive. In addition, note that (D.1) implies that the delta for ϵ_t is smaller if h_t is larger due to the concavity of $A(\cdot)$ in assumption 3. That is, the values of firms with a large amount of the intangible capital (h) are less sensitive to productivity shocks (ϵ) than those with less intangible capital, proving (24).

For (24), or $Cov_t \left(\frac{D_{t+1} - D_t}{D_t}, \frac{V_{t+1}}{D_{t+1}} \right) > 0$, we can show the following using (D.4):

$$Cov_t \left(\frac{D_{t+1} - D_t}{D_t}, \frac{V_{t+1}}{D_{t+1}} \right) \approx \frac{V_t}{D_t} \left[Cov_t \left(\frac{D_{t+1} - D_t}{D_t}, \frac{V_{t+1} - V_t}{V_t} \right) - Var_t \left(\frac{D_{t+1} - D_t}{D_t} \right) \right]$$

Therefore, if $Cov_t \left(\frac{D_{t+1} - D_t}{D_t}, \frac{V_{t+1} - V_t}{V_t} \right) > Var_t \left(\frac{D_{t+1} - D_t}{D_t} \right)$, then, the covariance will be positive. Since the randomness of the model is entirely due to ϵ and ϕ , the following differentials shed light on this issue:

$$\frac{1}{V_t} \frac{\partial V_t}{\partial \epsilon_t} = \frac{1}{D_t} \frac{\partial D_t}{\partial \epsilon_t} + \frac{1}{\left(\frac{V}{D}\right)_t} \frac{\partial \left(\frac{V}{D}\right)_t}{\partial \epsilon_t}, \quad (\text{D.5})$$

$$\frac{1}{V_t} \frac{\partial V_t}{\partial \phi_{t,t+1}} = \frac{1}{D_t} \frac{\partial D_t}{\partial \phi_{t,t+1}} + \frac{1}{\left(\frac{V}{D}\right)_t} \frac{\partial \left(\frac{V}{D}\right)_t}{\partial \phi_{t,t+1}}. \quad (\text{D.6})$$

In equation (D.5), the second term of the right hand side is zero from assumption 1. Thus, the sensitivity with respect to ϵ is the same for V and D . On the other hand, for default risk (ϕ), the second term of the right hand side of (D.5) is positive from the assumption 2. Thus, $\frac{1}{V_t} \frac{\partial V_t}{\partial \phi_{t,t+1}} > \frac{1}{D_t} \frac{\partial D_t}{\partial \phi_{t,t+1}}$ holds, and as a result, $Cov_t \left(\frac{D_{t+1} - D_t}{D_t}, \frac{V_{t+1} - V_t}{V_t} \right) > Var_t \left(\frac{D_{t+1} - D_t}{D_t} \right)$. This proves the result.

Appendix E. Proof of Proposition 4

Equation (25) is derived by substituting equations (13), (14), and (15) into equation (10). If $\phi_{t,t+1}^W = \phi_{t,t+1}^L = 1 - \varepsilon$, where $1 > \varepsilon > 0$. As $\varepsilon \rightarrow 0$, $E_t(\pi_{t+1}^L - \pi_{t+1}^W) \rightarrow 0$ and $\Lambda_{\phi,t}^L \eta_t^L Cov_t \left(r_{t+1}^L, \frac{V_{t+1}^L}{D_{t+1}^L} \right) - \Lambda_{\phi,t}^W \eta_t^W Cov_t \left(r_{t+1}^W, \frac{V_{t+1}^W}{D_{t+1}^W} \right) \rightarrow 0$. From the monotonicity of π and Λ with respect to ϕ , the sign of $E_t(r_{t+1}^W - r_{t+1}^L)$ is determined by the first term in equation (25) which is negative. On the other hand, if $\phi_{t,t+1}^W = \phi_{t,t+1}^L = \varepsilon$ where $1 > \varepsilon > 0$, then as $\varepsilon \rightarrow 0$,

$$E_t(\pi_{t+1}^L - \pi_{t+1}^W) \rightarrow \eta_t^L E_t \left(\ln \left[\left(\frac{V_{t+1}}{D_{t+1}/N} \right)_L \right] \right) - \eta_t^W E_t \left(\ln \left[N \left(\frac{V_{t+1}}{D_{t+1}/N} \right)_W \right] \right).$$

Since $\eta_t^L > \eta_t^W$, $E_t(\pi_{t+1}^L - \pi_{t+1}^W) > 0$ holds. In addition, when $\phi_{t,t+1}^W = \phi_{t,t+1}^L$ is very small, from assumption 2, $Cov_t \left(r_{t+1}^L, \frac{V_{t+1}^L}{D_{t+1}^L} \right)$ and $Cov_t \left(r_{t+1}^W, \frac{V_{t+1}^W}{D_{t+1}^W} \right)$ converge to each other. Since $\Lambda_{\phi,t}^L > \Lambda_{\phi,t}^W$, it is clear that

$$\Lambda_{\phi,t}^L Cov_t \left(r_{t+1}^L, \frac{V_{t+1}^L}{D_{t+1}^L} \right) - \Lambda_{\phi,t}^W Cov_t \left(r_{t+1}^W, \frac{V_{t+1}^W}{D_{t+1}^W} \right) > 0.$$