ANNUAL REVIEWS

Annual Review of Financial Economics

What Do We Know About Corporate Bond Returns?

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Annu. Rev. Financ. Econ. 2021. 13:363–99

First published as a Review in Advance on July 20, 2021

The *Annual Review of Financial Economics* is online at financial.annualreviews.org

https://doi.org/10.1146/annurev-financial-110118-123129

JEL codes: G11, G12, G13

Keywords

corporate bond returns, Merton model–implied expected corporate bond returns, credit spreads, spread changes, corporate bond sensitivity to equity or leverage, structural credit risk models

Abstract

Recently, there has been a fast-growing literature on the determinants of corporate bond returns, in particular, the driving force of cross-sectional return variation. In this review, we first survey recent empirical studies on this important topic. We discuss cross-sectional evidence as well as time-series evidence. We then present a model-based analysis of individual corporate bond returns using the structural approach for credit risk modeling. We show, among other things, that the expected corporate bond return implied by the Merton model predicts 1-month-ahead corporate bond returns in the cross section.

1. INTRODUCTION

The corporate bond market is large, with more than $10 trillion outstanding in the USA alone at the end of the second quarter of 2020, according to the Securities Industry and Financial Markets Association.[1] As such, what drives corporate bond prices and returns is a very important question. There is a large and growing body of research on the determinants of corporate bond prices or yield spread changes (e.g., Collin-Dufresne, Goldstein & Martin 2001; Eom, Helwege & Huang 2004; Huang & Huang 2012; and references therein). One main takeaway from this literature is that both credit risk and liquidity variables are needed to explain corporate bond spread levels or changes in the spread. In contrast, the literature on the determinants of corporate bond returns is relatively underdeveloped. Although the determinants of corporate bond spreads and spread changes or simply spreads themselves contain information about corporate bond returns and sometimes actually predict such returns, the latter are generally different from yield spreads and changes in the spread.

Research focusing on the determinants of corporate bond returns sheds light on some important questions in credit markets. For instance, how much are corporate bond returns in excess of government bond returns, at least in the US debt markets? Such return differentials are referred to as excess corporate bond returns, credit excess returns, or credit risk premia in the literature. A related question is whether credit risk premia are already reflected in equity risk premia and therefore not a new source of risk premia, especially given insights from structural credit risk models originating from Black & Scholes (1973) and Merton (1974) (e.g., Chen, Collin-Dufresne & Goldstein 2009, Huang & Huang 2012; see Sundaresan 2013 for a survey of structural credit risk models). If, as noted by Titman (2002), the answer to this question is no, as implied by the main finding of Huang & Huang (2012), then a follow-up question is: What drives credit risk premia?

This review has two objectives. First, we aim to provide a survey of literature on the determinants of corporate bond returns that is based largely on factor models. Second, we analyze such determinants using an alternative approach—the structural approach for credit risk modeling.

We divide our survey into two main parts. The first part (Section 2) focuses on studies on the cross section of corporate bond returns. We begin with risk factors or factor portfolios of corporate bond returns that are identified/constructed in the empirical literature. One takeaway from this literature is that at least four factors are needed to explain the cross-sectional variation in average corporate bond returns. We then review anomalies uncovered in the corporate bond market. Interestingly, some of these anomalies have documented counterparts (e.g., momentum) in the equity market.

The second main part of the survey (Section 3) concerns time-series evidence. We first consider studies focusing on corporate bond portfolios and investigating one of two important issues. One is risk and return of investment-grade (IG) and high-yield (HY) corporate bonds as asset classes. The other is corporate bond return predictability. We then turn to the determinants of individual corporate bond returns. To this end, we use regression models to estimate the relative explanatory power of three sets of variables for corporate bond returns: those suggested by structural models, by equity market variables, and by liquidity measures. We find, among other things, robust evidence for strong explanatory power of certain structural model–suggested variables.

Next, motivated partly by the abovementioned evidence, we examine the implications of structural models for individual corporate bond returns. Compared with alternative approaches

[1] See **https://www.sifma.org/wp-content/uploads/2021/02/US-Corporate-Bonds-Statistics-SIFMA.xlsx**.

used in the literature, our model-based analysis utilizes the nonlinear relationship between corporate bond returns and their theoretical determinants as derived from structural models. For illustration, we implement the Merton (1974) model in our analysis. We show that on average the Merton model–implied excess corporate bond return alone can explain 36.7% of variations in corporate bond returns for our sample. Moreover, this explanatory power is robust to corporate bond illiquidity as well as to equity market factors. We also derive an analytical formula for the expected corporate bond return implied by the Merton model. Importantly, we find that the model-implied expected corporate bond returns predict 1-month-ahead bond returns in the cross section. Overall, the results from our Merton model–based analysis support the view that structural models help us better understand the cross-sectional determinants of corporate bond returns. Lastly, given our focus on the empirical literature, we include a summary of corporate bond databases commonly used in the academic literature.[2]

In summary, what drives corporate bond returns, especially their cross-sectional variation, is becoming a very active research area. Not surprisingly, the cross-sectional determinants of corporate bond returns are often motivated by their counterparts in the equity market. One implication of this study is that one can construct new cross-sectional determinants in the structural framework of credit risk.

The rest of this review is organized as follows. Section 2 focuses on cross-sectional studies. Section 3 discusses evidence from time series. Section 4 examines the predictive power of structural model–based predictors. Section 5 summarizes commonly used corporate bond databases and standard corporate bond indexes. Section 6 concludes.

2. CROSS-SECTIONAL EVIDENCE

In this section, we first review risk factors and factor portfolios that are constructed or used in the empirical literature on corporate bond returns. Broadly speaking, these factors or factor portfolios can be divided into bond market, stock market, and macro factors. We then review findings of anomalies in the corporate bond market.

2.1. Risk Factors and Factor Portfolios

We begin with the Fama & French (1993) two-factor model that captures two key risks for corporate bond investors: credit risk and interest rate risk. We then consider other bond market factors—such as liquidity, downside risk, volatility, and inflation volatility—and factor portfolios including carry, safety, size, and value factors. We next review standard equity market factors, followed by macro factors.

The existing evidence suggests that we need at least four factors to explain average corporate bond returns in the cross section, although what the standard benchmark model is for corporate bond returns remains an open question. Interestingly, as illustrated below, the benchmark (factor) models used in this literature tend to be one-size-fits-all models. The corporate bond market is, however, more heterogeneous than the equity market. Indeed, studies on the determinants of credit spreads and spread changes typically consider IG and HY bonds separately and, in fact, often present their results for each rating class (e.g., Collin-Dufresne, Goldstein & Martin 2001; Huang & Huang 2012). As such, there may be a need to first develop different benchmark models for IG and HY bonds before developing a one-size-fits-all benchmark. Intuitively, benchmark models for

[2]We thank Matt Richardson for suggesting this idea.

IG and HY bonds may focus relatively more on returns on Treasury securities and stock returns, respectively.[3]

2.1.1. Fama–French two-factor model.

Fama & French (1993) introduce the following model for corporate bond returns:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,\mathrm{TERM}}\mathrm{TERM}_t + \beta_{i,\mathrm{DEF}}\mathrm{DEF}_t + \epsilon_{i,t}, \qquad 1.$$

where $r_{i,t}$ and $r_{f,t}$ denote the time-t return of corporate bond i and the risk-free rate, respectively; TERM is the difference between the monthly long-term government bond return (LTGBR) and 1-month Treasury bill rate measured at the end of the previous month; and DEF is the difference between the monthly return on a value-weighted market portfolio of all long-term IG corporate bonds and the monthly LTGBR. Fama & French (1993) find that these two factors explain average returns on credit rating-based bond portfolios (see Section 3.1 for the model's explanatory power for return variations).

Gebhardt, Hvidkjaer & Swaminathan (2005b) find that β_{DEF} and, to a lesser extent, β_{TERM} are important determinants of the cross-sectional variation in returns on rating- and duration-sorted portfolios. They also examine the relationship between betas and individual corporate bond returns using the Fama & MacBeth (1973) cross-sectional regression approach. They find that β_{DEF} is highly important in explaining the cross section of individual bond returns, whereas β_{TERM} performs poorly in the Fama–MacBeth regressions.

2.1.2. Aggregate liquidity shocks.

Pástor & Stambaugh (2003) and Acharya & Pedersen (2005) show empirically and theoretically that the exposure to market-wide illiquidity—which is usually negative—carries a separate, positive risk premium in the stock market. Lin, Wang & Wu (2011) investigate whether or not this type of liquidity risk is priced in the cross section of corporate bonds. Specifically, they focus on the following model:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,\mathrm{TERM}}\mathrm{TERM}_t + \beta_{i,\mathrm{DEF}}\mathrm{DEF}_t + \beta_{i,\mathrm{LIQ}}\mathrm{LIQ}_t + Z_t + \epsilon_{i,t}, \qquad 2.$$

where TERM_t and DEF_t are as defined above, LIQ_t captures systematic liquidity risk, and Z_t encapsulates variables controlling for factor premia in the equity market and bond characteristics. Lin, Wang & Wu construct two alternative proxies for LIQ_t based on the Amihud (2002) and Pástor & Stambaugh (2003) liquidity measures, respectively. They estimate each of these two liquidity measures at the security level and then aggregate them month by month to generate the market-wide liquidity series. An error correction model is then estimated for each liquidity series, and the derived innovation term is used as LIQ_t. Lin, Wang & Wu (2011) find that β_{LIQ} is persistently significant in presence of different combinations of LIQ_t and Z_t. This result is confirmed by Chung, Wang & Wu (2019) with a longer sample period and more controlling variables.

2.1.3. Carry, safety, size, and value.

Houweling & Van Zundert (2017) construct size, low-risk, value, and momentum factor portfolios in the corporate bond market and provide evidence that these factor portfolios generate alphas in this market. Israel, Palhares & Richardson (2018) consider carry, safety/quality (a defensive factor), momentum, and value and find strong evidence

[3] Some factors and factor portfolios are in fact constructed controlling for ratings. Still, a benchmark model that includes only one Treasury bond factor (e.g., the Treasury bond market factor) may not be able to fully explain IG bond returns, given that they are dominated by Treasury bond returns—three Treasury bond factors may be needed.

of positive risk premia for all characteristics except carry. We focus on carry, safety/low risk, size, and value below and discuss the momentum factor in Section 2.2.1.

Carry of a corporate bond is measured using its option-adjusted spread over Treasury bonds, as reported in the Bank of America Merrill Lynch (BofAML) bond database (see also Koijen et al. 2018). Houweling & Van Zundert (2017) construct low-risk factor portfolios using both maturity and rating: The low-risk top portfolio consists of high-rated, short-dated bonds, and the bottom portfolio consists of low-rated, long-dated bonds. Israel, Palhares & Richardson (2018) consider three measures of safety: market leverage, gross profitability as defined by Novy-Marx (2013), and duration.

A bond issuer's size in a given month is defined as the sum of the market-value weights of all its bonds in the Bloomberg Barclays US Corporate IG Index or HY Index in that month. One way to determine whether a corporate bond is cheap or not is to compare its observed spread with a model-implied spread. Houweling & Van Zundert (2017) construct their value factor portfolios as follows: First, they run a cross-sectional regression of individual corporate bond credit spreads on rating dummies, time to maturity, and 3-month spread change each month. Then, they calculate the percentage difference between the actual credit spread and the fitted/model credit spread for each bond. Lastly, for each month, they rank all bonds on this percentage pricing error from high to low and select the top (bottom) 10% of bonds for the top (bottom) value portfolio. Israel, Palhares & Richardson (2018) use two proxies for fundamental default risk. One is the physical default probability as implied by the Merton distance to default, which can be computed only for publicly listed issuers. The other is derived from a regression-based approach that combines credit rating, bond duration, and bond excess return volatility in the last 12 months.[4]

2.1.4. Downside risk factor.

Bai, Bali & Wen (2019) propose to construct factors based on distributional characteristics of corporate bond returns. Specifically, they introduce a downside risk factor (DRF), defined as the value-weighted average return difference between the highest– and lowest–value at risk (VaR) portfolios within each rating portfolio. They propose the following model:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,\mathrm{MKT}}\mathrm{MKT}_t + \beta_{i,\mathrm{CRF}}\mathrm{CRF}_t + \beta_{i,\mathrm{DRF}}\mathrm{DRF}_t + \beta_{i,\mathrm{LRF}}\mathrm{LRF}_t + \epsilon_{i,t}, \quad 3.$$

where MKT_t, CRF_t, DRF_t, and LRF_t denote the bond market, credit risk, downside risk, and liquidity risk factors, respectively. The LRF is defined as the value-weighted average return difference between the highest- and lowest-illiquidity portfolios within each rating portfolio. The CRF is calculated as the average of the rating-based long–short portfolios obtained during the construction of the DRF, the LRF, and the short-term reversal factor (STR). Bai, Bali & Wen (2021) implement a simplified version of the CRF, defining it as the value-weighted average return difference between the highest– and lowest–credit risk portfolios within each illiquidity portfolio.

Bai, Bali & Wen (2019) find that the model given in Equation 3 accounts for approximately 10% of variations in cross-sectional returns on individual bonds. In addition, this model performs better than alternative factor models in explaining the 5 × 5 independently sorted bivariate value-weighted portfolios of size and maturity as well as 30 value-weighted industry-sorted portfolios.

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[4]Israel, Palhares & Richardson (2018) also explore possible risk or mispricing explanations for the return premia on these characteristics-based portfolios. The authors show that these returns are not explained by traditional market premia, macroeconomic exposures, or their counterparts in the equity market. Overall, their results indicate that returns of the momentum portfolios "seem to be the most tightly linked to mispricing," but the evidence about the source of the other characteristics-based portfolio returns is less clear.

In particular, the model outperforms the five-factor model consisting of MKT, TERM, DEF, LIQ, and a bond market momentum factor.

2.1.5. Volatility factor. Chung, Wang & Wu (2019) investigate whether the aggregate volatility risk is priced in the cross section of corporate bond returns. Focusing on the Chicago Board Options Exchange's CBOE Volatility Index (VIX) as the volatility measure, they show that the difference in average monthly excess returns between the highest and lowest VIX beta decile portfolios is −20 basis points (bps), which is significant at the 5% level.

Augmenting the time-series regression in Equation 2 with the volatility factor, one obtains the following cross-sectional regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \gamma_{\mathrm{TERM}}\beta_{i,\mathrm{TERM}} + \gamma_{\mathrm{DEF}}\beta_{i,\mathrm{DEF}} + \gamma_{\mathrm{LIQ}}\beta_{i,\mathrm{LIQ}} + \gamma_{\mathrm{VIX}}\beta_{i,\mathrm{VIX}} + Z_{i,t} + \epsilon_{i,t}, \qquad 4.$$

where the controlling betas and characteristics as encapsulated by $Z_{i,\,t}$ are essentially the same as those used by Lin, Wang & Wu (2011). Chung, Wang & Wu (2019) find that γ_{VIX} is significantly negative, implying that the market price of volatility is negative in the corporate bond market. Together, the four factors included in Equation 4 and the Fama–French three (equity) factors (FF3Fs)—$\mathrm{MKT}^{\mathrm{eqty}}$, SMB, and HML—account for 6.6–6.8% of variation in individual bond returns.

2.1.6. Inflation volatility risk factor. Ceballos (2021) documents a negative relationship between inflation risk volatility and the cross section of corporate bond returns. He analyzes the predictive power of the unexpected inflation volatility risk captured by the inflation innovation of an autoregressive integrated moving average model. He documents a negative alpha of 50 bps per month on the portfolio spread between the highest and lowest quintile portfolios sorted by inflation volatility risk–beta corporate bond returns. The findings remain significant when using bivariate portfolios and cross-sectional regressions and when adjusting by other relevant volatility factors.

2.1.7. Equity market factors. Equity market factors used to explain corporate bond returns include the $\mathrm{MKT}^{\mathrm{eqty}}$, SMB, HML, UMD (momentum), and Pástor–Stambaugh liquidity factors. For example, in addition to studying TERM and DEF, Fama & French (1993) examine the explanatory power of the FF3Fs in capturing bond portfolio returns; these five factors are referred to as the Fama–French five factors (FF5Fs) below. Lin, Wang & Wu (2011) specify Z_t in Equation 2 as follows:

$$Z_t = \beta_{i,\mathrm{MKT\_}E}\mathrm{MKT}_t^{\mathrm{eqty}} + \beta_{i,\mathrm{SMB}}\mathrm{SMB}_t + \beta_{i,\mathrm{HML}}\mathrm{HML}_t + \beta_{i,\mathrm{LIQ\_}E}\mathrm{LIQ}_t^{\mathrm{eqty}}, \qquad 5.$$

where $\mathrm{LIQ}^{\mathrm{eqty}}$ denotes the Pástor–Stambaugh liquidity factor. The authors find that only $\beta_{i,\mathrm{LIQ\_}E}$ gains robust statistical significance in various regression specifications. On the basis of a forward-looking measure of expected corporate bond returns, Bongaerts, de Jong & Driessen (2017) show that exposure to the equity market liquidity risk is priced. However, they find that $\beta_{i,\mathrm{MKT\_}E}$ is also highly important in explaining cross-sectional bond returns, which is inconsistent with the finding of Lin, Wang & Wu (2011). Chung, Wang & Wu (2019) show that $\beta_{i,\mathrm{MKT\_}E}$ is significant if the TERM and DEF factors are not controlled for.

2.1.8. Economic uncertainty. Motivated by the theoretical implications of Bloom (2009), Bali, Subrahmanyam & Wen (2020) study whether exposure to macroeconomic uncertainty predicts the cross-sectional variation in future bond returns using the economic uncertainty index of Jurado, Ludvigson & Ng (2015). At the portfolio level, Bali, Subrahmanyam & Wen (2020) find that bonds with the lowest uncertainty betas generate 0.76% more average monthly returns than bonds with the highest uncertainty betas. At the security level, they estimate the following Fama–MacBeth regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \gamma_{\text{TERM}}\beta_{i,\text{TERM}} + \gamma_{\text{DEF}}\beta_{i,\text{DEF}} + \gamma_{\text{VIX}}\beta_{i,\text{VIX}} + \gamma_{\text{UNC}}\beta_{i,\text{UNC}} + Z_{i,t} + \epsilon_{i,t}, \qquad 6.$$

where the uncertainty beta, $\beta_{i,\,\text{UNC}}$, is estimated with a 36-month rolling window, and $Z_{i,\,t}$ includes multiple controlling characteristics. The estimated γ_{UNC} is significantly negative, consistent with the results from portfolio sorting. Surprisingly, the explanatory power of $\beta_{i,\,\text{VIX}}$—which is supposed to measure the exposure to expected aggregate volatility—is subsumed in the presence of $\beta_{i,\,\text{UNC}}$.

2.2. Anomalies in the Corporate Bond Market

In this subsection, we implicitly assume that the Fama–French two-factor model discussed in Section 2.1.1 is the benchmark against which a corporate bond anomaly is defined. We can group anomalies into those based on bond issuer-level characteristics (which include equity characteristics) and those based on bond-level characteristics.

Although equity characteristics are a natural choice, their predictive power for cross-sectional corporate bond returns seems to be limited, net of transaction costs (see Section 2.2.7). Anomalies based on equity characteristics' counterparts in the corporate bond market may not survive transaction costs either. Therefore, characteristics unique to the bond market, such as some reviewed below, may be more promising as bond return predictors. One such characteristic is value signals, discussed in Section 2.2.6. While value signals in the equity market are based on valuation multiples or use a model of (stock) returns as the benchmark, value signals here are constructed by using a valuation model for corporate bonds as the benchmark. Furthermore, if the valuation model is based on the contingent claims approach, then value signals here can be motivated from the credit spread puzzle (à la Huang & Huang 2012) in the bond market. Another unique characteristic is the valuation model–implied corporate bond return itself. We construct one such predictor—the expected corporate bond return implied by the Merton (1974) model—and examine its predictive power for corporate bond returns in Section 4.5.

2.2.1. Momentum.

Using Lehman Brothers data from January 1976 to March 1998, Khang & King (2004) find no evidence of momentum in IG bond returns. Gebhardt, Hvidkjaer & Swaminathan (2005a) examine the interaction between momentum in the returns of equities and of corporate bonds using Lehman data from 1973 to 1996. They find that IG bonds do not exhibit momentum at the 3- to 12-month horizons and, instead, exhibit reversals. However, they find significant evidence of a momentum spillover from equities to IG bonds of the same firm.

Pospisil & Zhang (2010) find evidence that HY bonds exhibit momentum, especially for holding periods of 1–12 months, on the basis of Merrill Lynch data over the period December 1996–August 2009. Using a comprehensive sample of US corporate bonds with both transaction and dealer-quote data from 1973 to 2011, Jostova et al. (2013) find that winners in the corporate bond market over the past 6 months outperform losers by 37 bps per month. The resultant momentum portfolio has a significant alpha ranging from 59 to 72 bps against various factor models, in which risk factors include the FF5Fs and the equity momentum factor, UMD. Moreover, the corporate bond momentum is driven mainly by HY bonds, consistent with empirical evidence from the equity market (Avramov et al. 2007). Interestingly, bond momentum is distinct from equity momentum, both in time series and in cross section. For instance, equity and bond momentum profits in public firms have a correlation of merely 34%, equity momentum can explain approximately 20% of the bond momentum profits, and 22% of the public firms that are corporate bond winners are also stock winners. Finally, when double sorts are performed on past equity and past bond returns, there are large and significant bond-specific momentum effects in HY bonds.

Chordia et al. (2017) complement the portfolio analysis of Jostova et al. (2013) by presenting results from Fama–MacBeth regressions of individual bond returns. They find, however, that bond returns from month $t-5$ to month $t-1$ negatively predict returns in month $t+1$, robust to different regression specifications. This apparent contradiction to the results of Jostova et al. (2013) may be due to differences in their empirical choices. First, Chordia et al. focus on bonds issued by publicly listed firms. Second, they include other characteristics (e.g., short-term reversal, the issuer's distance to default, and the illiquidity of the issuer's stock), which Jostova et al. do not consider, in all regression specifications.

2.2.2. Security-level illiquidity. Bongaerts, de Jong & Driessen (2017) focus on another type of liquidity effect on corporate bond returns—whether the return demanded by bond investors directly increases with the (expected) level of relative transaction costs. Taking into account the effect of liquidity risk (as examined by Lin, Wang & Wu 2011), they consider the following Fama–MacBeth regression:

$$\hat{E}\left(r_{i,t}\right) - r_{f,t} = \alpha_i + \gamma_{\mathrm{TC}}\mathrm{TC}_{i,t} + \gamma_{\mathrm{LIQ}}\beta_{i,\mathrm{LIQ}} + \gamma_{\mathrm{MKT\_}E}\beta_{i,\mathrm{MKT\_}E} + \gamma_{\mathrm{LIQ\_}E}\beta_{i,\mathrm{LIQ\_}E} + \epsilon_{i,t}, \qquad 7.$$

where $\hat{E}(r_{i,t})$ is their measure of expected bond returns and $\mathrm{TC}_{i,t}$ denotes transaction costs, derived from a repeat-sales model in the spirit of Edwards, Harris & Piwowar (2007). Instead of testing individual bond returns, Bongaerts, de Jong & Driessen (2017) form triple-sorted portfolios, which are sorted first on credit rating, then on a static liquidity proxy (issuance size or bond age), and finally on the liquidity beta of a bond. The authors find that while γ_{TC} is highly significant with the expected sign, γ_{LIQ} loses its significance or has a counterintuitive sign when $\mathrm{TC}_{i,t}$ is included as a characteristic.

Richardson & Palhares (2019) examine whether less liquid corporate bonds have higher future credit excess returns. They consider six liquidity measures—including bid–ask spreads, daily trading volume, issue size, market impact (Amihud 2002), percentage of no-trading days, and bond age—and construct 24 sets of long–short portfolios (six liquidity measures, IG/HY, and equally or value weighted). They find a significant relation between liquidity and credit excess returns for the age characteristic only. To better control for credit risk, the authors select pairs of bonds that have the same issuer and similar time to maturity but differ along each liquidity dimension (similar to Helwege, Huang & Wang 2014), and create a so-called pair asset that is long the less liquid bond from a given issuer and short the more liquid bond. Still, none of 20 such pair assets (five liquidity measures, IG/HY, and dollar or risk neutral) have a significantly positive return. In other words, this study finds little evidence of a liquidity premium in corporate bonds.[5]

2.2.3. Downside risk and short-term reversal. In addition to constructing a DRF based on the 5% VaR, Bai, Bali & Wen (2019) examine the effect of the 5% VaR as a characteristic. They find that it has highly significant predictive power for future bond returns, with and without controlling for the four risk factors, as presented in Equation 3. The same remarks apply to the short-term

[5]This finding is intriguing given the evidence that corporate bond spreads include a liquidity component (e.g., Longstaff, Mithal & Neis 2005; Chen, Lesmond & Wei 2007; Bao, Pan & Wang 2011; Dick-Nielsen, Feldhütter & Lando 2012; Friewald, Jankowitsch & Subrahmanyam 2012).

reversal characteristic for IG bonds, which is based on the previous-month return. Adding these two characteristics leads to an incremental R^2 of 4.9% and 2.2%, respectively, over the four-factor model. Studies documenting STR in IG bonds include those by Khang & King (2004); Gebhardt, Hvidkjaer & Swaminathan (2005a); and Pospisil & Zhang (2010).

2.2.4. Long-term reversal. Bali, Subrahmanyam & Wen (2021) show that contrarian strategies based on long-term returns are statistically and economically profitable in the corporate bond market. Specifically, when long-term winners and losers are defined with cumulative returns from month $t - 48$ to month $t - 13$, losers generate 47-bps-greater raw returns than do winners in month $t + 1$. Also, the alphas from regressions of long-term reversal (LTR) portfolio returns on various corporate bond and equity market factors are statistically significant and economically sizable.

Bali, Subrahmanyam & Wen (2021) also examine the cross-sectional relation between LTR and expected returns at the security level by estimating the following regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \gamma_{\text{MKT}}\beta_{i,\text{MKT}} + \gamma_{\text{TERM}}\beta_{i,\text{TERM}} + \gamma_{\text{DEF}}\beta_{i,\text{DEF}} + \text{LTR}_{i,t} + Z_{i,t} + \epsilon_{i,t}, \quad 8.$$

where $Z_{i,t}$ includes STR, momentum, and other bond characteristics. They find that the predictive power of LTR remains significant with different controlling variables and that LTR, STR, and momentum jointly explain 15.1% of variations in cross-sectional bond returns.

Finally, Bali, Subrahmanyam & Wen (2021) explore the empirical relevance of different interpretations of LTR in corporate bonds. They find evidence supporting the hypothesis of risk compensation (long-term losers experience increases in credit risk during the portfolio formation period) and the hypothesis of institutional constraints (long-term losers happen to be those bonds that are more subject to regulatory restrictions and more sensitive to regulatory shocks).

2.2.5. Idiosyncratic volatility. In addition to studying the pricing of volatility risk, Chung, Wang & Wu (2019) examine the cross-sectional relation between expected bond returns and idiosyncratic volatility. The latter is measured by the standard deviation of return residuals from a model similar to Equation 2 that includes the FF5Fs and VIX. In a univariate portfolio analysis, the authors sort bonds into deciles based on idiosyncratic volatility over the past 6 months. The difference in characteristic-adjusted returns between the highest and lowest decile portfolios is 30 bps per month. In their cross-sectional regression analysis, Chung, Wang & Wu (2019) show that the predictive power of idiosyncratic volatility is not subsumed by the VIX beta or the total volatility. In a related study, Bao et al. (2015) document a strong positive cross-sectional relation between corporate bond yield spreads or returns and corporate bond return volatilities.

Bai, Bali & Wen (2021) show that the positive relationship between idiosyncratic volatility and future bond returns documented by Chung, Wang & Wu (2019) disappears, however, once the former is constructed using return residuals from the model given in Equation 3. Instead, the systemic component of individual bond return variance is shown to be positively associated with subsequent bond returns. The return spread between the high– and low–systemic risk quintile portfolios averages 0.85% per month and remains significant after controlling for commonly used risk factors. This positive relation between systemic risk and expected returns is contrary to the findings of many studies on cross-sectional equity return predictability.

2.2.6. Value signals and other bond-level characteristics. In an early study on value investing in the corporate bond market, Correia, Richardson & Tuna (2012) constructed value signals equal to the percentage difference between the actual and theoretical credit spreads. The latter is calculated as follows:

$$\mathrm{CS}_{t,T} = -\frac{1}{T-t} \ln \left\{ 1 - \mathrm{LGD} \times N \left[N^{-1}(\pi^{\mathbb{P}}) + \theta^{\mathrm{SR}} \sqrt{T-t} \right] \right\},$$

where $\mathrm{CS}_{t,T}$ denotes the time-t credit spread for a zero-coupon bond with maturity T, LGD is the loss given default, θ^{SR} is the asset Sharpe ratio, $\pi^{\mathbb{P}}$ is the physical default probability over $(t, T]$ (estimated using a default model), and $N(\cdot)$ is the standard normal distribution function.[6] Correia, Richardson & Tuna (2012) document that the resulting percentage difference in credit spread predicts corporate bond returns and spread changes in the cross section.

Houweling & Van Zundert (2017) consider a slightly different version of value signals, in which the theoretical credit spreads are estimated with cross-sectional regressions of observed credit spreads on maturity, rating, and the 3-month change in credit spread. They find that the 12-month return on the long–short hedge portfolio has an alpha of 2.56–3.01% for IG bonds and 5.14–5.33% for HY bonds. Ben Slimane et al. (2019) regress log option-adjusted spreads on maturity, face value (both in log as well), and dummy variables for callable, hybrid, sector, and region, taking into account the complexity of corporate bonds. They then use the residual of this regression as a value indicator.

Guo et al. (2020) focus on the scaled difference between observed and theoretical credit spreads, where the latter refers to the fitted value from rolling-window panel regressions of observed spreads on the FF5F model and the scaling factor is the standard deviation of regression residuals. Guo et al. argue that this scaled difference captures investor sentiment in the corporate bond market. The corresponding low-minus-high return spread averages 0.88% per month for all bonds and 1.57% for HY bonds. Huang, Qin & Wang (2018) document a significant positive relation between changes in corporate bond ownership breadth and the cross section of future corporate bond returns.

2.2.7. Issuer-level characteristics. Chordia et al. (2017) investigate whether equity return characteristics—which capture stock return anomalies—can explain corporate bond returns. By running Fama–MacBeth regressions of excess bond returns on lagged equity characteristics (among other things), they find that asset growth, profitability, equity reversal, and equity momentum offer significant predictive power for corporate bond returns after controlling for bond characteristics. Among the four significant characteristics, the effect of the 1-month-behind equity return is particularly notable, as it is highly positive and thus contrasts with the STR anomaly in the equity market. Notably, Chordia et al. show that anomaly-based returns in corporate bonds do not survive transaction costs; that is, the challenges in earning arbitrage profits in the illiquid corporate bond market significantly attenuate anomaly-based profit. Thus, overall, bond markets are largely efficient net of transaction costs and possibly an omitted risk factor. Cross-sectional bond return predictors generally do not provide materially high Sharpe ratios after accounting for trading costs.

Choi & Kim (2018) also examine the existence of firm characteristics–based anomalies in the corporate bond market, but they focus on whether the associated risk premia are consistent across equity and corporate bond markets. Their results indicate that asset growth and investment–asset ratio are negatively related to bond returns but that the effect of equity momentum is positive. However, they find that the bond risk premia associated with these characteristics are too large to

[6]This approach is in the spirit of Huang & Huang (2012) and Chen, Collin-Dufresne & Goldstein (2009), who calculate the model-implied spreads using $\pi^{\mathbb{P}}$ proxied by rating-based historical default rates in the context of the credit spread puzzle.

be reconciled with equity return premia, given the hedge ratios as implied by structural models. This finding points to limited market integration between the equity and corporate bond markets (see also Titman 2002, Huang & Huang 2012).

Aside from characteristics based on an issuer's balance sheets and equity returns, information from derivatives markets contributes to our understanding of the cross-sectional corporate bond returns as well. For instance, Cao et al. (2019) document that changes in option implied volatility (IV) predict such returns. Specifically, bonds with large increases in IV over the past month underperform those with large decreases in IV by 0.6% per month. Huang, Jiang & Li (2021) find a positive, issuer-level correlation between downside variance premium—defined as the difference between the risk-neutral and physical downside variances—and future corporate bond returns, where the risk-neutral downside variance is estimated from out-of-money put option premia. This positive correlation is significant after controlling for various issue- and issuer-level characteristics but disappears when the downside variance premium is replaced with the total variance premium (Han & Zhou 2011, Wang, Zhou & Zhou 2013).

3. TIME-SERIES EVIDENCE

In this section, we discuss studies that focus on time-series variations of corporate bond returns. We begin with evidence from corporate bond portfolios. We then examine the time-series behavior of individual corporate bond returns.

3.1. Evidence from Corporate Bond Portfolios

We focus on two issues in this subsection. One is evidence on the risk and return of IG and HY bonds as asset classes. The other is corporate bond return predictability.

3.1.1. Risk and return. A basic yet important question is whether, as an asset class, long-term corporate bonds provide any excess returns over long-term Treasury bonds. Fama & French (1993) document that the DEF factor in their sample is on average 2 bps per month. Using data from Ibbotson Associates and Global Financial Data, Dimson, Marsh & Staunton (2002) estimate that the average excess return on long-term high-grade bonds (AAA and AA bonds) is 53 bps per year over the 1900–2000 period. More recently, Ng & Phelps (2011) have found that the average spread premium—defined as the total return on a corporate bond less the total return on a duration-matched Treasury—is 48 bps for IG bonds and 341 bps for HY bonds over the period 1990–2009. Luu & Yu (2011) document that the average excess return on IG bonds is 140 bps over the period 1926–2010. Using data spanning 80 years in the USA and approximately 20 years in Europe, Asvanunt & Richardson (2017) find strong evidence of credit risk premia. For example, the average credit excess return on IG bonds is 137 bps. Importantly, the credit risk premium is not spanned by other known risk premia such as the equity risk premium; it is also time-varying and correlated with economic growth and aggregate default rates.

Some studies focus on both risks and returns of corporate bonds and/or examine what variables can explain their return variations and average returns. For instance, Blume, Keim & Patel (1991) consider a sample of long-term corporate bonds for the period 1977–1989. They document that HY bonds realized higher returns but exhibited less volatility compared with IG bonds because of their call features and high coupons. They also show that HY bonds behave like both bonds and stocks; in particular, HY bonds are less sensitive to interest rates and more sensitive to movements in the stock market than are IG bonds. Interestingly, these authors find that both IG and HY bonds are fairly priced relative to a market-weighted portfolio of stocks and bonds. Cornell & Green (1991) obtain similar findings based on a sample of HY bond funds; however, they note that HY bonds are riskier than IG bonds under beta (other early studies on corporate bond betas include Alexander 1980, Weinstein 1983, and Chang & Huang 1990). Kozhemiakin (2007) examines the performance of corporate bonds by rating from 1985 to 2005. He finds that lower-rated bonds have lower risk-adjusted returns under the information ratio, although BB bonds have the highest ex post credit risk premium among all rating groups—consistent with Huang & Huang's (2012) finding on an ex ante basis.

Fama & French (1993) examine the pricing of five corporate bond portfolios for rating groups Aaa, Aa, A, Baa, and HY from Ibbotson Associates over the period 1961–1991. They show that TERM and DEF explain 97–98%, 90%, and 49% of the time variation in returns on Aaa–A, Baa, and HY portfolios, respectively. Augmenting the two factors with the FF3Fs raises the (adjusted) R^2 to 91% and 58% for the Baa and HY portfolios, respectively. Elton et al. (2001) construct monthly excess returns on 27 portfolios of constant-maturity zero-coupon risky bonds for the period 1987–1996, one for each rating class (AA, A, and BBB) and maturity (2–10 years), where excess returns are relative to the otherwise identical Treasury bonds and thus equal to spread changes by construction. The R^2 from regressions of these excess returns on the FF3Fs ranges from 0% to 9.9% for AA portfolios, from 12.0% to 27.5% for A portfolios, and from 9.7% to 31.3% for BBB portfolios. The regression coefficients for the FF3Fs tend to increase as maturity increases or as credit rating decreases.

While most studies in this stream of literature focus on the contemporaneous correlation between risk and return, recent research by Bai, Bali & Wen (2021) has examined the intertemporal relationship between the conditional mean and the conditional variance. These authors find that the market-wide risk, as proxied by the lagged return variance, positively predicts future corporate bond market returns. Moreover, this temporal predictability is driven solely by aggregate systematic risk instead of aggregate idiosyncratic risk. These results are consistent with the implication of Merton's (1973) intertemporal capital asset pricing model as well as the findings of the risk–return trade-off in the equity market (e.g., Ghysels, Santa-Clara & Valkanov 2005).

3.1.2. Are corporate bond returns predictable? One strand of literature examines corporate bond return predictability. Broadly speaking, predictors constructed or documented are based either on fundamentals or on behavioral patterns. In terms of the former group, in an early study Chang & Huang (1990) constructed six long-term corporate bond portfolios with six different credit ratings (Aaa through B) over the period 1963–1979. They found that these portfolios are predictable using lagged excess 2-month Treasury bill returns, the excess Baa yield, and a January dummy (particularly highly significant for Baa-, Ba-, and B-rated portfolios). More recently, using transaction-based corporate bond index data from October 2002 to December 2010, Hong, Lin & Wu (2012) have shown that past stock market returns can predict corporate bond returns, especially for HY bonds. Lin, Wu & Zhou (2018) consider 27 macroeconomic, stock, and bond predictors and find that their iterated weighted-average combination forecast outperforms the Greenwood & Hanson (2013) model (see the next paragraph), among others.

Regarding behavioral pattern–based predictors, Baker, Greenwood & Wurgler (2003) investigate whether variation in the maturity of corporate debt issues over time can predict excess long-term corporate bond returns. They find that the maturity of new debt issues predicts such returns, using annual returns on an index of IG corporate bonds over commercial paper from 1953 to 2000 from Ibbotson Associates. Greenwood & Hanson (2013) link patterns of corporate debt financing to time-varying pricing of credit risk. They construct an annual measure of issuer quality from 1926 to 2008 and find that a low level of this measure forecasts excess corporate bond returns. Huang, Rossi & Wang (2015) provide evidence that the stock market sentiment measure of Baker & Wurgler (2006) predicts monthly returns on corporate bond portfolios by credit rating over the period 2002–2010. Specifically, when sentiment is high, future corporate bond returns tend to be low. While the negative impact of sentiment is significant overall, the significance comes mostly from lower-rated bonds. Choi & Kronlund (2018) focus on the behavior of corporate bond mutual fund managers to reach for yields.

3.2. Evidence from Individual Corporate Bond Returns

In this subsection, we examine what variables drive the temporal variations in corporate bond returns using regressions. Specifically, we consider 10 regression models that estimate the relative explanatory power of three sets of variables: those suggested by structural models, by equity market variables, and by liquidity measures.

The bond pricing data we use are from the Trade Reporting and Compliance Engine (TRACE). We limit our sample to US corporate debentures or medium-term notes that are senior unsecured, have no embedded options, have a fixed coupon rate, are denominated in US dollars, and are issued by an industrial firm. We then use transaction filters and bond filters as specified by Dick-Nielsen (2009) and Schaefer & Strebulaev (2008). In particular, a sample bond has to have at least 20 consecutive monthly observations available for all regression variables. The final sample consists of 513 corporate bonds from 241 issuers from July 2002 to December 2012.

Table 1 presents results from the 10 regression models. We begin with the following model, as examined by Schaefer & Strebulaev (2008):

$$rx^{\tau}_{i,t} = \alpha_r + \beta^r_{i,rf}\, rf^{10}_t + \beta^r_{i,E}\, rx^E_{i,t}, \qquad 9.$$

where rx^{τ}_i denotes the excess return (relative to the 1-month Treasury bill) on corporate bond i (with τ years to maturity), rx^E_i is the excess return on the bond issuer's equity, and rf^{10} is the excess return on a 10-year Treasury note. Both slope coefficients are positive and highly significant, consistent with the implications of structural models. The second regression model concerns the incremental power of the firm's equity volatility ($\sigma^E_{i,t}$). The results in column 2 of **Table 1** confirm the economic intuition that an increase in volatility would produce the asset substitution effect, leading to a depreciation in corporate debts. On average, the three structural model inputs, $\Theta_S \equiv (rf^{10}, rx^E_i, \sigma^E_i)$, jointly explain 38.3% of bond return variations.

Column 3 of **Table 1** examines the impact of five aggregate equity risk factors shown to predict corporate bond returns or credit spreads, including the FF3Fs, UMD, and ΔVIX. The coefficient signs for SMB_t, HML_t, and ΔVIX_t are consistent with those reported by Schaefer & Strebulaev (2008). As shown in the other columns, UMD_t has two properties distinct from other equity market factors. First, its regression coefficient is overwhelmingly negative, while the FF3Fs generally have positive signs. Second, its significance in explaining bond returns is highly robust to the inclusion of other explanatory variables.

What happens if we augment the above five risk factors with Θ_S? Their joint explanatory capacity is assessed in column 4. The average R^2 value (denoted $\bar{R}^2$) of 0.412 is a notable improvement from the value of 0.383 shown in column 2, confirming the result of Schaefer & Strebulaev (2008) that stock market factors provide added value for our understanding of bond return determinants. However, economically it is not clear why corporate bond returns should have any exposure to these factors after controlling for a firm's equity return. Another interesting finding is that the explanatory power of equity volatility persists and is not absorbed by the VIX, which mirrors Campbell & Taksler's (2003) result.

Next, we turn to the liquidity effect on corporate bond returns. Column 5 of **Table 1** considers two comprehensive measures of bond-specific liquidity. One is the λ measure proposed by Dick-Nielsen, Feldhütter & Lando (2012), defined as the first principal component extracted

Table 1 Time-series regressions of corporate bond returns

	1	2	3	4	5	6	7	8	9	10
Intercept	−0.003***	0.002***	0.005***	0.003***	0.006***	0.001**	0.004***	0.002***	0.005***	0.002***
	(−11.02)	(10.53)	(13.38)	(8.06)	(14.03)	(2.40)	(11.81)	(6.80)	(16.75)	(6.77)
rf_t^{10}	0.470***	0.459***		0.448***		0.571***		0.415***		0.412***
	(16.34)	(16.80)		(13.32)		(8.67)		(12.43)		(12.42)
$xr_{i,t}^E$	0.106***	0.080***		0.056***		0.050***		0.049***		0.048***
	(14.71)	(10.08)		(7.51)		(3.27)		(6.79)		(6.58)
$\Delta\sigma_{i,t}^E$		−0.027***		−0.018***		−0.036***		−0.012***		−0.010***
		(−9.41)		(−6.52)		(−5.14)		(−4.22)		(−3.62)
S&P$_t$			−0.001	0.033		0.131***		0.067***		0.079***
			(0.06)	(1.60)		(2.84)		(3.20)		(3.55)
SMB$_t$			0.040*	0.023		0.024		−0.016		−0.012
			(1.87)	(1.03)		(0.62)		(−0.84)		(−0.64)
HML$_t$			0.116***	0.042**		0.127***		0.023		0.035*
			(3.94)	(2.19)		(3.39)		(1.15)		(1.69)
UMD$_t$			−0.143***	−0.082***		−0.136***		−0.065***		−0.061***
			(5.86)	(5.89)		(−3.79)		(−5.04)		(−4.41)
ΔVIX$_t$			−0.082***	−0.033**		−0.082***		0.021		0.030*
			(−5.73)	(−2.15)		(−3.04)		(1.26)		(1.82)

(*Continued*)

Table 1 (*Continued*)

	1	2	3	4	5	6	7	8	9	10
$\Delta\lambda_{i,t}$					−0.082	0.072				
					(−0.27)	(0.56)				
$\Delta\phi_{i,t}$					−0.999***	−0.320				
					(−3.65)	(−1.48)				
$\Delta\Lambda_t$							−0.389			
							(−1.04)			
$\Delta\Phi_t$							−2.663***	−1.966***		−1.726***
							(−12.54)	(−12.38)		(−9.51)
Δfund_t									−0.560***	−0.197**
									(−6.74)	(−2.20)
$\bar{R}^2$	0.344	0.383	0.105	0.412	0.048	0.456	0.134	0.457	0.047	0.472
N	513	513	513	513	332	332	513	513	513	513

This table reports results from time-series regressions of excess returns on corporate bonds under 10 different models estimated using Trade Reporting and Compliance Engine data from July 2002 to December 2012. Variables $rx^{\tau}_{i,t}$ (the dependent variable), rf^{10}_t, and $rx^{E}_{i,t}$ denote excess returns on corporate bond i, a 10-year Treasury bond, and the equity of bond i's issuer, respectively. Other regressors include equity-based regressors and five liquidity measures. The former group includes changes in equity volatility of bond i's issuer ($\Delta\sigma^{E}_{i,t}$), the S&P 500 return (S&P$_t$), the size factor (SMB$_t$), the book-to-market factor (HML$_t$), the stock momentum factor (UMD$_t$), and changes in the Chicago Board Options Exchange's CBOE Volatility Index (ΔVIX$_t$). The five liquidity measures include changes in bond i's liquidity measure $\lambda_{i,t}$ ($\Delta\lambda_{i,t}$), changes in bond i's transaction cost $\phi_{i,t}$ ($\Delta\phi_{i,t}$), changes in the bond market liquidity factor ($\Delta\Lambda_t$), changes in the bond market transaction cost factor ($\Delta\Phi_t$), and changes in the funding liquidity factor (Δfund$_t$). The reported coefficient values are averaged estimates across bonds. Associated t statistics in parentheses are calculated according to the standard error estimator outlined by Schaefer & Strebulaev (2008). For a given regression model, bonds with fewer than 20 consecutive monthly observations for any independent variables are excluded. N is the number of bonds in the sample. Single, double, and triple asterisks denote significance at 10%, 5%, and 1%, respectively.

from seven potential liquidity proxies.[7] The second measure, denoted ϕ, is constructed in a similar way but based on the six transaction cost measures as advocated by Schestag, Schuster & Uhrig-Homburg (2016).[8] The sign of estimated slope coefficients indicates that high bond valuation is associated with high liquidity levels, which is consistent with the evidence found by Chen, Lesmond & Wei (2007) on yield spread changes. Interestingly, while $\phi_{i,t}$ is highly significant, $\lambda_{i,t}$ is not, even though it is significant at the 5% level in a univariate regression (untabulated).[9] This result is consistent with the finding of Schestag, Schuster & Uhrig-Homburg (2016) that, compared with liquidity proxies measuring transaction costs, price impact proxies [such as the Amihud (2002) measure, an important component of λ] have conceptual issues in the over-the-counter bond market and perform worse than they do in the stock market.

The results in column 6 temper the apparently strong liquidity effect shown in column 5: In the presence of the independent variables in column 4, neither λ nor ϕ is significant. Note that the $\bar{R}^2$ value of 0.456 in column 6 is the average of a subsample of 332 bonds for which estimates of λ or ϕ are available. For comparison, the $\bar{R}^2$ in column 4 would be 0.440 for the same subsample (untabulated).

In the models in columns 7 and 8, we replace bond-specific liquidity levels with (innovations in) aggregate bond market liquidity and thus shed light on the average liquidity exposures of corporate bonds. That is, we construct the market-wide liquidity measures by averaging $\{\lambda_{i,t}\}_i$ and $\{\phi_{i,t}\}_i$ across bonds (in the spirit of Lin, Wang & Wu 2011):

$$\Lambda_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\lambda_{i,t}, \quad \Phi_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\phi_{i,t},$$

where N_t is the number of bonds in month t. Column 7 shows that, for both liquidity factors $\Delta\Lambda_t$ and $\Delta\Phi_t$, the average liquidity beta is negative, consistent with findings by Bongaerts, de Jong & Driessen (2017).[10] Echoing the result in column 5, $\Delta\Lambda_t$ is insignificant in the presence of $\Delta\Phi_t$. As a result, we focus on $\Delta\Phi_t$ for the impact of bond market liquidity in the remaining columns. As shown in column 8, $\Delta\Phi_t$ is indeed one of the most significant variables even in the presence of both the structural model variables and equity market factors. Compared with the (percentage) change in the coefficient associated with $\Delta\phi_{i,t}$ in columns 5 and 6, the effect of $\Delta\Phi_t$ on bond returns is weakened by a much slighter degree in column 8. In addition, incorporating $\Delta\Phi_t$ into regression 4 leads to a greater improvement in the explanatory capacity, raising $\bar{R}^2$ from 0.412 to 0.457. These results suggest that liquidity factors might hold greater promise than proxies measuring bond liquidity levels in explaining the time-series variations in bond returns.

Next, we examine the influence of funding conditions on corporate bond returns. We construct a funding liquidity factor (denoted fund_t) using the first principal component of three correlated

[7]These liquidity proxies include the Amihud (2002) measure and its standard deviation, the imputed round-trip cost from Feldhütter (2012) and its standard deviation, the Roll (1984) measure, the bond turnover rate, and zero trading days (Chen, Lesmond & Wei 2007).

[8]The six measures as constructed from TRACE data are the bid–ask spread estimators of Roll (1984), Hong & Warga (2000), Edwards, Harris & Piwowar (2007), and Schultz (2001); the imputed round-trip costs; and the interquartile range (Han & Zhou 2016). Schestag, Schuster & Uhrig-Homburg (2016) find that these six measures are highly correlated with one another and imply similar magnitudes of transaction cost.

[9]The average slope coefficient in the univariate regression is −0.795, suggesting that the effect of $\lambda_{i,t}$ is weakened by approximately 90% in the presence of $\phi_{i,t}$.

[10]The regression results are qualitatively the same if we follow Bongaerts, de Jong & Driessen (2017) by defining liquidity factors as the monthly AR(4) innovations in Λ_t and Φ_t.

proxies for funding conditions: the "noise" of Hu, Pan & Wang (2013), the spread between the 3-month London Interbank Offered Rate (LIBOR) and Treasury bills (the TED spread), and the betting-against-beta (BAB) factor of Frazzini & Pedersen (2014).[11] Column 9 shows that a deterioration in funding conditions is significantly associated with lower returns on corporate bonds, consistent with Frazzini & Pedersen's (2014) finding that the BAB portfolio formed in credit markets has significant, positive excess returns. Interestingly, Chen & Lu (2019) and Malkhozov et al. (2017) find that their measures for funding conditions show modest correlations with stock market illiquidity measures but contain information on funding liquidity risk not driven purely by market liquidity.

We therefore run the following kitchen-sink regression:

$$rx^{\tau}_{i,t} = \alpha_i + \beta_{i,1} rf^{10}_t + \beta_{i,2} rx^E_{i,t} + \beta_{i,3} \Delta\sigma^E_{i,t} + \beta_{i,4} \text{S\&P}_t + \beta_{i,5} \text{SMB}_t + \beta_{i,6} \text{HML}_t + \beta_{i,7} \text{UMD}_t + \beta_{i,8} \Delta\text{VIX}_t + \beta_{i,9} \Delta\Phi_t + \beta_{i,10} \Delta\text{fund}_t, \quad 10.$$

where $\text{S\&P}_t$ represents the S&P 500 return and Δ denotes changes as mentioned above. As shown in column 10 of **Table 1**, Δfund_t is not subsumed by $\Delta\Phi_t$. Together, the 10 explanatory variables in Equation 10 have an $\bar{R}^2$ of 47.2%.

Overall, the most telling finding from **Table 1** is about the pivotal role of the three structural model variables (Θ_S): They are robust and together account for more than 80% of variations in expected bond returns, as implied by our most comprehensive regression specification. **Table 2** reports regression results of model 10 by rating class. Note that the effects of rf^{10} and rx^E_i spread well across rating categories, while the significance of $\Delta\sigma^E_{i,t}$ is confined to HY bonds. Among the other determinants of bond returns, UMD_t and $\Delta\Phi_t$ exhibit reasonably robust explanatory power.

In Section 4, we incorporate more insights from structural models to study the determinants of corporate bond returns using a model-based approach.

4. STRUCTURAL MODEL–BASED ANALYSIS

In this section, we present a model-based analysis of individual corporate bond returns using the Merton (1974) model. We conduct the analysis in two steps. First, to capture the potential nonlinear nature of the relationship between corporate bond returns and their determinants, we incorporate the model-implied sensitivities of corporate bond returns into return regressions. Second, we focus on the model-implied realized and expected corporate bond returns themselves and examine their predictive power for corporate bond returns in both time series and cross section. Because corporate bond returns and spread changes are closely related, we also include the latter in part of the analysis.

4.1. Model Implications for Corporate Bond Returns

In this subsection, we review the Merton (1974) model and its model-implied sensitivities of corporate bond returns and credit spreads. We also derive a formula for expected corporate bond returns implied by the model.

[11]The first principal component explains more than 60% of the variation in the three proxies and is close to their simple average. The time series of the noise and BAB factor are available at **https://en.saif.sjtu.edu.cn/junpan/** and **https://www.aqr.com/Insights/Datasets**, respectively.

Table 2 Determinants of corporate bond returns by rating group

	Rating categories						
	All	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**
Intercept	0.002	0.001	0.001	0.002	0.003	0.004	0.004
	(6.77)	(1.25)	(2.93)	(5.69)	(6.46)	(3.13)	(1.84)
rf_t^{10}	0.412	0.705	0.560	0.580	0.404	0.175	0.216
	(12.42)	(6.40)	(8.19)	(19.57)	(8.53)	(3.46)	(1.88)
$xr_{i,t}^E$	0.048	0.020	−0.004	0.018	0.056	0.041	0.121
	(6.58)	(1.18)	(−0.49)	(1.83)	(4.65)	(1.87)	(4.92)
$\Delta\sigma_{i,t}^E$	−0.010	0.004	−0.010	−0.002	−0.010	−0.010	−0.038
	(−3.62)	(0.33)	(−1.21)	(−0.46)	(−1.86)	(−1.14)	(−3.41)
$\text{S\&P}_t$	0.079	0.065	0.019	−0.013	0.066	0.147	0.334
	(3.55)	(1.29)	(0.63)	(−0.70)	(2.04)	(2.21)	(2.59)
SMB_t	−0.012	−0.090	−0.022	0.061	−0.036	0.044	−0.113
	(−0.64)	(−1.49)	(−0.50)	(3.01)	(−1.25)	(0.81)	(−1.65)
HML_t	0.035	−0.016	−0.024	−0.027	0.006	0.021	0.347
	(1.69)	(−0.35)	(−0.79)	(−1.37)	(0.18)	(0.34)	(3.14)
UMD_t	−0.061	0.034	0.008	−0.047	−0.030	−0.093	−0.232
	(−4.41)	(1.64)	(0.37)	(−4.30)	(−1.66)	(−2.13)	(−2.85)
ΔVIX_t	0.030	−0.004	−0.016	−0.017	0.064	−0.040	0.126
	(1.82)	(−0.16)	(−0.89)	(−1.19)	(2.29)	(−0.68)	(1.96)
$\Delta\Phi_t$	−1.726	−0.715	−0.180	−1.536	−1.848	−3.481	−1.004
	(−11.41)	(−2.42)	(−0.54)	(−8.95)	(−6.99)	(−8.06)	(−1.75)
Δfund_t	−0.197	0.164	−0.285	0.093	−0.326	−0.213	−0.658
	(−2.20)	(0.73)	(−1.47)	(1.26)	(−1.78)	(−1.14)	(−2.04)
$\bar{R}^2$	0.472	0.570	0.603	0.528	0.421	0.332	0.434
N	513	11	38	168	160	73	44

This table reports results from bond-by-bond time-series regressions as specified in Equation 10. $rx_{i,t}^{\tau}$ (the dependent variable), rf_t^{10}, and $rx_{i,t}^E$ denote excess returns on corporate bond i, on a 10-year Treasury note, and on equity of bond i's issuer, respectively. Other regressors include changes in the equity volatility of bond i's issuer ($\Delta\sigma_{i,t}^E$), the S&P 500 return ($\text{S\&P}_t$), the size factor (SMB_t), the book-to-market factor (HML_t), the stock momentum factor (UMD_t), changes in the Chicago Board Options Exchange's CBOE Volatility Index (ΔVIX_t), changes in the bond market liquidity factors ($\Delta\Phi_t$), and changes in the funding liquidity factor (Δfund_t). The reported coefficient values are averaged estimates across bonds in the entire sample or within each rating category. Associated t statistics in parentheses are calculated according to the standard error estimator outlined by Schaefer & Strebulaev (2008). N is the number of bonds in each rating category. The sample period is from July 2002 to December 2012.

We begin with the model setup. A firm is assumed to have a zero-coupon bond outstanding with face value F and maturity T. Default can occur at T only. The risk-free rate, r, is constant. The firm asset value process, denoted $(A_t)_{t\geq 0}$, follows a log-normal process with drift r and asset return volatility σ_A under the risk-neutral measure $\mathbb{Q}$.

Let D_t^{τ} and CS_t^{τ} denote the time-t price and yield spread of the zero-coupon bond with $\tau = T - t$ years to maturity, respectively. It is known that

$$D_t^{\tau} = A_t N(-d_1) + F e^{r\tau} N(d_2), \qquad 11.$$

$$\text{CS}_t^{\tau} = -\frac{1}{\tau}\ln[\ell_t^{-1} N(-d_1) + N(d_2)], \qquad 12.$$

where $\ell_t = F/A_t$ (the quasi-book leverage at t) and

$$d_1 = \frac{\ln(A_t/F) + (r + \sigma_A^2/2)\tau}{\sigma_A\sqrt{\tau}}; \quad d_2 = d_1 - \sigma_A\sqrt{\tau}.$$

Given that equity value $E_t = A_t - D_t^\tau$, one can use Equations 11 and 12 to obtain formulas for sensitivities of corporate bond returns and spreads to, say, equity return. The model-implied realized corporate bond return can be calculated using Equation 11. We consider the dynamics of $(A_t)_{t\geq 0}$ under the physical measure $\mathbb{P}$ and examine the model-implied expected corporate bond return in Section 4.1.2.

4.1.1. Sensitivities of corporate bond returns and spreads. Section 3.2 has shown evidence of the explanatory power of three structural model variables (rf^{10}, $rx_{i,t}^E$, and $\sigma_{i,t}^E$) for corporate bond returns. One question that arises and that we address below is whether or not incorporating sensitivities of corporate bond returns in return regressions helps raise the explanatory power of these variables. Given the use of the Merton model in this study, we focus on equity return (among the three variables) as well as the quasi-book leverage.[12] In addition, we include corporate bond credit spreads in this analysis.

Let h_E^r denote the sensitivity/hedge ratio of corporate bond return to equity return, and h_ℓ^{CS} and h_E^{CS} the sensitivities of credit spreads to leverage and equity return, respectively. These three hedge ratios under the Merton model are

$$h_E^r \equiv \frac{\partial D/D}{\partial E/E} = \frac{N(-d_1)}{N(d_1)}\frac{E}{D}, \quad 13.$$

$$h_\ell^{CS} \equiv \frac{\partial(\text{CS})}{\partial\ell} = \frac{1}{\tau\ell(1+\theta)}, \quad 14.$$

$$h_E^{CS} \equiv \frac{\partial(\text{CS})}{\partial E/E} = -\frac{1}{\tau}\frac{N(-d_1)}{N(d_1)}\frac{E}{D}, \quad 15.$$

where subscripts and superscripts for D, E, and CS are omitted to simplify notation, and $\theta = \ell e^{-r\tau}N(d_2)/N(-d_1)$. We incorporate the above three Merton hedge ratios in time-series regressions of corporate bond returns in Section 4.3.

4.1.2. The Merton model–implied expected corporate debt returns. To examine the implications of the Merton model for cross-sectional bond returns as well as their time-series predictability, below we derive a formula for the expected corporate bond return (under $\mathbb{P}$) in the Merton model. We do so by constructing an equivalent expectation measure $\mathbb{R}$ as proposed by Nawalkha & Zhuo (2020).

Given an investment horizon $h\,(\leq T)$ for return calculation and a standard Brownian motion under $\mathbb{P}$, the standard Brownian motion under the equivalent expectation measure $\mathbb{R}$ is given as

[12]Two recent studies on the interest rate sensitivity of corporate bond returns are those by Huang & Shi (2016) and Choi, Richardson & Whitelaw (2020). Huang & Shi (2016) show that incorporating a three-factor term structure model into the Merton model and using returns on three Treasury securities (instead of one) as explanatory variables can better explain IG bond returns and help resolve the "interest rate sensitivity puzzle" documented by Schaefer & Strebulaev (2008). Choi, Richardson & Whitelaw (2020) find that the sensitivity of corporate security returns to interest rate changes is related to the firm's capital structure priority and market leverage.

follows:

$$W_s^{\mathbb{R}} = W_s^{\mathbb{P}} + \int_0^s \gamma \mathbb{1}_{\{u \geq h\}} \mathrm{d}u, \tag{16.}$$

where γ is the market price of risk and $\mathbb{1}_{\{\cdot\}}$ is an indicator function that equals one if the condition is satisfied (and zero otherwise). It follows that the dynamics of $(A_t)_{t \geq 0}$ under $\mathbb{R}$ are given by

$$\begin{aligned}\frac{\mathrm{d}A_s}{A_s} &= \left(r + \sigma_A \gamma\ \mathbb{1}_{\{s<h\}}\right) \mathrm{d}s + \sigma_A \mathrm{d}W_s^{\mathbb{R}} \\ &= \left(\mu \mathbb{1}_{\{s<h\}} + r \mathbb{1}_{\{s \geq h\}}\right) \mathrm{d}s + \sigma_A \mathrm{d}W_s^{\mathbb{R}},\end{aligned} \tag{17.}$$

where μ is the asset return drift under $\mathbb{P}$.

A highly intuitive property of the $\mathbb{R}$ measure is that any stochastic process under this measure, such as the firm value process in Equation 17, can be obtained by a simple inspection of that process under $\mathbb{P}$ and $\mathbb{Q}$ as follows: The stochastic process under $\mathbb{R}$ is the physical stochastic process until before the horizon h, but it becomes the risk-neutral process on or after the horizon h. Note that the $\mathbb{R}$ measure reduces to $\mathbb{Q}$ when $h = 0$.

By invoking theorem 1 of Nawalkha & Zhuo (2020), we obtain the time-t expectation for the zero-coupon bond price at time $t + h$ (with $h \leq \tau = T - t$) as follows:

$$\mathbb{E}_t^{\mathbb{P}}[D_{t+h}^{\tau-h}] = \mathbb{E}_t^{\mathbb{R}}\left[\mathrm{e}^{-r(\tau-h)} D_{t+\tau}^0\right] = \mathbb{E}_t^{\mathbb{R}}\left[\mathrm{e}^{-r(\tau-h)} \min(F, A_{t+\tau})\right]. \tag{18.}$$

Since Equation 17 implies that $A_{t+\tau}$ is log-normally distributed under the $\mathbb{R}$ measure, we obtain the following formula for the expected corporate bond price in the Merton model:

$$\mathbb{E}_t^{\mathbb{P}}[D_{t+h}^{\tau-h}] = F\mathrm{e}^{-r(\tau-h)} N\left(d_2^h\right) + A_t \mathrm{e}^{\mu h} N\left(-d_1^h\right), \tag{19.}$$

where

$$d_1^h = \frac{\ln(A_t/F) + \mu h + r(\tau - h) + \frac{1}{2}\sigma_A^2 \tau}{\sigma_A \sqrt{\tau}}; \quad d_2^h = d_1^h - \sigma_A \sqrt{\tau}.$$

We can then calculate the Merton model–implied expected corporate bond return under $\mathbb{P}$ using Equations 11 and 19.

4.2. Estimation of Input Parameters

In this subsection, we discuss how to estimate input parameters in the Merton model–implied sensitivities and expected corporate bond returns discussed in Section 4.1. The time to maturity, τ, of a given bond is set equal to the average duration of all bonds issued by the same firm.[13] The risk-free rate r used is the Treasury zero yield with a time to maturity of τ. We estimate F using the firm's total liability (Compustat item LTQ), following Eom, Helwege & Huang (2004). An alternative measure is the firm's short-term debt (DLCQ) plus one-half of its long-term debt (DLTTQ), first proposed by Moody's KMV (Crosbie & Bohn 2019).[14]

We estimate A_t and σ_A, two variables not directly observable, by matching the model-implied equity value and equity volatility with their observed values. Specifically, we solve the following

[13]We find that setting τ to bond-specific duration improves the model prediction of hedge ratios (untabulated); however, this specification implies that the same firm can have different estimated asset values.

[14]In an untabulated analysis, we find that although this measure has little impact on the model prediction of corporate bond return and spread sensitivities, it lowers the performance of the model spreads in explaining the temporal variations in actual spreads in our sample.

system of two equations for A_t and σ_A:

$$E_t = A_t N(d_1) - Fe^{-r\tau} N(d_2); \quad 20.$$

$$\sigma_E = \frac{A_t}{E_t} N(d_1)\sigma_A, \quad 21.$$

where σ_E is equity volatility. This approach, proposed by Jones, Mason & Rosenfeld (1984), is widely used in the literature (e.g., Hillegeist et al. 2004, Campbell, Hilscher & Szilagyi 2008).[15] Note that we obtain A_t and σ_A period by period and calibrate the time-t risk-free rate r to match the yield of a Treasury bond with the same maturity (TY_t^τ). This scheme generates a time-varying asset volatility and risk-free rate and, thus, likely improves the model performance (although both parameters are assumed to be constant in the model). We estimate μ (the asset growth rate under $\mathbb{P}$) from the time series of asset values as generated by iterations of Equations 20 and 21, and do so over a 12-month rolling window for each bond issuer to ensure that we do not make use of any future information.

4.3. Time-Series Regressions on Model-Implied Sensitivities

Given the input parameters, the three Merton hedge ratios, h_ℓ^{CS}, h_E^{CS}, and h_E^r, can be calculated using Equations 13, 14, and 15, respectively. Below, we examine whether the three hedge ratios are consistent with data and whether they help raise the explanatory power of equity return and leverage ratios for corporate bond returns or spread changes. The data we use in this analysis are as described in Section 3.2.

We consider credit spread changes first, as their Merton model–implied sensitivities are seldom examined empirically in the literature. **Table 3*a*** reports results from the following time-series regression of spread changes for bond i that incorporates h_ℓ^{CS}:

$$\Delta \mathrm{CS}_{i,t}^\tau = \alpha_{\mathrm{CS}} + \beta_{i,Y}^{\mathrm{CS}}\, \Delta \mathrm{TY}_t^{10} + \beta_{i,l}^{\mathrm{CS}}\, h_\ell^{\mathrm{CS}}\, \Delta \ell_{i,t}, \quad 22.$$

where Δ denotes changes as above and $\ell_{i,\,t}$ is calculated with estimates of A_t. If the Merton model accurately describes the leverage sensitivity of spreads, $\beta_{i,l}^{\mathrm{CS}}$ should be close to one. As such, we test the null hypothesis that the average of these coefficients across bonds is one—specifically, $\bar{\beta}_{i,l}^{\mathrm{CS}} = 1$. Note that in **Table 3*a*** the estimate of $\bar{\beta}_{i,l}^{\mathrm{CS}}$ indeed lies close to one for the whole sample, as well as for individual rating groups except BB bonds, for which the null hypothesis is only marginally rejected. The average adjusted R^2 value, denoted $\bar{R}^2$, is 0.227 for the full sample and ranges from 0.145 for AA bonds to 0.299 for B bonds.

For comparison, we also run the following regression without h_ℓ^{CS}:

$$\Delta \mathrm{CS}_{i,t}^\tau = \alpha_{\mathrm{CS}} + \beta_{i,Y}^{\mathrm{CS}}\, \Delta \mathrm{TY}_t^{10} + \beta_{i,l}^{\mathrm{CS}}\, \Delta \ell_{i,t}. \quad 23.$$

The estimates of $\bar{\beta}_{i,l}^{\mathrm{CS}}$ are 0.078, 0.044, 0.041, 0.050, 0.067, 0.083, and 0.148 for the full sample and for the AAA, AA, A, BBB, BB, and B subsamples, respectively, and are all significantly different from zero (untabulated). That is, the empirical sensitivity of spreads to leverage is greater for lower-rated bonds, except for the AAA group, which includes only 11 bonds. **Table 3*a*** presents the average adjusted R^2 value obtained from regression 23, denoted $\bar{R}_0^2$. Note that $\bar{R}^2$ is higher than $\bar{R}_0^2$ except for A-rated bonds. This result suggests that including model-implied slope

[15]We also estimate σ_A using the sample standard deviation of the time series of asset returns, $\ln(A_{t+1}/A_t)$ (e.g., Vassalou & Xing 2004; Duffie, Saita & Wang 2007; Crosbie & Bohn 2019); however, such estimates do not help improve the performance of the model-implied sensitivities for our sample.

Table 3 Bivariate regressions incorporating the Merton model–implied sensitivities of corporate bond returns and credit spreads

	Rating categories						
	All	AAA	AA	A	BBB	BB	B
a $\Delta CS_{i,t}^{\tau} = \alpha_{CS} + \beta_{i,Y}^{CS}\Delta TY_t^{10} + \beta_{i,l}^{CS} b_{\ell}^{CS}\Delta\ell_{i,t}$							
Intercept	−0.003	0.001	−0.008	−0.012	−0.004	−0.005	−0.016
	(−0.85)	(0.50)	(−4.40)	(−7.88)	(−3.63)	(−2.66)	(5.73)
ΔTY_t^{10}	−0.557	−0.196	−0.206	−0.241	−0.452	−0.909	−1.128
	(−13.57)	(−2.66)	(−5.37)	(−8.25)	(−7.92)	(−11.95)	(−7.14)
$b_{\ell}^{CS}\Delta\ell_{i,t}$	1.109	0.893	1.244	1.048	1.158	0.616	1.031
	(0.72)	(−0.28)	(1.39)	(0.16)	(0.59)	(−1.67)	(0.43)
$\bar{R}^2$	0.227	0.213	0.145	0.182	0.241	0.278	0.299
N	513	11	38	168	160	73	44
$\bar{R}_0^2$	0.216	0.213	0.135	0.183	0.227	0.269	0.258
b $\Delta CS_{i,t}^{\tau} = \alpha_{CS} + \beta_{i,Y}^{CS}\Delta TY_t^{10} + \beta_{i,E}^{CS} b_E^{CS} r_{i,t}^E$							
Intercept	0.007	−0.011	−0.019	0.032	0.011	0.021	−0.006
	(2.46)	(−3.89)	(−5.48)	(6.83)	(1.80)	(2.08)	(−2.91)
ΔTY_t^{10}	−0.532	−0.228	−0.243	−0.209	−0.456	−0.835	−1.221
	(−12.48)	(−2.72)	(−4.85)	(−9.23)	(−5.71)	(−7.06)	(−4.62)
$b_E^{CS} r_{i,t}^E$	1.063	1.179	0.643	1.155	0.832	1.305	0.618
	(0.87)	(1.02)	(−0.58)	(0.83)	(−0.37)	(0.78)	(−0.84)
$\bar{R}^2$	0.213	0.205	0.101	0.136	0.218	0.273	0.304
N	513	11	38	168	160	73	44
$\bar{R}_0^2$	0.202	0.203	0.105	0.134	0.204	0.261	0.302
c $rx_{i,t}^{\tau} = \alpha_r + \beta_{i,rf}^{r} rf_t^{\tau_0} + \beta_{i,E}^{r} b_E^{r} rx_{i,t}^E$							
Intercept	−0.004	−0.003	−0.004	−0.004	−0.003	−0.004	−0.011
	(−9.17)	(−5.00)	(−13.51)	(−17.00)	(−6.23)	(−2.08)	(−2.88)
$rf_t^{\tau_0}$	0.484	0.723	0.594	0.759	0.554	0.244	−0.088
	(13.73)	(4.40)	(7.92)	(18.19)	(12.84)	(5.94)	(−1.58)
$b_E^{r} rx_{i,t}^E$	1.057	1.526	0.806	1.191	0.842	1.169	0.978
	(0.37)	(1.20)	(−0.41)	(0.38)	(−0.64)	(0.49)	(−0.06)
$\bar{R}^2$	0.356	0.632	0.540	0.450	0.300	0.184	0.319
N	513	11	38	168	160	73	44
$\bar{R}_0^2$	0.344	0.627	0.509	0.434	0.303	0.180	0.298

This table reports test results on the Merton (1974) model–implied sensitivities through time-series regressions for each corporate bond. (*a*,*b*) Sensitivities of credit spreads to firms' leverage ratio and equity (b_{ℓ}^{CS} and b_E^{CS}), respectively, which are given by Equations 14 and 15. (*c*) The equity hedge ratio for corporate bond returns (b_E^r) given by Equation 13. $\Delta CS_{i,t}^{\tau}$ denotes changes in the time-*t* credit spread of corporate bond *i* with τ years to maturity. $rx_{i,t}^{\tau}$ and $rx_{i,t}^E$ are excess returns on bond *i* and on equity of bond *i*'s issuer, respectively. $r_{i,t}^E$ is the equity return. $\Delta\ell_{i,t}$ denotes changes in the time-*t* quasi-book leverage. TY_t^{10} represents the 10-year Treasury yield. $rf_t^{\tau_0}$ represents excess return on a Treasury bond whose time to maturity τ_0 is close to τ. The reported regression coefficients and R^2 values are averaged estimates across bonds. $\bar{R}_0^2$ indicates the average R^2 values from the corresponding regression without incorporating the model-implied sensitivities. In parentheses are *t* statistics calculated using the standard error estimator outlined by Schaefer & Strebulaev (2008), while those for coefficients related to the Merton sensitivities, b_{ℓ}^{CS}, b_E^{CS}, and b_E^r, are computed against unity. *N* is the number of bonds in each rating category. The sample period is from July 2002 to December 2012.

coefficients helps capture the nonlinear relation between credit spreads and the firm leverage and thus improves the explanatory power of the latter.[16]

Next, we examine h_E^{CS}, the equity sensitivity of credit spreads given in Equation 15. **Table 3*b*** reports results from the following regression:

$$\Delta CS_{i,t}^{\tau} = \alpha_{CS} + \beta_{i,Y}^{CS}\, \Delta TY_t^{10} + \beta_{i,E}^{CS}\, h_E^{CS}\, r_{i,t}^{E}, \tag{24.}$$

where $r_{i,t}^E$ is the equity return.[17] None of the estimates of $\beta_{i,E}^{CS}$ are significantly different from one at the 10% significance level, especially for IG bonds; that is, the theoretical h_E^{CS} works reasonably well. Note that our sample period arguably works against model-implied hedge ratios, as the asymmetric treatment of debt and equity in government bail-outs after the financial crisis may have affected debt and equity differently (Schweikhard & Tsesmelidakis 2012). **Table 3*b*** also reports two sets of the average R^2 values: $\bar{R}^2$ from regression 24 and $\bar{R}_0^2$ from an otherwise identical regression without h_E^{CS}. Note that $\bar{R}^2$ is higher than $\bar{R}_0^2$ across different rating groups except for AA bonds. This finding provides further evidence of the Merton model's ability to capture the nonlinear relationship between credit spreads and the underlying variables.

Finally, **Table 3*c*** shows results from the following regression of corporate bond excess returns that incorporates h_E^r:

$$rx_{i,t}^{\tau} = \alpha_r + \beta_{i,rf}^{r}\, rf_t^{\tau_0} + \beta_{i,E}^{r}\, h_E^r\, rx_{i,t}^{E}, \tag{25.}$$

where rf^{τ_0} is the excess return on a τ_0-year Treasury with $\tau_0 \approx \tau$. For the entire sample, the estimate of $\bar{\beta}_{i,E}^r$ is 1.06 and is insignificantly different from one (with a t statistic of 0.37), consistent with Schaefer & Strebulaev (2008). The estimate of $\bar{\beta}_{i,E}^r$ is also insignificantly different from one across rating groups, ranging from 0.81 for AA bonds to 1.53 for AAA bonds. The AAA and AA groups with the two largest deviations from unity are the smallest (with 11 and 38 bonds, respectively), for which the estimates of $\bar{\beta}_{i,E}^r$ tend to be less precise.[18] A comparison of the $\bar{R}^2$ and $\bar{R}_0^2$ values, shown in **Table 3*c***, indicates that incorporating h_E^r helps raise the explanatory power of equity for corporate bond returns.

There are two main takeaways from this subsection. First, the Merton model–implied sensitivities of credit spread changes, h_ℓ^{CS} and h_E^{CS}, are not rejected in our time-series tests.[19] This finding complements Schaefer & Strebulaev's (2008) result for the equity sensitivity of corporate bond returns, h_E^r. Second, h_ℓ^{CS}, h_E^{CS}, and h_E^r capture certain exposures of corporate bonds to credit risk, if not to other risks.

4.4. Time-Series Regressions on Modeled Spreads and Returns

The analysis in Section 4.3 is based on a linear, additive structure of structural model–motivated variables. In this subsection, we examine the ability of the Merton model to explain serial variations in corporate bond returns and credit spreads.

[16]We also run regression 22 with ℓ replaced by $l_t = F/(F+E_t)$, the quasi-market leverage. Using this observable leverage lowers the performance, however, as h_ℓ^{CS} depends on ℓ_t and not l_t. Indeed, the estimated $\beta_{i,l}^{CS}$ is higher than one by 32% over the entire sample (untabulated).

[17]Huang, Shi & Zhou (2020) examine a similar regression specification using CDS data.

[18]Our sample is not big enough to have a sufficient number of bonds for every subrating group. Otherwise, we can follow Schaefer & Strebulaev (2008) and use h_E^r estimates averaged across firms within the same subrating group to smooth out firm-specific noise and obtain more precise estimates of $\beta_{i,E}^r$.

[19]Extending this analysis to alternative structural models is straightforward (see our working paper titled "A Resolution to the Equity-Credit Market Integration Puzzle"). In a related study, He, Khorrami & Song (2019) examine the explanatory power of two intermediary-based factors for commonality in credit spread changes.

Consider credit spreads first. In addition to the Merton credit spread given in Equation 12—denoted $\widehat{\mathrm{CS}}_{i,t}^{\tau}$ here—we implement a variation on the Merton model with exogenous recovery rates that admits the following formula of credit spreads (e.g., Chen, Collin-Dufresne & Goldstein 2009):

$$\widetilde{\mathrm{CS}}_{i,t}^{\tau} = -\frac{1}{\tau} \ln\left[1 - (1 - w)N(-d_2)\right], \qquad 26.$$

where w is the recovery rate and is assumed to be constant. We estimate w according to the average senior unsecured bond recovery rates reported by Moody's, assuming that firms with the same credit rating in the same calendar year have the same recovery rate.

To see how much of the temporal variation in observed credit spreads can be explained by the model, we regress observed spread changes, $\Delta \mathrm{CS}_{i,t}^{\tau}$, on the model spread changes, $\Delta\widehat{\mathrm{CS}}_{i,t}^{\tau}$ ($\Delta\widetilde{\mathrm{CS}}_{i,t}^{\tau}$), and report the results in **Table 4*a*** (**Table 4*b***). Consider **Table 4*a*** first. For the full sample, the mean of slope coefficients is 0.60, statistically different from both zero and one. That is, while the robust t-test rejects the hypothesis that $\Delta\widehat{\mathrm{CS}}_{i,t}^{\tau}$ contains no information, we cannot consider it to be an unbiased estimator of changes in the realized spread. The $\bar{R}^2$ value indicates that, for the full sample, the model spread explains 29.8% of serial variations, much higher than the $\bar{R}^2$ values of the linear models reported in **Table 3*a*,*b***.

Results reported in **Table 4*b*** indicate that the Merton model with exogenous recovery rates lowers $\bar{R}^2$. Nonetheless, $\bar{R}^2$ generally increases as the rating decreases (except for AAA bonds), as illustrated in **Table 4*a*,*b***. This finding is consistent with the empirical evidence that model-suggested variables perform better in explaining spread changers for HY bonds (Collin-Dufresne, Goldstein & Martin 2001; Avramov, Jostova & Philipov 2007).

Table 4*c* shows the effect of $\widehat{\mathrm{CS}}_{i,t}^{\tau}$ on credit spread levels. For our sample, a panel regression of the spread levels on firms' debt ratio and Treasury yields results in an $\bar{R}^2$ value of 48.8%. In line with this finding, $\widehat{\mathrm{CS}}_{i,t}^{\tau}$ possesses much greater explanatory power for credit spread levels with an average $\bar{R}^2$ value of 58.5% for the full sample, although the t-test still rejects a one-for-one comovement between the model and observed spreads. Hence, even if we focus on the (purely credit risk–based) Merton spread, regressions with spread levels still yield higher R^2 values than regressions with spread changes. This finding is consistent with evidence suggesting that theoretical determinants do a much better job of explaining spread levels than spread changes (Chen, Lesmond & Wei 2007; Cremers, Driessen & Maenhout 2008; Rossi 2014). Still, the Merton model tends to underestimate the observed bond yield spreads, consistent with the literature (e.g., Eom, Helwege & Huang 2004; Huang & Huang 2012): The average bias for the entire sample is −63.9 bps for $\widehat{\mathrm{CS}}_{i,t}^{\tau}$ and −70.3 bps for $\widetilde{\mathrm{CS}}_{i,t}^{\tau}$ (untabulated).

Table 4*d* reports the results of regressing observed excess bond returns on their model-implied counterparts ($\widehat{rx}_{i,t}^{\tau}$). Conceptually, the estimated model should be more capable of explaining the return variations compared with variations in spread changes, as a large fraction of the former is driven by variations in the default-free yield curve. Since in our implementation of the Merton model the risk-free rate used is the Treasury yield with the same maturity as that of the corporate bond, the model's prediction of contemporaneous bond returns encompasses the information on the yield curve movements. As expected, $\widehat{rx}_{i,t}^{\tau}$ appears to deliver an empirical performance superior to that of $\Delta\widehat{\mathrm{CS}}_{i,t}^{\tau}$ and $\Delta\widetilde{\mathrm{CS}}_{i,t}^{\tau}$ in terms of both the regression slope and $\bar{R}^2$. $\bar{R}^2$ is 36.7% for the full sample and ranges from 30.2% for BB bonds to 46.2% for AAA bonds across rating groups. These findings reflect the intuitive result that the model's explanatory power for bond returns is more directly comparable to that for changes in the bond yield, rather than changes in the spread.

Table 4 Explanatory power of the Merton model–implied yield spreads, spread changes, and corporate bond returns

	Rating categories						
	All	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**
a $\Delta CS^{\tau}_{i,t} = \alpha + \beta \Delta \widehat{CS}^{\tau}_{i,t}$							
Intercept	0.010	−0.010	−0.008	0.001	0.008	0.025	0.029
	(2.83)	(−0.73)	(−0.99)	(0.38)	(1.56)	(2.46)	(0.99)
$\Delta\widehat{CS}_{i,t}$	0.599	0.659	0.521	0.597	0.641	0.549	0.625
	(7.19)	(5.78)	(4.48)	(5.39)	(6.18)	(4.53)	(5.89)
$\bar{R}^2$	0.298	0.279	0.256	0.258	0.306	0.332	0.414
N	513	11	38	168	160	73	44
b $\Delta CS^{\tau}_{i,t} = \alpha + \beta \Delta \widetilde{CS}^{\tau}_{i,t}$							
Intercept	−0.004	−0.003	−0.007	−0.006	−0.013	0.006	0.022
	(−1.38)	(−0.59)	(−1.30)	(−2.79)	(−2.47)	(0.83)	(0.76)
$\Delta\widetilde{CS}_{i,t}$	0.541	0.589	0.502	0.499	0.528	0.573	0.592
	(6.33)	(4.68)	(3.85)	(3.72)	(4.67)	(5.14)	(5.05)
$\bar{R}^2$	0.257	0.220	0.205	0.203	0.273	0.391	0.400
N	513	11	38	168	160	73	44
c $CS^{\tau}_{i,t} = \alpha + \beta \widehat{CS}^{\tau}_{i,t}$							
Intercept	0.013	0.004	0.006	0.009	0.013	0.023	0.026
	(6.96)	(3.31)	(3.65)	(4.47)	(5.85)	(6.91)	(6.52)
$\widehat{CS}_{i,t}$	0.697	0.665	0.553	0.593	0.736	0.698	0.914
	(7.52)	(4.48)	(3.76)	(3.93)	(5.57)	(5.23)	(7.26)
$\bar{R}^2$	0.585	0.507	0.418	0.442	0.631	0.711	0.749
N	513	11	38	168	160	73	44
d $rx^{\tau}_{i,t} = \alpha + \beta \widehat{rx}^{\tau}_{i,t}$							
Intercept	−0.003	−0.004	−0.001	−0.004	−0.003	−0.002	−0.009
	(−7.00)	(−3.71)	(−1.85)	(−8.28)	(−5.57)	(−2.71)	(−6.03)
$\widehat{rx}^{\tau}_{i,t}$	0.743	0.579	0.536	0.738	0.838	0.853	0.863
	(6.84)	(6.69)	(5.76)	(6.22)	(6.62)	(8.31)	(8.06)
$\bar{R}^2$	0.367	0.462	0.438	0.351	0.334	0.302	0.311
N	513	11	38	168	160	73	44
e $rx^{\tau}_{i,t+1} = \alpha + \beta \widehat{E}_t(rx^{\tau}_{i,t+1})$							
Intercept	0.002	−0.007	−0.003	−0.002	0.003	0.006	0.007
	(8.55)	(−3.78)	(−5.20)	(−2.54)	(8.52)	(9.68)	(11.43)
$\widehat{E}_t(rx^{\tau}_{i,t+1})$	1.371	5.479	4.756	3.331	1.041	−0.601	−0.713
	(15.47)	(8.10)	(17.26)	(15.21)	(7.73)	(−3.08)	(−3.80)
$\bar{R}^2$	0.026	0.042	0.029	0.025	0.023	0.026	0.033
N	513	11	38	168	160	73	44

This table reports results from univariate regressions of (*a*,*b*) changes in observed credit spread, (*c*) observed spread, or (*d*,*e*) excess corporate bond returns on their counterparts predicted by the Merton (1974) model or its variation with exogenous recovery rates (*b*). $CS^{\tau}_{i,t}$ denotes the time-*t* credit spread of corporate bond *i* with τ years to maturity. $\widehat{CS}^{\tau}_{i,t}$ and $\widetilde{CS}^{\tau}_{i,t}$ are credit spreads implied by the Merton model and its variation, respectively. $\widehat{rx}^{\tau}_{i,t}$ and $\widehat{E}_t(rx^{\tau}_{i,t+1})$ are the Merton model–implied excess return and 1-month expected return on corporate bond *i*, respectively. The reported coefficient values are averaged estimates across bonds. Associated *t* statistics in parentheses are calculated according to the standard error estimator outlined by Schaefer & Strebulaev (2008). *N* is the number of bonds in each rating category. The sample period is from July 2002 to December 2012.

For comparison, **Table 4*e*** examines the predictive power of the Merton model–implied expected corporate bond return, $\widehat{E}_t(rx^{\tau}_{i,t+1})$, for the 1-month-ahead return. Note that $\widehat{E}_t(rx^{\tau}_{i,t+1})$ is highly significant regardless of the rating group. $\bar{R}^2$ is 2.6% for the full sample and as high as 4.2% for AAA bonds. However, the estimated β is negative for HY bonds, which may be partly due to the simple method we use to estimate μ.

Next, we augment $\widehat{rx}^{\tau}_{i,t}$ with control variables to examine its conditional explanatory power for excess bond returns. Results reported in **Table 5*a*** show that $\widehat{rx}^{\tau}_{i,t}$ remains highly significant, controlling for liquidity measures. A comparison with **Table 4*d*** indicates that the coefficient of $\widehat{rx}^{\tau}_{i,t}$ is slightly lower for the full sample but larger for certain rating groups, such as the AA and B groups. **Table 5*b*** shows that the strong conditional predictive power of $\widehat{rx}^{\tau}_{i,t}$ for observed excess bond returns is robust to the inclusion of more controls, such as the standard equity market variables.

Overall, the results from Section 4.4 provide evidence that the Merton model has strong explanatory power for corporate bond spread changes as well as excess bond returns. Studies have shown that structural models can explain some of the cross-sectional variation in credit spreads (see, e.g., Bao 2009 and Bai & Wu 2016 for evidence based on individual corporate bonds or single-name CDS spreads and Huang & Huang 2012 for evidence at the aggregate bond spread level). In the following subsection, we examine whether the Merton model helps explain the cross-sectional variation in individual corporate bond returns.

4.5. On the Cross Section of Corporate Bond Returns

In this subsection, we study the implications of the Merton model–implied expected excess bond return, $\widehat{E}_t(rx_{t+1})$, for cross-sectional pricing of corporate bonds. We focus on the 1-month-ahead excess returns. For a more accurate inference of cross-sectional predictive power of $\widehat{E}_t(rx_{t+1})$, we augment the panel of corporate bond returns used above with BofAML corporate bond data for this analysis, and obtain a bigger sample from 1997 to 2012. When there are returns available for the same bond-month from both sources, we give priority to those from TRACE.

Over the full sample period, 1997–2012, we sort all bonds on the basis of their corresponding $\widehat{E}_t(rx_{t+1})$ into deciles, then form a hedge portfolio that is long the high $\widehat{E}_t(rx_{t+1})$ bond portfolio and short the low $\widehat{E}_t(rx_{t+1})$ bond portfolio at the end of each month. To limit the impact of transactions/quotes for illiquid and small bonds, in **Table 6** we report the results from the value-weighted portfolios using the bond's outstanding dollar values as weights.

The first row of **Table 6*a*** suggests considerable cross-sectional variation in expected returns. The average expected excess return of decile portfolio P1 is −0.30% per month, largely reflecting the deteriorating financial condition of the issuers of bonds in P1 (and perhaps the simple estimation of μ), while decile portfolio P10 has an average expected return of 0.56%. These estimates imply a spread of roughly 0.86% per month between high and low expected returns. If we hold these decile portfolios over the next month, the average realized excess return almost monotonically increases with expected returns, as shown in the second row. More importantly, the monthly average excess return of the high-minus-low hedge portfolio is approximately 0.53%, with a Newey–West-adjusted t statistic of 3.14. These results suggest a strongly positive cross-sectional relationship between model-implied expected corporate bond returns and subsequently realized corporate bond returns.

We further examine whether $\widehat{E}_t(rx_{t+1})$-based portfolios can be explained by commonly used risk factors. We consider three benchmark models: the four-factor model of Bai, Bali & Wen (2019), the FF5F model (including MKT$^{\text{stock}}$, SMB, HML, DEF, and TERM), and the six-factor model proposed by Lin, Wang & Wu (2011), which augments the FF5F model with an aggregate

Table 5 The conditional explanatory power of the Merton model–implied corporate bond returns

	Rating categories						
	All	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**
a $rx^{\tau}_{i,t} = \alpha + \beta_{i,1}\widehat{rx}^{\tau}_{i,t} + \beta_{i,2}\Delta\Phi_t + \beta_{i,3}\Delta \text{fund}_t$							
Intercept	0.003	0.001	0.002	0.002	0.003	0.004	0.004
	(10.44)	(4.58)	(3.44)	(8.37)	(8.15)	(4.14)	(3.43)
$\widehat{rx}^{\tau}_{i,t}$	0.704	0.550	0.597	0.669	0.725	0.827	0.917
	(8.34)	(5.15)	(9.09)	(6.81)	(5.41)	(5.91)	(9.07)
$\Delta\Phi_t$	−1.582	−0.428	−0.351	−1.315	−1.567	−3.442	−1.112
	(−12.83)	(−2.70)	(−1.65)	(−11.42)	(−7.10)	(−8.64)	(−2.04)
Δfund_t	−0.217	−0.205	−0.065	−0.142	−0.073	−0.410	−0.421
	(−2.50)	(−1.51)	(−0.77)	(−2.41)	(−0.65)	(−1.63)	(−0.86)
$\bar{R}^2$	0.430	0.524	0.506	0.478	0.408	0.378	0.361
N	513	11	38	168	160	73	44
b $rx^{\tau}_{i,t} = \alpha + \beta_{i,1}\widehat{rx}^{\tau}_{i,t} + \beta_{i,2}\text{S\&P}_t + \beta_{i,3}\text{SMB}_t + \beta_{i,4}\text{HML}_t + \beta_{i,5}\text{UMD}_t + \beta_{i,6}\Delta\text{VIX}_t + \beta_{i,7}\Delta\Phi_t + \beta_{i,8}\Delta\text{fund}_t$							
Intercept	0.002	0.001	0.001	0.002	0.003	0.004	0.005
	(7.02)	(1.48)	(3.54)	(6.73)	(5.58)	(3.36)	(2.38)
$\widehat{rx}^{\tau}_{i,t}$	0.688	0.534	0.591	0.676	0.698	0.759	0.862
	(7.33)	(4.32)	(6.26)	(8.52)	(6.73)	(4.59)	(7.14)
$\text{S\&P}_t$	0.060	0.053	0.013	−0.021	0.043	0.115	0.271
	(3.48)	(1.41)	(0.65)	(−1.68)	(1.82)	(2.08)	(2.74)
SMB_t	−0.013	−0.072	−0.013	0.048	−0.026	0.025	−0.127
	(−0.93)	(−1.76)	(−0.42)	(3.21)	(−1.11)	(0.61)	(−2.36)
HML_t	0.034	−0.006	−0.027	−0.025	0.002	0.013	0.342
	(2.07)	(−0.19)	(−1.13)	(−1.82)	(0.09)	(0.28)	(3.89)
UMD_t	−0.056	0.033	0.009	−0.041	−0.033	−0.080	−0.201
	(−5.45)	(1.94)	(0.55)	(−4.86)	(−2.84)	(−2.34)	(−3.25)
ΔVIX_t	0.031	−0.003	−0.001	−0.007	0.065	−0.051	0.103
	(2.36)	(−0.13)	(−0.06)	(−0.71)	(3.16)	(−1.04)	(1.90)
$\Delta\Phi_t$	−1.572	−0.331	−0.242	−1.361	−1.662	−3.373	−0.972
	(−11.14)	(−1.20)	(−0.93)	(−8.81)	(−7.28)	(−7.97)	(−1.74)
Δfund_t	−0.200	0.072	−0.250	0.096	−0.358	−0.151	−0.720
	(−2.33)	(0.35)	(−1.28)	(1.41)	(−2.09)	(−0.85)	(−2.29)
$\bar{R}^2$	0.484	0.586	0.578	0.532	0.432	0.392	0.449
N	513	11	38	168	160	73	44

This table reports results from regressions of excess corporate bond returns on their counterparts predicted by the Merton (1974) model ($\widehat{rx}^{\tau}_{i,t}$), conditional on liquidity measures (*a*,*b*) as well as equity market variables (*b*). $rx^{\tau}_{i,t}$ denotes excess returns on corporate bond *i*. Other regressors used include the S&P 500 return ($\text{S\&P}_t$), the size factor (SMB_t), the book-to-market factor (HML_t), the stock momentum factor (UMD_t), changes in the Chicago Board Options Exchange's CBOE Volatility Index (ΔVIX_t), changes in the bond market liquidity factors ($\Delta\Phi_t$), and changes in the funding liquidity factor (Δfund_t). The reported coefficient values are averaged estimates across bonds. Associated *t* statistics in parentheses are calculated on the basis of the standard error estimator outlined by Schaefer & Strebulaev (2008). *N* is the number of bonds in each rating category. The sample period is from July 2002 to December 2012.

Table 6 Cross-sectional pricing of corporate bonds with the Merton model–implied expected bond returns

a Decile portfolios sorted by the model-implied expected bond returns													
	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P10–P1**		
Avg. $\widehat{E}_t(rx_{t+1})$	−0.301	0.064	0.125	0.167	0.201	0.232	0.260	0.295	0.333	0.564	0.865		
Avg. return	0.069	0.264	0.330	0.385	0.384	0.429	0.417	0.416	0.561	0.600	0.531		
	(0.34)	(2.26)	(3.31)	(3.87)	(3.26)	(3.15)	(3.02)	(2.64)	(2.80)	(3.23)	(3.14)		
4-factor alpha	−0.476	−0.109	0.016	0.102	0.035	0.051	0.019	−0.016	0.039	0.096	0.573		
	(−4.79)	(−1.85)	(0.31)	(2.11)	(0.58)	(0.76)	(0.38)	(−0.25)	(0.51)	(1.09)	(4.17)		
5-factor alpha	−0.230	0.101	0.168	0.182	0.143	0.144	0.109	0.053	0.134	0.211	0.441		
	(−1.94)	(1.44)	(2.75)	(3.28)	(2.14)	(2.01)	(2.16)	(0.89)	(2.30)	(2.63)	(3.13)		
6-factor alpha	−0.240	0.080	0.168	0.182	0.147	0.143	0.109	0.045	0.126	0.208	0.448		
	(−2.01)	(1.17)	(2.72)	(3.25)	(2.19)	(1.98)	(2.15)	(0.76)	(2.15)	(2.57)	(3.16)		
b Security-level Fama–MacBeth regressions													
	Intercept	$\widehat{E}_t(rx_{t+1})$	β^{MKT}	β^{CRF}	β^{DRF}	β^{LRF}	MOM	REV	IVOL	Rating	ln(MAT)	ln(size)	ILLIQ	Adj. R^2
Regression 1	0.303***	0.598***												0.044
	(2.76)	(3.34)												
Regression 2	0.228***	0.352***	0.068	0.069	0.136	0.059								0.203
	(4.53)	(3.11)	(0.83)	(0.28)	(0.57)	(0.63)								
Regression 3	0.175***	0.416***	−0.109	0.175	0.098	0.416	−0.010*	−0.228***	0.142***					0.280
	(2.99)	(4.19)	(−0.28)	(−0.48)	(−0.88)	(0.93)	(−1.78)	(−9.13)	(4.72)					
Regression 4	−0.003	0.386***	−0.141	0.014	−0.240	0.098	−0.013**	−0.240***	0.098***	0.039***	0.386	0.039	−0.073	0.306
	(−0.51)	(4.12)	(−0.43)	(−1.04)	(−1.21)	(0.77)	(−2.30)	(−10.99)	(3.14)	(3.69)	(1.51)	(−0.18)	(1.56)	

(*a*) The results of a portfolio analysis based on the Merton (1974) model–implied expected excess corporate bond returns over a 1-month horizon $[\widehat{E}_t(rx_{t+1})]$. Bonds are sorted into deciles every month by $\widehat{E}_t(rx_{t+1})$, each with an equal number of bonds. P1 denotes the portfolio with the lowest $\widehat{E}_t(rx_{t+1})$, and P10 denotes the portfolio with the highest $\widehat{E}_t(rx_{t+1})$. Reported statistics include the average expected returns, the average realized returns, and alphas for each decile portfolio as well as for the long–short (P10–P1) portfolio spreads; returns and alphas are all expressed in percentages; the associated t statistics are shown in parentheses. Alphas are estimated with time-series regressions of portfolio excess returns on the four factors of Bai, Bali & Wen (2019), the five factors of Fama & French (1993), and the six factors of Lin, Wang & Wu (2011). (*b*) The average intercept and slope coefficients from the Fama & MacBeth (1973) cross-sectional regressions of 1-month-ahead corporate bond excess returns on $\widehat{E}_t(rx_{t+1})$, with and without control variables. β^{MKT}, β^{CRF}, β^{DRF}, and β^{LRF} measure the individual bond exposure to the four risk factors of Bai, Bali & Wen (2019). REV refers to the bond short-term reversal factor proxied by the previous month's bond return; MOM is the bond momentum, defined as the past-6-month cumulative returns from $t-6$ to $t-1$, skipping month t; and IVOL is the bond idiosyncratic volatility relative to the Fama & French (1993) five-factor model. Other bond characteristics include credit rating, logarithm of years to maturity [ln(MAT)], logarithm of amount outstanding [ln(size)], and Bao, Pan & Wang's (2011) measure of bond illiquidity (ILLIQ). Reported in parentheses are t statistics with Newey–West-adjusted standard errors. The last column reports the average adjusted R^2 value. The sample period is from July 2002 to December 2012. Single, double, and triple asterisks denote significance at 10%, 5%, and 1%, respectively.

liquidity factor.[20] Regressions of portfolio excess returns on the three benchmark models deliver the same message shown above: The high-minus-low hedge portfolio's alpha is positive, economically sizable (ranging from 0.44% to 0.57%), and highly statistically significant (with t statistics of 3.13∼4.17). These findings indicate that, even after controlling for commonly used risk factors, the positive cross-sectional relationship between the expected and realized bond returns remains.

The portfolio-level analysis does not allow for extensive controls of variables found to have predictive power for bond returns. For a more powerful test of the role of the model-implied expected returns, we turn to cross-sectional regressions of individual corporate bond returns. **Table 6*b*** presents the time-series averages of the slope coefficients from regressions of 1-month-ahead excess bond returns on expected bond returns, with or without control variables. Regression 1 shows the unconditional predictive power of $\widehat{E}_t(rx_{t+1})$, which reinforces the conclusion drawn from portfolio sorts. Statistically, its coefficient has a t statistic of 3.34, and $\widehat{E}_t(rx_{t+1})$ alone captures 4.4% of cross-sectional variations in realized bond returns. Economically, a 30-bps increase in the expected bond return—which is close to its cross-sectional standard deviation—is associated with an increase in the realized excess return of 18 bps.

In regression 2, we control for individual bonds' exposures to the four Bai, Bali & Wen (2019) factors. Regression 3 includes three additional bond characteristics based on past bond returns: bond momentum, STR, and bond idiosyncratic volatility. Finally, we add other security-level controlling variables, including credit rating, the logarithm of years to maturity and bond amount outstanding, and the Bao, Pan & Wang (2011) measure of corporate bond illiquidity. We find that the coefficient on $\widehat{E}_t(rx_{t+1})$ remains highly significant, with t statistics ranging from 3.11 to 4.12. We also repeat the above analysis using the IG and HY subsamples. The results are qualitatively similar to those from the full sample. Interestingly, while regression R^2 is higher for IG bonds than for HY bonds under each of the four specifications, $\widehat{E}_t(rx_{t+1})$ has higher t values for HY bonds.

The results from Section 4.5 show that $\widehat{E}_t(rx_{t+1})$ offers distinct, significant information beyond corporate bonds' risk exposure, their distributional features of past returns, and other security-level characteristics. In other words, expected corporate bond returns as implied from the Merton model serve as a strong and robust predictor of future excess bond returns.

5. CORPORATE BOND DATA

5.1. Sources of Data on Individual Corporate Bonds

We discuss the following seven data sets that have been used in the literature: the Lehman Brothers Fixed Income Database, the National Association of Insurance Commissioners (NAIC) database, the BofAML (now Bank of America and BofA Securities) database, the Reuters fixed income database, TRACE, the IHS Markit bond pricing database, and the Bloomberg database.

The Lehman database has month-end bid prices from January 1973 to March 1998 for all corporate bonds. Some of these prices are, however, so-called matrix prices, which are derived from price quotes of bonds with similar characteristics (Warga & Welch 1993) and considered to be less reliable than trader quotes. Other early studies using these data include those by Collin-Dufresne, Goldstein & Martin (2001) and Eom, Helwege & Huang (2004).

[20]Lin, Wang & Wu (2011) construct the time series of market-wide liquidity shock using the Amihud (2002) and Pástor & Stambaugh (2003) measures. As both proxies involve the trading volume information and thus are not applicable to the BofAML data, we employ the Roll (1984) measure to infer aggregate liquidity innovations. As shown by Schestag, Schuster & Uhrig-Homburg (2016), the Roll measure is one of the best-performing liquidity measures that do not require transaction-level observations.

Beginning in 1994, the NAIC has provided transaction data based on Schedule D filings by all of its member insurance companies. These transactions compose a significant portion of the market for publicly traded corporate bonds (e.g., Hong & Warga 2000, Campbell & Taksler 2003). In contrast, Mahanti et al. (2008) find that insurance companies are typically buy-and-hold investors and have low portfolio turnover. For this reason, the overlap between the NAIC and TRACE is rather modest (less than 10%, according to Jostova et al. 2013 and Chordia et al. 2017).

The BofAML database provides daily quotes for individual bonds covered by ICE BofA bond indexes, with the sample period beginning in January 1997. These quotes are commonly used by bond mutual funds and other institutional investors to mark their portfolios to market. Bonds included in either the ICE BofA US Corporate Index (C0A0) or the ICE BofA US High Yield Index (H0A0) are often used in the literature (e.g., Schaefer & Strebulaev 2008).

The Reuters fixed income database collects daily quotes provided by major dealers in the US corporate bond market since 1991. Unlike the Lehman and BofAML data, the Reuters data do not target a specific set of bonds that comprises their indexes. Choi (2013) and Choi & Richardson (2016) show that Reuters dealer quotes at monthly frequency reflect transaction prices quite well.

TRACE provides comprehensive coverage of transactions for publicly traded over-the-counter corporate bonds, starting in July 2002. Public dissemination of transaction information was implemented in three phases.[21] Many recent studies on corporate bond returns focus on TRACE Enhanced data, which include more HY bond transactions in early years and more precise information about transaction volumes than TRACE Standard data.[22] Also, the Wharton Research Data Services Bond Return database provides monthly corporate bond returns.

The IHS Markit bond pricing database provides daily composite quotes for corporate bonds in different markets. Composite quotes are the mid prices based on the daily bid and ask prices as collected from more than 30 dealers. Similar to the Reuters database, this database presumably provides a comprehensive picture of the corporate bond universe and has been used in studies on secondary market liquidity (e.g., Friewald, Jankowitsch & Subrahmanyam 2012; Schestag, Schuster & Uhrig-Homburg 2016). The sample of the Markit bond pricing data dates from January 2003.

Aside from the Reuters and Markit databases, the Bloomberg Generic Quote (BGN) constitutes another source of daily bid and ask quotes. The BGN quotes are computed as a weighted average of actual quotes from participating dealers. The sample of historical BGN data can be traced back to at least 1999. Longstaff, Mithal & Neis (2005) and Schestag, Schuster & Uhrig-Homburg (2016), among others, examine the properties of BGN bid–ask spreads.

The seven data sources described above are for corporate bond prices. Information about corporate bond characteristics, such as seniority, coupon, and maturity, is available from different sources. Three such sources available for academia are the Mergent Fixed Income Securities Database, Bloomberg, and Refinitiv Eikon (formerly Thomson Reuters Eikon).

5.2. Corporate Bond Indexes and Index Exchange-Traded Funds

Three well-known groups of corporate bond indexes are those of Bloomberg Barclays, ICE BofA, and the Financial Times Stock Exchange (FTSE; formerly Citi). For brevity, we limit

[21] Bessembinder, Maxwell & Venkataraman (2006); Edwards, Harris & Piwowar (2007); and Goldstein, Hotchkiss & Sirri (2007) exploit different TRACE dissemination events to study the effect of improving market transparency on effective transaction costs.

[22] In TRACE Standard, trade size is provided for IG bonds if the par value transacted was US$5 million or less; otherwise, an indicator variable denotes a trade of more than $5 million.

the discussion in this subsection to one IG index and one HY index in each group and related index exchange-traded funds (ETFs) when available, as well as the Ibbotson Associates long-term (20-year) corporate bond return series (sources of the information used for the discussion in Section 5.2 are provided in the **Supplemental Material**).

Supplemental Material >

Bonds included in the six indexes from the three groups share some common features, such as US dollar–denominated fixed-rate debt with at least 1 year remaining to maturity and being priced on a daily basis. The indexes are all rebalanced monthly at month end. Below, we focus on some of the main differences between these indexes.

The Bloomberg Barclays US Corporate Bond Index (ticker: LUACTRUU) and High Yield Index (ticker: LF98TRUU) measure IG and HY corporate bond markets in the USA, respectively. The IG (HY) index was launched in July 1973 (July 1986), with historical data backfilled to January 1, 1973 (July 1, 1983). Eligible issues for the IG (HY) index need to have at least $300 ($150) million par value outstanding. The two indexes share many other rules for inclusion, such as eligibility of both senior and subordinated issues, and bullet, putable, sinkable/amortizing, and callable bonds are all permitted. Also, constituent bonds are priced on the bid side. Furthermore, most issues in the IG index are priced using a spread to Treasury securities, and some in the index are marked on a dollar price basis, as are those in the HY index.

The main ICE BofA IG and HY indexes are the US Corporate Index (C0A0) and High Yield Index (H0A0), respectively. Qualifying securities in both indexes must have a minimum amount outstanding of $250 million. The inception date of C0A0 is December 31, 1972, and that of H0A0 is August 31, 1986. Constituent bonds are priced on the bid side.

The FTSE Goldman Sachs Investment Grade Corporate Bond Index (ticker: CFIIGIGB) is created from the FTSE US Broad Investment-Grade Corporate Index (SBI). CFIIGIGB requires $750 million minimum outstanding per issue and has a base date of February 28, 2007. The FTSE US High-Yield Market Index (ticker: SBHYMI) measures the performance of HY debt issued by corporations domiciled in the USA or Canada. The index requires a minimum size outstanding of $250 million and has a base date of December 31, 1988. Constituent bonds are priced on the mid side.

Not surprisingly, the above three IG or HY indexes are highly correlated with one another. For instance, from 1997 to 2020, LUACTRUU and C0A0 have a correlation of 0.994 and LF98TRUU and H0A0 have a correlation of 0.997. These high correlations across index families can be readily perceived by referring to **Figure 1**, which plots the cumulative returns on these four indexes over the 1997–2020 period. Overall, HY bonds achieve higher average returns than IG bonds, but suffer greater losses in recessions. For example, the average monthly return is 59.2 bps for LF98TRUU and 49.7 bps for LUACTRUU, but it is 40.6 bps for the Barclays Treasury Bond Index (ticker: LUATTRUU).

One index often used in studies employing a long return series (see, e.g., Section 3.1.2) is the abovementioned Ibbotson Associates series, which goes back to 1926. This series uses the FTSE USBIG Corporate AAA/AA 10+ Year (formerly Citigroup Long-Term High-Grade Corporate Bond Index) for 1969 and after, the backdated Salomon Brothers index for 1946 through 1968, and returns derived from the S&P monthly High Grade Corporate Composite yield data for the period 1926–1945.

In terms of ETFs tracking the above corporate bond indexes (except the Ibbotson one), SPDR Bloomberg Barclays IG Floating Rate (ticker: FLRN) and HY (ticker: JNK) ETFs track LUACTRUU and LF98TRUU, respectively. Vanguard Total Corporate Bond ETF (ticker: VTC) is another example that tracks LUACTRUU. PIMCO IG Corporate Bond ETF (ticker: CORP) tracks C0A0, and iShares Broad USD HY ETF (ticker: USHY) tracks H0A0 with issuer exposure

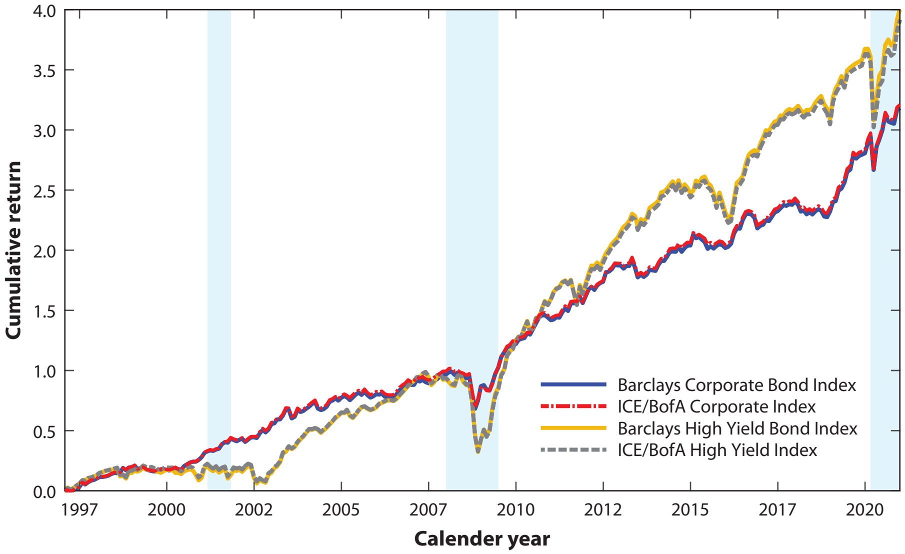

Figure 1

Cumulative returns of Bloomberg Barclays and ICE/BofA US Corporate Bond indexes. This figure plots cumulative (total) returns of Bloomberg Barclays US Corporate Bond Index (*blue line*), ICE BofA US Corporate Index (*red line*), Bloomberg Barclays US Corporate High Yield Bond Index (*yellow line*), and ICE BofA US High Yield Index (*gray line*), from January 1997 to December 2020. Shadow bars denote months designated as recessions by the National Bureau of Economic Research. Data are from Bloomberg and Refinitiv Eikon.

capped at 2%. Goldman Sachs Access IG (ticker: GIGB) and HY (ticker: GHYB) Corporate Bond ETFs track CFIIGIGB and SBHYMI, respectively.

The largest IG and HY ETFs by net assets are iShares iBoxx USD IG ETF (ticker: LQD) and HY ETF (ticker: HYG), respectively. They also have a relatively longer history: LQD (HYG) has an inception date of July 22, 2002 (April 4, 2007). LQD and HYG track the Markit iBoxx USD Liquid IG and HY Indexes, respectively.

6. CONCLUSIONS

This review concerns the determinants of corporate bond returns. We first provide a survey of the related empirical literature, in particular, studies following a standard asset pricing approach. We then conduct a structural model–based analysis of the determinants of corporate bond returns.

The factors and factor portfolios proposed and constructed in the literature include the term, default, aggregate liquidity shock, downsize risk, inflation volatility risk, value, momentum, and economic uncertainty factors. Evidence to date suggests that the benchmark model of corporate bond returns consists of at least four factors, but what the benchmark is and which model provides the highest hurdle for alpha remain open questions. Not surprisingly, an active research area in this literature involves the search for new factor(s). To this end, it may be worthwhile to first develop benchmark models separately for IG and HY bonds. Doing so may facilitate the construction of a one-size-fits-all benchmark model for the entire corporate bond market. Similarly, considerable research is aiming to uncover new characteristics that drive the cross section of corporate bond returns. In reality, IG and HY sectors could be quite different, and their corresponding investors tend to have distinct focuses and attention allocations. As such, characteristics driving cross-sectional IG bond returns could also differ from those driving cross-sectional HY bond returns.

Another observation is that studies on cross-sectional corporate bond returns seem to be driven largely by their counterparts in the equity market. We argue that structural models of credit risk may provide new insights and perspectives on cross-sectional determinants of corporate bond returns. For instance, such models may help to better capture the nonlinear relationship between corporate bond returns and their determinants. We provide empirical evidence that the expected corporate bond return implied by the standard Merton (1974) model can indeed predict corporate bond returns in the cross section. Therefore, one line of inquiry that may be worth pursuing is to examine the implications of alternative structural models for cross-sectional corporate bond returns.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

We are very grateful to Editorial Committee Member Matt Richardson for his extensive and detailed comments that helped to improve the article substantially, in terms of both content and exposition. We also thank Li An, Turan Bali, Francisco Barillas, Luis Ceballos, Zhuo Chen, Amit Goyal, Olesya Grischenko, Grace Hu, Yoshio Nozawa, Yinan Su, and Paige Tan (IHS Markit) for their helpful comments and suggestions. This article includes analysis from our working paper titled "A Resolution to the Equity-Credit Market Integration Puzzle." We thank the following people for helpful comments and suggestions: Jun Kyung Auh, Hui Chen, Jaewon Choi, Jens Dick-Nielsen, Phil Dybvig, Jan Ericsson, Jean Helwege, Nikunj Kapadia, Anh Le, Marco Rossi, and Jason Z. Wei; seminar participants at Concordia University, the Federal Reserve Board, Florida State University, the Securities and Exchange Commission, the University of California at Riverside, and York University; and participants at the 2013 Derivatives Securities & Risk Management Conference at the FDIC, the 2013 ITAM Conference in Mexico City, the 2013 Asian Finance Association Annual Meeting in China, the 2013 Northern Finance Association Annual Conference in Quebec City, and the 2014 Midwest Finance Association Orlando meetings.

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