Resurrecting the Merton Model: A Model-Free Benchmark for Corporate Bond Valuation*

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Abstract

The main insight of the Merton model is that corporate debt is equal to risk-free debt minus a put option on the value of the firm. While the Merton model notoriously fails to match the empirical properties of traded corporate bonds, we show that its insight proves surprisingly robust in the data: A portfolio of risk-free debt minus *traded* options ("pseudo-bonds") closely match the properties of traded corporate bonds. We find that our pseudo-bonds generate a credit spread puzzle, both in yields and returns, and the credit spread puzzle is stronger at short maturities. Our methodology provides a novel model-free benchmark for corporate bond valuation.

VERY PRELIMINARY VERSION. NOT FOR CIRCULATION.

* We thank Bryan Kelly for providing data on the tail risk factor.

1. Introduction

The Merton model on the pricing of corporate debt is the backbone of modern corporate bond valuation. The main insight of Merton (1974) is that corporate debt is economically equivalent to risk-free debt minus a put option on the assets of the firm. It is hard to overstate the impact that this insight has had on the finance literature. In asset pricing, the basic insight of the Merton model lies at the heart of the vast literature regarding the variation in credit spreads and their dynamic relation to leverage, asset volatility, risk, and the like. In corporate finance, the Merton framework is a foundational building block in the theory of capital structure, agency-theoretic relations and conflicts between equity and bond holders, the incentive of equity holders to engage risk-shifting activities, and more.

The Merton model, however, does not produce theoretically implied credit spreads that are at all similar to empirical estimates of credit spreads observed from actual, traded corporate bonds. This disjoint between theory and actual data has been christened "the credit spread puzzle," and is illustrated in Figure 1. In this figure, we show the credit spreads of corporate bonds with two years to maturity for several categories of credit ratings.[1] Specifically, we present the average empirical credit spreads along with spreads implied by the Merton model corresponding to the credit rating categories shown on the horizontal axis. In this Figure 1 (as in most of this paper), the model-implied spreads shown are based on the original version of the Merton model that assumes the firm's assets are log-normally distributed on the date that the firm's debt matures (henceforth the "lognormal Merton model"). We calibrate the fundamental parameters of the model to match the default probability of each credit rating category. The credit spread puzzle result is immediately apparent from Figure 1. Namely, for high credit rating categories (Aaa/Aa and A/Baa) the Merton model implies negligible credit spreads (0.00% and 0.04%, respectively), whereas the corresponding empirical credit spreads are substantial in the observed data (0.68% and 1.33%, respectively). The disparity in actual credit spreads versus spreads implied by the lognormal Merton model is also significant for speculative-grade debt – *i.e.,* a two-year, B-rated bond has an average empirical credit spread of over 6%, whereas the Merton model implies only a 0.68% spread for such bonds. A large literature has emerged that purports to explain this credit spread puzzle.

In this paper we adopt a new, model-free empirical approach to determine the true, observable implications of the Merton model about credit spreads (*i.e.,* that corporate debt

[1] Throughout this paper we adopt the credit ratings classification scheme of Moody's Investor Services. For simplicity, we omit plus-or-minus ratings within each category – *e.g.,* category A includes bonds rated A1, A2, and A3.

is economically equivalent to risk-free debt minus a put option on the assets of the firm). Our approach is to use *traded* options to extract the empirical properties of the debt values of hypothetical firms, whose assets are given by the stocks the options are written on. As an underlying intellectual construct, consider a fictitious firm whose assets are just shares of stocks in the S&P 500 index (held in exactly identical proportions to the index). Then imagine that such a fictitious firm finances the purchase of that stock portfolio by issuing a zero-coupon bond with principal K and maturity T and by issuing common stock. According to the Merton model, the value of the zero-coupon debt issued by such a firm is exactly equal to the value of a risk-free zero-coupon bond with maturity T and principal K minus the value of a European put on the S&P500 index with a strike price of K and maturity T. Using data on traded S&P500 index options ("SPX options") together with U.S. Treasury bonds (as proxies for the risk-free asset), we recover the *observable* empirical implications of the Merton model about corporate credit spreads. By varying strike price K and maturity date T, moreover, we can estimate the implied values of bonds with different probabilities of default and times to maturity. We call these bonds issued by our fictitious firm "pseudo-bonds." We then compare credit spreads on our pseudo-bonds with spreads on the corresponding actual corporate bonds by estimating the *ex ante* default probability for each pseudo-bond and assigning it to a corresponding credit rating category.

The implications of our empirical results are striking. First, as is the case for actual corporate bonds, the credit spread puzzle is also prominent in the pseudo-bond credit spreads. For example, the credit spreads of two-year pseudo-bonds corresponding to the default probabilities for Aaa/Aa and A/Baa bonds are 0.53% and 1.31%, respectively. Those spreads are very similar to the average credit spreads observed for actual Aaa/Aa and A/Baa corporate bonds (shown in Figure 1) – *i.e.,* 0.68% and 1.33%, respectively. For speculative grade bonds, the pseudo-bonds have relatively large credit spreads of between 2.36% for Ba-rated bonds and 5.15% for Caa-rated bonds. Although these credit spreads are large, they are smaller than empirical spreads on real corporate bonds (3.97% for Ba-rated bonds and 12.13% for Caa- rated bonds, respectively). The implied credit spread on our pseudo-bonds are nevertheless far greater than those implied by the lognormal Merton model, which are only 0.30% for Ba-rated bonds and 2.49% for Caa-rated bonds (see Figure 1).

Second, like actual corporate bonds and in contrast with the theoretical implications of the lognormal Merton model, monthly returns on portfolios of pseudo-bonds exhibit different Sharpe ratios across credit rating categories, and the highest Sharpe ratio corresponds to bonds with intermediate credit ratings. The lognormal Merton model, moreover, implies that excess returns on bonds can be fully explained by excess returns on the firm's assets or on any other firms' traded securities, such as excess returns on equity. In contrast, our

pseudo-bonds show that a substantial alpha emerges both when we regress excess pseudo-bond returns on the excess returns of the fictitious firm's traded assets (*i.e.,* the SPX) and on the firm's pseudo-equity (*i.e.,* values of traded call options on the SPX). Those estimated alphas are consistent with a model in which asset dynamics exhibit leptokurtic returns and in which investors demand a risk premium to compensate for the tail risk of those returns. Notably, very similar results hold for actual corporate bonds.

Third, our empirical results hold not only for medium-term bonds – *i.e.,* bonds with two years to maturity in our implementation (due to data limitations) – but also for very short-term pseudo-bonds. For example, investment-grade pseudo-bonds with 30 and 90 days to maturity have average credit spreads of 0.78% and 0.64%, respectively, as compared to average credit spreads of 0.62% and 0.60% for actual investment-grade bonds and zero spreads as implied by the lognormal Merton model. This empirical result is especially important because the vast majority of theoretical models stemming from the original Merton model can typically only explain the credit spreads of long-term bonds. Except for a handful of cases, modifications of the lognormal Merton model fail to explain credit spreads on debt with short maturities. In contrast, our empirically-based pseudo-bonds – based on Merton's basic insight on the valuation of corporate securities but not on his restrictive distributional assumptions – display very high short-term credit spreads.

Our empirical results are model-free and depend only on the empirical properties of Treasury bonds and traded options. As such, our empirical results indicate that the credit spread puzzle is plausibly due to the additional insurance risk premium that investors require to hold securities that are subject to tail risk. In other words, the explanation for the credit spread puzzle is related to the equally notorious "put option overpricing puzzle" – *i.e.,* the well-established result in the options literature that put options are relatively overpriced *vis-a-vis* the theoretical prices implied by the Black-Scholes formula and lognormal distribution. We do not take a stand on whether the overpricing is rational (i.e., risk based) or behavioral (i.e., overpaying for insurance), but our results provide an indirect argument that the underlying source of the credit spread puzzle should be investigated in investors' risk preferences (as in the models of e.g. Chen, Collin-Dufresne, and Goldstein (2009), or Chen (2012)) rather than in other elaborate theories of corporate finance, such as optimal default (e.g. Leland and Toft (1996)), uncertainty and learning (e.g. Duffie and Lando (2001)), agency costs (e.g. Leland (1998)), investment behavior (e.g. Kuhen and Schmid (2014)) and the like. The reason is that our firm is a very simple firm that only has shares of the SPX as its asset, and its debt is very simple debt – just a zero-coupon bond with T years to maturity. Yet, our pseudo-bonds display properties that are surprisingly close – qualitatively and quantitatively – to those of real corporate bonds.

One worry of our analysis so far is that our results may be driven by the fact that our pseudo-firm is highly systematic in the sense that its assets are the overall market.[2] We thus repeat the same analysis using individual firms to form other pseudo-firms. For example, consider a fictitious firm that only purchase shares of Apple's common stock and finances those Apple share purchases by issuing a zero-coupon bond and equity. In this case, the value of debt of our Apple pseudo-firm is equal to the value of a risk-free zero-coupon bond minus the value of a traded European put on Apple stock. Because we observe option prices on Apple stock, we can do the same computations for the Apple pseudo-firm that we described above for the SPX pseudo-firm.[3] Our results using individual options confirm the results we obtained using SPX options – *viz.*, the credit spread on individual pseudo-firms' pseudo-bonds are very high compared to the default probability of their ratings category, and similar to the empirical spreads of real corporate bonds. Also as is the case for real corporate bonds, a strong alpha exists when we try to explain individual pseudo-bond excess returns by using the excess return on firms' (pseudo-) equity.

To further investigate the relation between pseudo-bonds and real corporate bonds, we undertake a number of additional tests. In particular, we show that the large excess return on pseudo-bonds cannot be explained away by the Fama-French three factor model (market, HML, SMB), augmented by a term-premium factor and a default factor. We do find, however, that pseudo-bonds returns load positively on market, the term premium factor, and the default factor. Interestingly, real corporate bond returns' alphas are not explained by the same factors either, but we do find they also load positively on a term premium and default factor, confirming a strong similarity in the dynamic behavior of pseudo-bonds and corporate bonds. When we add volatility, liquidity, and tail-risk factors, however, we find that pseudo-bonds returns load negatively on the volatility factor – an intuitive result – but not on the liquidity factor. Tail risk only affects pseudo-bonds that are formed out of the SPX options, but not those formed from individual stocks. Real corporate bonds also load mostly negatively on the volatility factor, but results are mostly not significant. Liquidity and tail risk do not seem to affect corporate bonds. For both pseudo-bonds and corporate bonds, however, such additional factors do not explain the alpha in excess returns.

Our model-free, option-based approach to the valuation of corporate securities follows the basic insight of Merton (1974), but uses traded options as opposed to a model to provide predictions on what we should see in the data. From this perspective, the prediction of

[2]The credit spread should only capture the systematic component of a firm's risk. As such, this worry is only justified by convexity arguments on the relation between the credit spread of an average versus the average credit spread.

[3]One difficulty in using individual firms' options for our investigation is that such options are American rather than European. Section 4.4. discusses this and other issues in detail.

the model-free approach to corporate bonds are supported in the real corporate bond data. Indeed, our empirical results show that the source of the credit spread puzzle is unlikely to be stemming from the lack of liquidity of corporate bonds, as our pseudo-bonds show a much higher liquidity than corporate bonds, at least when liquidity is measured using the popular Roll (1984) illiquidity measure.

Our model-free approach can also be used to study counterfactual experiments that would be hard to implement in the real world. For instance, in our model we provide credit ratings to our bonds at a monthly frequency – *i.e.*, every month we use a model-free approach to predict the default probability of each pseudo-bond and we assign such a bond to a credit rating category. We can investigate empirically the impact of assigning credit ratings at a lower frequency. For example, we show that if we assign credit rating at the quarterly, semi-annual, or annual frequencies, the average credit spreads of highly rated bonds do not change much, whereas average spreads on lower-rated bonds increases substantially. The variation over time of the yield due to variation in the asset value generates a convexity effect that increases the yield. In contrast, we find average *returns* decrease as we lower the frequency of credit rating assignment. In this case, the variation of the firm beta – which is concave in the underlying leverage – acts to decrease the average return.

As a second application of our approach, we investigate the impact of capital structure on credit spreads. For instance, a firm may have a choice between issuing stand-alone Baa bonds, or issuing both senior and junior bonds with the same total face value. Because junior bonds offer a cushion to senior bonds, senior bonds have high credit ratings (e.g. Aaa) and low spreads. In constrast, the junior Baa bonds will have higher credit spreads than stand-alone Baa bonds, due to the the higher risk of losing the full capital. The relevant empirical question is what we should expect the differential in credit spreads to be for different choices of capital structure. We find the impact to be substantial: For instance, while a A/Baa pseudo-bond has a spread of 1.31% when issued as stand-alone bond, it has a spread of 2.18% when issued as a junior bond. Similarly, a Caa- pseudo-bond has a spread of 5.15% when it is issued as a stand-alone bond, but it has a spread of 9.87% when issued as a junior bond. Such computations, which only depend on the empirical properties of options, could be useful to establish a benchmark on the total cost of debt of firms for different choices of capital structure.

Our paper is clearly related to the large literature that sprang from the basic insight of Merton (1974). We do not attempt an exhaustive survey here, as the number of papers are counted to the 100s. We refer the reader to Lando (2004) and the recent survey article by Sundaresan (2013). Huang and Huang (2012) discusses the failure of the Merton model and

it elaborates on credit spread puzzle. In particular, it shows that numerous structural models carefully calibrated to match true default probabilities generate credit spreads that are too small compared to the empirical data. David (2008) show that a model with difference of opinions about the underlying economic regime and learning can generate higher credit spreads. Chen, Collin-Dufrense and Goldstein (2009) show that habit formation and time varying default boundaries may explain both the level and the dynamics of credit spreads over time. Bahmra, Kuhen, and Strabulaev (2010) and Chen (2010) demonstrate that macro-finance models based on Epstein-Zin preferences, time varying volatility, and optimal default induces a higher risk exactly in bad times, a mechanism that pushes up the credit spread. Most of these models have only implications for very long-term debt and do not explain short-term credit spreads. On this front, Zhou (2001) shows that a model with jumps can explain the credit spreads at the short horizon, while Duffie and Lando (2001) show that in an optimal default model, learning about the true value of assets of the firm may lead to high short-term credit spreads, as the default boundary may be closer than investors' expect due to uncertainty about asset values. The approach of all of these papers is different from ours, as we do not use any model, but go straight to the data to verify the empirical relevance of Merton's original insight.

A small number of papers link options to credit spreads. Cremers, Driessen, and Maenhout (2008) propose a structural jump-diffusion model for asset values for each firm in the S&P100 and estimate the jump risk premium from S&P 100 index options. The calibrated model that takes into account the jump risk increases the credit spread to levels comparable to the data. Carr and Wu (2011) show theoretically and empirically that deep of the money put options are related to credit default swap spreads. The results in these papers are consistent with our empirical results, but our empirical approach differs as we directly test the empirical implications of the basic insight of Merton model on traded options. One important benefit of our approach, which also differentiates us from much of the earlier literature, is that our fictitious firm's assets are observable and tradeable – unlike the assets underlying real corporate bonds – and thus we can precisely define Merton model's empirical implications with real data. Finally, our approach is related to Coval et al. (2012) who study the valuation of collataralized debt obligations (CDOs) using traded options on the S&P 500 as the basis for measuring the credit spread on put spreads (*i.e.*, long-short positions in put options with different strike prices that resemble tranches of CDOs). They show that the credit spreads in their S&P500-based tranches are smaller than the spreads on corresponding CDO tranches. Although we also use options and the Merton model to study bonds, we focus on the empirical performance of the Merton model itself and in fact show that the credit spreads from Merton model are actually very much in line with corporate credit spreads.

The paper is organized as follows. Section 2. discusses the Merton model. We begin by recalling some theoretical foundations of the original Merton model and then move to describe our model-free methodology for implementing the Merton model. Section 3. describes the data, as well as our estimation of *ex ante* default probabilities and *ex post* default frequencies of pseudo-bonds. Section 4. contains our main empirical results for credit spreads, and Section 5. digs deeper on the sources of variations in credit spreads. Section 6. offers some additional applications of our methodology, and Section 7. concludes. An Appendix contains proofs and additional results.

2. The Merton Model

The original lognormal Merton (1974) model assumes that assets of the firm A_t follow a lognormal process,with mean drift rate μ_A and volatility σ_A:

$$dA_t = \mu_A A_t dt + \sigma_A A_t dW_{A,t} \tag{1}$$

where $dW_{A,t}$ is a Brownian motion. At time t, the firm issues a zero-coupon bond with face value K and maturity T. At maturity, if the assets of the firm exceed the face value of its date ($A_T > K$), the firm can pay its debt fully – *i.e.*, debt holders receive K. If instead $A_T < K$, the firm defaults and debt holders receive A_T. The payoff to debt holders at T is given by

$$CF_T = K - \max(K - A_T, 0) \tag{2}$$

The value of debt today $B_t(T, K)$ is therefore given by

$$B_t(T, K) = KZ_t(T) - P_t(T, K) \tag{3}$$

where $Z_t(T)$ is the price of a zero-coupon bond at t with maturity T, and $P_t(T, K)$ is the price of a put option with maturity T and strike price K. From the assumptions on A_t, one can compute the value of put options $P_t(T, K)$, and thus analyze bond prices in equation (3). The dynamics of assets in (1) is only convenient inasmuch as it provides a closed-form solution for the value of the put option in equation (3).

2.1. The Original Merton Model

Before we turn to our model-free, empirical approach to implementing the Merton model, it is useful to recall some of the properties of the original Merton (1974) model. Specifically, let the corporate bond yield under the Merton model be given by

$$y_t(T,K) = \frac{1}{T-t}\log(B_t(T,K))$$

Proposition 1. Under the asset dynamics in Equation (1), the bond price $B_t(T,K)$ in expression (3) has the following properties:

(a) The credit spread $y-r$ is positively related to leverage (K/A) and asset volatility (σ_A);

(b) The bond's excess return follows the process

$$\frac{dB_t}{B_t} = \mu_B\,dt + \sigma_B\,dW_t$$

where the expected excess return $\mu_B - r$ and volatility σ_B are given by

$$\mu_B - r = \beta\,(\mu_A - r);\ \text{and}\ \sigma_B = \beta\sigma_A$$

with $\beta = \frac{Cov(dB/B, dA/A)}{\sigma_A^2} > 0$ increasing in leverage $L = K/A$; and

(c) The bond's Sharpe ratio is equal to the Sharpe ratio of the firm's underlying assets:

$$\frac{\mu_B - r}{\sigma_B} = \frac{\mu_A - r}{\sigma_A}$$

Note, in particular, that the bond inherits the properties of expected excess returns from the firm's underlying assets through its beta β, and that the Sharpe ratio of corporate bonds is the same as the one for the firm's underlying assets. The Merton model thus implies that the Sharpe ratio for the firm's debt is independent of the bond's maturity or face value (*i.e.*, strike price). It is also convenient to re-express the excess return of the bond's return with respect to the excess return of the firm's levered equity:

Corollary 1: Under the lognormal Merton model, the expected excess return on a corporate bond is equal to

$$\mu_B - r \;=\; \beta_E\,(\mu_E - r) \tag{4}$$

with $\beta_E = \frac{Cov(dB/B, dE/E)}{\sigma_E^2} > 0$.

This expression – which stems from the simple one-factor structure of the model – is often convenient because, in analyzing real corporate bonds, we cannot observe the value of the firm's assets but do observe the value of equity. Thus, for such securities, (4) has an empirical counterpart. On this front, it is useful to note that we are not assuming that the CAPM has to hold under the lognormal Merton model. Indeed, under process (1) the normalized shock $dW_{A,t}$ could itself load on several pricing factors, which then would affect the level of the asset's expected return μ_A. The statements in Proposition 1 and Corollary 1 only pertain to the Merton model's implications about the relation between the bonds' expected excess returns versus its underlying assets and firm equity, respectively, and not whether the CAPM holds or not in this context.[4]

2.2. Extensions of the Merton Model

Much of the literature expanding the lognormal Merton model has focused on generalizing the stochastic process (1) – e.g., by adding jumps, incorporating stochastic volatility, stochastic interest rates, and endogenous default, allowing for a firm to experience insolvency prior to maturity T, etc. In this paper, we make no assumptions about A_t and instead use U.S. Treasuries and traded options to analyze the properties of bonds in expression (3) directly.

However, in order to interpret some of our empirical results below, it is useful also to develop the implications of the Merton model under a different specification of the shocks driving asset values. In particular, assume now that the market value of the firm's assets A_t follows a jump-diffusion process:

$$dA_t = [\mu_A - \lambda E(J_A - 1)]\, A_t dt + \sigma_A A_t dW_{A,t} + (J_A - 1) A_t dQ_t \tag{5}$$

where dQ_t is the increment of a Poisson process with intensity λ, and J_A is a random variable determining the size of the jump.[5] In this case, we obtain the following result:

Proposition 2. Under the asset dynamics in Equation (5), the bond price $B_t(T, K)$ in

[4]For instance, assets could be driven by two systematic factors and an idiosyncratic factor – $dA/A = \mu_A dt + \sigma_1 dW_1 + \sigma_2 dW_2 + \sigma_i dW_i$ where dW_1 and dW_2 are priced factors and dW_i is an idiosyncratic factor. In this two-factor model, the expected excess return on assets has a two-factor structure $\mu_A - r = \sigma_1\lambda_1 + \sigma_2\lambda_2$, where λ_1 and λ_2 are the market prices of risk of priced factors dW_1 and dW_2. Nevertheless, we can still express the process for assets as in equation (1) by defining $\sigma_A = \sqrt{\sigma_1^2 + \sigma_2^2 + \sigma_i^2}$ and the Brownian motion dW_A such that

$$dW_A = \frac{1}{\sigma_A}\left(\sigma_1 dW_1 + \sigma_2 dW_2 + \sigma_i dW_i\right)$$

Clearly, dW_A is a Brownian motion and we recover the expressions for expected excess bond returns in Proposition 1 and Corollary 1.

[5]*See, e.g.*, Zhou (2001).

expression (3) has a risk premium given by

$$\mu_B - r = \alpha_B + \beta \left(\mu_A - r\right)^{Diff} \tag{6}$$

where $(\mu_A - r)^{Diff}$ is the diffusive component of the asset risk premium, and where

$$\beta = \frac{\sigma_B \sigma_A}{\sigma_A^2} = \frac{Cov^{Diff}(dB/B, dA/A)}{\sigma_A^2}$$

is the beta computed on the diffusive terms of the stochastic processes and α_B is a risk premium due to jumps in underlying asset values.

Expression (6) is useful to see how the violation of Merton's lognormality assumption manifests itself in the risk premium. Empirically, however, we do not observe the diffusive component of the asset excess returns. Instead we can equivalently write (6) as

$$\mu_B - r = (\alpha_B - \beta\, \alpha_A) + \beta\ (\mu_A - r) \tag{7}$$

where α_A is the jump risk premium for the underlying assets A_t. Because generally $\alpha_B \neq \beta\, \alpha_A$ we should therefore expect a non-zero estimated intercept in a regression of excess bond returns on excess asset returns if jumps reflect an important part of the bond excess return.[6]

2.3. Empirical Specification of the Merton Model

In this section we elaborate on our novel approach. Consider a hypothetical firm that finances the purchase of its assets by issuing equity and a zero-coupon bond with face value K and maturity date T, and where the only assets purchased by the firm are shares of stocks in the S&P500 (SPX) index. From expression (3), the value of this firm's debt is given by a portfolio comprised of a risk-free zero-coupon bond with face value K and maturity date T and a (short) SPX put option with strike price K and maturity date T. Both prices are observable in the data. Thus, we can study the properties of the bond issued by the fictitious firm by studying the properties of U.S. Treasuries and traded SPX put options. We call the bonds issued by our fictitious firm pseudo-bonds, and we will compare their empirical properties to real corporate bonds as well as the lognormal Merton model. Our pseudo-bonds exactly match the original insight of Merton (1974), with the difference that we choose the assets of the firm in a deliberate manner in order to have an empirical counterpart to the firm's debt.

[6]The beta here, however, is only the diffusive part. When we regress at a monthly frequency, the beta may also reflect the jump component.

More specifically, at every time t, we select all SPX put options with a specific target time to maturity τ. After applying some filters to ensure some minimum liquidity requirement (see Section 3.1.), we obtain a set of put options with strike prices $K_{i,t}$. For each available strike price $K_{i,t}$, we can compute the value of a τ-period zero-coupon defaultable bond using expression (3):

$$\widehat{B}_t\left(t+\tau, K_{i,t}\right) = K_{i,t}\widehat{Z}_t(t+\tau) - \widehat{P}_t(t+\tau, K_{i,t}) \tag{8}$$

where a "hat" indicates that the respective price is observable in the data – *i.e.*, there is no need of any model to compute their values. We can compute the empirical properties of our pseudo-bonds $\widehat{B}_t(t+\tau, K_{i,t})$ directly from observable option and U.S. Treasury prices. We refer to the ratio $L_{i,t} = K_{i,t}/A_t$ as the firm's leverage ratio, given by the face value of debt divided by the market value of assets.

To compare our pseudo-bonds to real corporate bonds and for consistency with the existing literature, we assign a credit rating to each pseudo-bond according to its *ex ante* probability of default. At each time t and for each bond with maturity τ and strike $K_{i,t}$ we want to compute

$$p_t(L_{i,t}) = \Pr\left[A_{t+\tau} < K_{i,t} \,|\mathcal{F}_t\right] \tag{9}$$

where $\mathcal{F}_t$ is the information available at time t.

Under the assumptions of the Merton model, the default probability (9) can be readily computed from the normal cumulative distribution as

$$p_t^M(L_{i,t}) = N(-d_2) \quad \text{where} \quad d_2 = \frac{-\ln\left(L_{i,t}\right) + (\mu_A - \frac{1}{2}\sigma_A^2)\tau}{\sigma_A\sqrt{\tau}}. \tag{10}$$

Because we do not want to make any distributional assumptions about asset returns, however, in this paper we use the empirical distribution of the underlying assets to compute $p_t(L_{i,t})$. Still, we want to take into account time-varying market conditions, which may have a substantial impact on default probabilities for given current leverage ratio $L_{i,t} = K_{i,t}/A_t$. As such, we first assume that the log asset value evolves according to the following dynamics:

$$\ln A_{t+\tau} = \ln A_t + \mu_{t,\tau} - \frac{1}{2}\sigma_{t,\tau}^2 + \sigma_t\varepsilon_{t+\tau} \tag{11}$$

where $\varepsilon_{t+\tau}$ are standardized unexpected returns that have an unknown probability distribution. Because we do not impose any distributional assumption on $\varepsilon_{t+\tau}$, this is just a statement that $\ln A_{t+\tau}$ has some expected components and a scaling parameter $\sigma_{t,\tau}$. We estimate $\mu_{t,\tau}$ by running return forecasting regressions (excluding dividends) for τ horizons, and $\sigma_{t,\tau}$ by fitting a GARCH(1,1) process using monthly asset returns.[7]

[7]Specifically, using monthly returns we estimate $\sigma_{t,1}^2$. We estimate $\sigma_{t,\tau}^2$ for $\tau > 1$ from the properties of a GARCH(1,1) model.

Given estimates of $\mu_{t,\tau}$ and $\sigma_{t,\tau}$, we can then rewrite the probability $p_t(L_{i,t})$ in (9) as follows:

$$p_t(L_{i,t}) = \Pr\left[\varepsilon_{t+\tau} < X_{i,t} \middle| \mathcal{F}_t\right] \qquad \text{where} \qquad X_{i,t} = -\frac{-\ln\left(L_{i,t}\right) + \left(\mu_{t,\tau} - \frac{1}{2}\sigma_{t,\tau}^2\right)}{\sigma_{t,\tau}} \tag{12}$$

In addition, we collect the (overlapping) history of shocks

$$\varepsilon_{t+\tau} = \frac{\ln\left(A_{t+\tau}/A_t\right) - \mu_{t,\tau}}{\sigma_{t,\tau}}$$

and use the empirical distribution of these shocks to compute empirical default probabilities for each leverage ratio $L_{i,t}$ at any given time t simply as

$$\widehat{p}_t(L_{i,t}) = \frac{n(\varepsilon_{s+\tau} < X_{i,t})}{n(\varepsilon_{s+\tau})} \quad \text{for all} \quad s + \tau < t. \tag{13}$$

where $n(x)$ counts the number of events x. From this collection of default probabilities, we assign pseudo credit ratings to each of the pseudo-bonds, as discussed in more detail in Section 3.2. Our approach is non-parametric and only relies on the empirical distribution of the shocks $\varepsilon_{t+\tau}$.

Because the default probability depends on the estimated $\mu_{t,\tau}$ and volatility $\sigma_{t,\tau}$, as market conditions change our pseudo-bonds will change credit ratings even if the pseudo leverage ratio $L_{i,t} = K_{i,t}/A_t$ is the same. We thus perform the computations above on an expanding window so that at any time t we only use information available at time t to predict the default probability of a pseudo-bond with leverage ratio $L_{i,t}$ at maturity $t + \tau$.

So far we assumed we could find the exact option with target maturity τ. In reality, options with any meaningful liquidity are only available for certain maturities . For this reason, at every t we take the Gaussian kernel-weighted average of all bonds with the same rating. Specifically, the weighting function has the form

$$w_t \propto \frac{1}{\sqrt{2\pi}s} \exp\left(-\frac{1}{2}\frac{\left(\hat{\tau}_t - \tau\right)^2}{s^2}\right),$$

where s =30 days. We use expression (8) with $\hat{\tau}_t$ instead of τ for all computations.

Given our empirical observations of pseudo-bonds in expression (8), we can compute all the necessary statistics to compare our pseudo-bonds to both actual corporate bonds and the Merton model. In particular, we compute the credit spread of a pseudo-bond from the continuously compounded yield of a pseudo-bond:

$$y_t^{cc} = -\frac{1}{\widehat{\tau}_t} \ln\left(\frac{\widehat{B}_t(t + \widehat{\tau}_t, K_{i,t})}{K_{i,t}}\right),$$

To make our yields comparable with corporate bond credit spreads, we convert the continuously compounded rates into semi-annual compounded rates, denoted by y_t^{sa} and r_t^{sa} for corporate and Treasury rates, respectively. The credit spread is then given by

$$cs_t = y_t^{sa} - r_t^{sa}.$$

In addition to credit spreads, we also analyze the credit spread puzzle by computing monthly returns of pseudo-bonds and relate them to their observable characteristics. We compute realized returns on pseudo-bonds as

$$R_{t,t+1} = \frac{\widehat{B}_{t+1}(t+\widehat{\tau}_t, K_{i,t}) - \widehat{B}_t(t+\widehat{\tau}_t, K_{i,t})}{\widehat{B}_t(t+\widehat{\tau}_t, K_{i,t})}$$

3. Preliminaries: Data and Default Frequencies

3.1. Data

We use the OptionMetrics Ivy DB database for daily prices on SPX index options and options on individual stocks from January 4, 1996, through August 31, 2013. To minimize the effects of quoting errors in the SPX options, we generally follow Constantinides, Jackwerth and Savov (2013) to filter the data. We apply the filters only to the prices to buy – not to the prices to sell – so that our portfolio formation strategy is feasible for real-time investors.

Level 1 filters: Following Constantinides, Jackwerth and Savov (2013), we remove all but one of any duplicate observations. If there are quotes with identical contract terms but different prices, we pick the quote with the implied volatility (IV) closest to that of the moneyness of its neighbors and remove the others. We also remove the quotes with bids of zero.

Level 2 and Level 3 filters: Because we need quotes for long-term, deep out-of-the-money puts and deep in-the-money calls, we do not apply filters based on moneyness. Following Constantinides, Jackwerth and Savov (2013), however, we remove options with less than seven days to maturity, and we apply "implied interest rate < 0," "unable to compute IV," "IV," and "put-call parity" filters.[8]

[8]The "implied interest rate <0" filter removes the options with negative interest rates implied by put-call parity. The "unable to compute IV" filter removes options that imply negative time value. The "IV" filter removes options for which implied volatility is one standard deviation away from the average among the peers. In this case, the peer group is defined by the bins of moneyness with a width of 0.05. The "put-call parity" filter removes options for which the put-call parity implied interest rate is more than one standard deviation away from the average among the peers.

For individual stock options, we apply the same filters as Frazzini and Pedersen (2012), including "time value $< 5\%$" filter, which removes the options that are likely to be exercised early.

We obtain stock prices and accounting information from CRSP. We use the S&P500 index returns in the postwar period (1946 - 2013) to compute asset returns and *ex ante* default probabilities for our pseudo-firm.

To construct the risk-free zero coupon bonds, we use the 1, 3 and 6 month T-Bill rate and the 1, 2 and 3 year constant maturity Treasury yield obtained from FRED. We convert the constant maturity yield into zero coupon yield, and linearly interpolate the yield to match option maturity.

We construct the panel data of corporate bond prices from the Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE, and DataStream. When there are overlaps among the four databases, we prioritize in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and DataStream. For the detailed descriptions of these databases and the effect of prioritization, see Nozawa (2014).

We remove bonds with floating rates and option features. We also apply several filters to remove observations that are likely to be subject to erroneous recording. First, following Duffee (1998), we remove bonds with prices greater than twice their par values and less than 1/100 of their par amounts. These two filters are applied to buy-in prices. In addition, we remove return observations that show a large bounce back. Specifically, we compute the product of the adjacent return observations and remove both observations if the product is less than -0.04. In other words, if the same bond jumps up more than 20 percent in one month and comes down more than 20 percent in the following month, we assume that the price observation in the middle is recorded with errors.

To compute the credit spread for the very short-term maturity, we also obtain the commercial paper rate from FRED

Finally, historical default probabilities of the corporate bonds are obtained from Moodys Default Risk Service.

3.2. Default Frequencies and Pseudo-Bond Default Probabilities

Our goal is to construct pseudo-bonds from U.S. Treasuries and put options that match the default frequencies of real corporate bonds that we use as our main empirical benchmark.

To that end, we employ a large dataset of corporate bonds spanning the 44-year period from 1970 to 2013. For each credit rating assigned by Moody's to our universe of firms, we estimate *ex post* default frequencies at various horizons from 30 days up to two years. We use our own dataset rather than the original Moody's default frequencies for two main reasons. First, we are interested in the variation of default frequencies over the business cycle, whereas Moody's historical default frequencies are only available as unconditional averages. Second, we are interested in the default frequencies at very short horizons of below one year, and Moody's does not provide default frequencies for such short time horizons.

Table 1 reports historical default rates from 1970 through 2013 from our sample of firms across credit rating categories and time horizons. We compute historical default frequencies separately for international and U.S.-only firms. For the one- and two-year horizons, we can compare our results to Moody's historical default rates over the same historical period, as reported in Moody's (2014). As Table 1 shows, our estimated default rates closely match the Moody's global default rates for the one- and two-year horizons.

The last two columns of Table 1 report default rates for U.S. firms in NBER-dated booms and recessions. Predictably, we find that default frequencies are far higher in recessions than in booms across all credit ratings. At the one-year horizon, for instance, A-rated bonds have a default frequency of only 0.02% in booms but 0.13% in recessions (as compared to an unconditional U.S. average of 0.04%). Speculative-grade bonds also show a large variation over the business cycle. For example, at the one-year horizon a B-rated bond has a 3.57% default rate during booms but over twice that during recessions (as compared to an unconditional average of 4.01%).

Table 1 also shows default frequencies at short horizons of 30, 91 days, and 183 days. At the 30-day horizon, all investment-grade bonds have essentially zero default frequency (although in recessions that ticks up 0.01% for A- and Baa-rated bonds). Some more action for these bonds is visible at the 91- and 183-day horizons, especially during recessions. For example, Baa-rated bonds may default with 0.04% and 0.12% probability at the 91 and 183 day horizons during recessions, which are much higher than the unconditional probabilities of 0.02% and .05%, respectively. Speculative-grade bonds have a substantial default frequency even at short horizons. For instance, a B-rated bond has 0.22%, 0.75%, and 1.69% unconditional default frequencies over 30, 91, and 183 days, and these numbers increase to 0.11%, 1.48%, and 3.33% during recessions, respectively.

We use our estimated default frequencies in Table 1 to assign a (pseudo) credit rating to each of our pseudo-bonds. For simplicity, we illustrate our procedure using two-year bonds,

as this is the case discussed most often in the rest of the paper. The Appendix (Table A1) presents the results for all the other maturities.

Specifically, for every month t and for the given target maturity of $\tau = 2$ years, we use equation (13) to compute the default probability $p_t(L_{i,t})$ for each available pseudo-bond with leverage ratio $L_{i,t} = K_{i,t}/A_t$. Availability here means that the strike price of the underlying traded options must exist and the options survive the filters discussed in the previous section. We next compare this default probability to the historical default frequencies contained in Table 1, taking into account whether month t is in boom or recession. In other words, we use the last two columns of Table 1 to guide our assignment of pseudo-bonds to credit ratings. For high credit ratings, however, the lack of sufficient granularity in available options' strike prices (*i.e.,* pseudo-bonds' leverage ratios) prevents us from distinguishing Aaa- and Aa-rated bonds from, say, a A-rated bonds. During booms, the default frequency of Aaa/Aa bonds is 0.02%, whereas the default frequencies of A- and Baa-rated bonds are 0.14% and 0.34%, respectively. If we were to keep all of these fine differences in credit ratings – and hence default probabilities – we would end up with zero observations for some credit ratings for potentially long time periods. We thus opt to merge the Aaa and Aa credit ratings into a single Aaa/Aa category and the A and Baa credit ratings into a single A/Baa category. We then recompute the default frequencies of these coarser ratings category group.[9] Panel A of Table 2 recomputes the 2-year default frequencies when we merge A and Baa credit rating. In addition, the third and fourth column also reports the 95% confidence intervals of default frequencies, showing the range of default frequencies for each credit rating bin.

Given the business-cycle default probabilities in the last two columns of Panel A of Table 2, we next assign each bond to a credit rating according to their estimated default probability $\widehat{p}_t(L_{i,t})$. We use the midpoint of default probabilities across credit ratings to define the probability thresholds and to automatically assign credit ratings to pseudo-bonds. For instance, from Panel A, we see that during recessions, the default frequencies of corporate bonds rated by Moody's as Aaa/Aa, A/Baa, B are 0.05%, 0.47%, and 3.76%, respectively. Thus, we assign a pseudo-bond a Aaa/Aa pseudo credit rating if its probability at t satisfies $\widehat{p}_t(L_{i,t}) \leq 0.05\%/2 + 0.47\%/2 = 0.26\%$, to the A/Baa rating if $0.26\% < \widehat{p}_t(L_{i,t}) \leq 0.47\%/2 + 3.76\%/2 = 2.11\%$, and so on.

Panel B of Table 2 reports the results of our credit rating methodology for pseudo-bonds. For each credit rating in the first column, the second and the third column report the weighted average *ex-ante* default probabilities for bonds in each credit rating. According to

[9]Even with this slightly coarser definition of credit ratings, Aaa/Aa group has 69 months of missing observations and A/Baa group has 6 months of missing observations.

the procedure, these probabilities should be close to the default frequencies in the last two columns of Panel A, and as can be seen, they are. To verify our credit rating procedure, we also compute *ex-post* average default frequencies of pseudo-bonds over the 1970 - 2013 sample.[10] The mean default rates across credit ratings are in the fourth column, and as can be seen, these default rates are close to the average historical default rates of corporate bonds (Panel A, second column). The next two columns contain the 95% confidence interval of the default frequencies of pseudo-bonds: As can be seen, these confidence intervals are large and in fact much larger than the corresponding confidence intervals for corporate bonds in Panel A. The reason of this difference underscores an important point about pseudo-bonds: Because of our construction of pseudo-bonds out of a fictitious firm that has only S&P500 shares as its assets, we do not have a cross-section of firms over which we average out default events. We only have one time series – the one of the S&P500 index. The difference across pseudo-bonds only refers to different leverage ratios of the same fictitious firm, but not different firms with different assets (Section 4.4. will consider different firms using options of individual stocks to compute pseudo-bonds.) For this reason, the mean ex-post default rate is noisy and the confidence intervals are large. Intuitively, out of our 44-year sample we only have 22 independent observations over which we can compute default frequencies for two-year pseudo-bonds, a rather small sample. For the same reasons, we do not compute ex-post default frequencies conditional on the business cycle, as for recessions, the number of observations would shrink to just a handful. Even so, the ex-post average default frequencies of pseudo-bonds are quite close to the historical corporate bond defaults, showing that our credit rating methodology produces reasonable results.

The last two columns of Panel B of Table 2 report some average characteristics of the options used for the pseudo-bonds. In particular, $\overline{K/S}$ is the average moneyness of the options used. As is evident, the options used for highly rated pseudo-bonds are rather far out-of-the-money in order to ensure a low probability of default. As noted, we sometimes lack sufficient data to compute Aaa/Aa bonds because options so far out-of-the-money do not satisfy our minimum liquidity filters. The last column reports the average maturity $\overline{\tau}$ of our options. This is a bit smaller than the two-year (730-day) target mainly due to lack of data in the first part of the sample. Even so, the lower average maturity would bias the empirical results against us, as shorter maturities imply lower probabilities for the put options to end up in-the-money at maturity. Notwithstanding the lower maturity, we continue to refer to our pseudo-bonds as "two-year bonds."

[10] We do not need options to compute default frequencies of pseudo-bonds, as default at $t+\tau$ only depends on whether $A_{t+\tau} < K_{i,t}$ or not. We choose $K_{i,t}$ as the average leverage K/A for each credit rating.

4. The Credit Spread Puzzle in Pseudo-Bonds

4.1. The Credit Spread Puzzle in Yields

Panel A of Table 3 reports the summary statistics of our two-year pseudo-bonds. Each row corresponds to a different credit rating category based on the assignment approach discussed in Section 3.2.. The probability of default is in column 2, and the corresponding credit rating is in column 1. Column 3 reports the average leverage ratio K/A of the bonds in the given (pseudo) credit rating.

Column 4 of Table 3 reports one of our main results – *viz.*, the credit spreads of our two-year pseudo-bonds display the same credit spread puzzle exhibited in real corporate bond data. The credit spreads of our pseudo-bonds (shown in Panel A of Table 3) are large across all credit ratings, ranging from 53 basis points for Aaa/Aa bonds to 5.15% for Caa-bonds. These credit spreads are remarkably comparable in magnitude to the credit spreads of actual corporate bonds shown in Panel B of Table 3. The match is especially close for bonds with high credit ratings. For instance, Aaa/Aa and A/Baa bonds, the pseudo-bonds credit spreads are 0.53% and 1.31%, respectively, against 0.68% and 1.33% for real corporate bonds. The empirical credit spreads for both pseudo-bonds and real corporate bonds, moreover, are much higher than the credit spreads implied by the original lognormal Merton model, whose values are contained in Panel C. Table 4 shows that the same credit spread puzzle is apparent across the two sub-sample periods of 1996 - 2004 and 2005 - 2013.

How can we interpret our empirical results? First, given that our pseudo-bonds are based solely on observed marked-based prices of U.S. Treasuries and put options, our empirical results are model-free (except for the fitting of a simple GARCH(1,1) model with forecasting regressions to obtain the distribution of shocks used for the calculation of default probabilities). Because the *ex post* default probabilities from the S&P500 index are comparable with *ex ante* predicted values, moreover, there should be little concern that our results are driven by excessive sampling from "likely-to-default pseudo-bonds." Furthermore, because the pseudo-bonds are mechanically computed straight from U.S. Treasury and put option prices, our results do not hinge on corporate-finance-based theories that relate credit spreads to corporate governance, funding constraints, investments, uncertainty about default threshold, and the like.

Instead, our results appear to be driven by investors' demand for greater compensation to cover the risk of relatively low payoffs when adverse tail events occur (and conversely). Our results thus are consistent with the large literature documenting that put options (especially

out-of-the-money puts) are overpriced compared to the Black-Scholes-Merton model. Our results so far do not shed any light on whether the overpricing is rational (*i.e.,* risk-based) or behavioral (*i.e.*, overpaying for insurance). The novelty of our approach is to document that such "overpricing" of put option is in fact consistent with observed spreads on actual corporate bond spreads. Our results thus suggest that the source of the credit spread puzzle may be better explained by the same forces that explain why put options are expensive. More importantly, we show that the basic insight of Merton (1974) model that corporate securities can be viewed as a portfolio of safe bonds plus a short put is quite accurate indeed, even if the exact model specification (*i.e.*, log-normal assets) is not.

As noted, our model matches the credit spreads of real corporate bonds especially well at high credit ratings. For the lowest speculative-grade Caa- rating, our empirical results suggest a credit spread of about 5.15% as compared to an empirical corporate bond spread over the same period of 11.99%. The illiquidity of corporate bonds may be source of this difference. Especially given the displacement of high-yield bonds as a leveraged financing source by leveraged commercial and industrial bank loans since the late 1990s, many high-yield speculative-grade bonds are relatively illiquid and thinly traded (see Section 5.2. for a discussion of the liquidity of corporate bonds). Indeed, the difference between our benchmark option-based model and the observed credit spreads on high-yield debt may provide an indication of the illiquidity risk premium, which is about 6% on average for Caa- bonds. In other words, over half of the credit spread of high-yield corporate bonds may be attributable to illiquidity considerations.

Finally, we note that the results for the lognormal Merton model reported in Panel C of Table 3 correct for the influence of or any bias generated by the stochastic volatility nature of stock returns. In particular, we report the spreads implied by the lognormal Merton model by simulating stock returns that follow a GARCH(1,1) model with time-varying returns. This correction shows that the source of our empirical results in Panel A are not due to our fitting of a GARCH(1,1) model and/or the fitting of predicting regressions. It is really about the distribution of the shocks $\varepsilon_{t+\tau}$ in model (11). Indeed, Panel A of Figure 2 shows the histograms of shocks $\{\varepsilon_{t+\tau}\}$ for maturity $\tau = 2$. It is apparent that these two-year shocks are not normally distributed and hence the two-year pseudo-bond credit spreads may be high due to a risk premium demanded by investors to cover tail events. Figure 2 also reports the p-values of Kolmogorov-Smirnov tests of non-normality, and normality is rejected at the 1% confidence level both for the SPX and our sample of individual firms, discussed in Section 4.4.

Figures 3 and 4 present graphical representations of the time series of credit spreads

on pseudo-bonds and actual corporate bonds, respectively.[11] The spreads of both pseudo-bonds and corporate bonds skyrocketed during the 2008 financial crisis, and then returned to normal levels by the end of the sample period. Both pseudo-and corporate-bond spreads also increased in 1998 around the time of the Asian and Russian macroeconomic crises. By contrast, pseudo-bonds did not react significantly to the 2001 recession, whereas Ba-rated corporate bond spreads increased substantially in this period. Nonetheless, the pseudo- and corporate-bond spreads still show a good degree of comovement. The average pairwise correlation among the series is 34%.

4.2. The Credit Spread Puzzle in Excess Returns

In this section we take a different approach to the analysis of the credit spread puzzle. Here we focus not on credit spreads directly, but rather on pseudo-bond excess returns. In particular, Proposition 1 and Corollary 1 (see Section 2.) provide us with testable hypotheses about the behavior of pseudo-bond excess returns. We also compare our empirical results on pseudo-bonds excess returns to the excess returns of actual corporate bonds.

4.2.1. Sharpe Ratios

We first examine the behavior of pseudo-bond excess returns across credit ratings. Columns 5 to 9 of Table 3 report the summary statistics of monthly excess returns of pseudo-bonds (Panel A), corporate bonds (Panel B) and the lognormal Merton model (Panel C). Consistent with the results discussed in the previous section, highly rated pseudo-bonds display lower average excess returns (*e.g.*, 0.14% for Aaa/Aa) than lower rated pseudo-bonds (*e.g.*, 0.36% for Caa-). Similarly, highly rated pseudo-bonds have higher volatility (*e.g.*, 0.65% for Aaa/Aa) than lower-rated pseudo-bonds (*e.g.*, 2.31% for Caa-). Both results are qualitatively consistent with the predictions of the Merton model (Proposition 1.b) because both average excess returns and volatility are increasing in leverage K/A. Pseudo-bonds' Sharpe ratios, however, exhibit an inverted U-shaped pattern that is highest at the A/Baa rating category (Sharpe ratio equal 0.30) and lowest at the Aaa/Aa (0.22) and Caa- (0.16) categories. These differences in Sharpe ratios of pseudo-bonds are in contrast with the testable implications of the lognormal Merton model, which implies that all zero-coupon corporate bonds should have the same Sharpe ratio (see Proposition 1).

Panel B of Table 3 shows that actual corporate bonds also display higher excess returns

[11] Figure 3 indicates that in the first part of the sample we do not have enough data to compute the spread of Aaa/Aa pseudo-bonds. An insufficient number of deep out-of-the-money SPX options were available.

and higher volatility for lower-rated bonds, consistent with the Merton model. Similar to pseudo-bonds (Panel A) and in contrast with the lognormal Merton model, real corporate bonds also have Sharpe ratios that differ across credit ratings, with the highest Sharpe ratio occurring for bonds with an intermediate credit rating (*i.e.*, Ba-rated bonds with a Sharpe ratio of 0.26).[12]

Panel C shows that even taking into account the influence of time-varying volatility on return series and discrete (*i.e.*, monthly) sampling of returns, the Merton model does not produce the kind of returns displayed in the first two panels. In particular, the magnitudes of average returns and volatility are much smaller than in the data, and the Sharpe ratios exhibit much higher values for highly rated bonds than for lower-rated bonds. We also note that the infrequent sampling and time-varying volatility induced average returns that are declining with credit rating, which move opposite to the average credit spread. The intuition for this result stems from the fact that lower-rated bonds are short put options that are closer to being at-the-money (see Column 3) and thus have higher vega. Because a pseudo-bond is short-volatility, time-varying volatility gives rise to lower average returns resulting from time-varying volatility. The Merton model (in its original form) does not adjust the option premium for stochastic volatility, which is a significant reason why average realized returns are lower for lower credit ratings.

The two subsamples 1996 - 2004 and 2005 - 2013 in Table 4 corroborate the empirical findings in the full sample for both pseudo-bonds and corporate bonds. In both subsamples and for both pseudo-bonds and actual corporate bonds, average excess returns and volatilities are higher for bonds with lower credit ratings, but Sharpe ratios display a roughly inverted U-shaped pattern.

The last two columns of Table 3 and 4 contain two other important statistics of excess bond returns – namely, their skewness and excess kurtosis. We see that for both pseudo-bonds and real corporate bonds, excess returns are leptokurtic, although no obvious pattern is visible across credit ratings in either case. In contrast, the skewness of excess pseudo-bond returns is negative for below-investment-grade bonds, but the same pattern is not visible for actual corporate bonds.[13]

[12]For both corporate and pseudo-bonds, the standard errors of Sharpe ratios are on the order of 0.07. As such, the differences across Sharpe ratios may be statistically significant only when comparing the highest and lowest Sharpe ratios across credit ratings.

[13]As is well known, skewness and kurtosis are typically imprecisely estimated. For both corporate and pseudo-bonds, standard errors (not reported) suggest that skewness estimates are not statistically different from zero. By contrast, excess kurtosis estimates are mostly statistically different from 3 for corporate bonds but not so much so for pseudo-bonds.

4.2.2. Alphas and Betas

A second set of tests we perform concerns what might explain the magnitude of excess bonds return, which are reported again in the second column Table 5 together with t-statistics for easier reference. According to the lognormal Merton model, the average excess return on pseudo-bonds should be explained either by the firm's excess returns on assets (Proposition 1) or the firm's excess returns on equity (Corollary 1). To assess whether this hypothesis holds true in the data, we ran the following monthly regressions and report our results in Table 5:

$$R^e_{B,t} \quad = \quad \alpha + \beta\, R^e_{i,t} + \varepsilon_t \tag{14}$$

where $R^e_{i,t}$ denotes the excess return of bonds ($i = B$), assets ($i = A$), or equity ($i = E$). For pseudo-bonds, we observe both assets (*i.e.*, the SPX) and pseudo-equity (*i.e.*, call options on the SPX). For actual corporate bonds, we only observe the firms' equity returns. The null hypothesis according to the lognormal Merton model is that $\alpha = 0$. We note that this null hypothesis really holds only for instantaneous returns conditional on a given leverage ratio. To address this issue at least in part, we rebalance our portfolios at the monthly frequency, so that the leverage ratio K/A is relatively constant over our unit of observation. In addition, Panel C reports the results from the simulated lognormal Merton model with time-varying volatility to assess whether we should observe any bias in the average α due to the time variation of β.

Panel A of Table 5 shows that pseudo-bonds display a significantly positive α across credit ratings when excess returns are regressed on the hypothetical firm's excess return on assets. The alphas are larger for lower credit ratings, ranging from 0.12% (for Aaa/Aa) and 0.18% (for Caa-) per month. The regression betas are also increasing with leverage and are strongly significant, with R^2 values ranging between 19% (for Aaa/Aa pseudo-bonds) to 83% (for Caa- pseudo-bonds). Panel B shows that similar results obtain when we regress pseudo-bond excess returns on pseudo-equity excess returns, as given by returns on corresponding SPX call options. Once again, alphas are significantly positive and larger for lower credit ratings, and regression betas are increasing with leverage. Both the betas and the R^2 of the regressions on pseudo-equity, however, are lower than the results of the regressions on assets shown in Panel A. This finding is exactly what we would expect from Merton's insight in the presence of time-varying volatility – *i.e.*, an increase in volatility results in a decline in defaultable bond prices but increases the value of levered equity, thereby breaking the high correlation between bonds and equity generated by the variation in asset value A_t. The strong positive alpha that appears in Panels A and B, moreover, are consistent with the

prediction of Proposition 2 that the likely source of the credit spread puzzle for pseudo-bonds is the existence of a jump risk premium that pushes average excess returns (and therefore credit spreads) higher.

Panel C of Table 5 repeats the regression analysis whose results appear in Panel B for actual corporate bonds. The results for corporate bonds are very similar to those for pseudo-bonds – *i.e.*, alphas are positive, higher for lower credit ratings, and generally large, except for Aaa/Aa bonds where the coefficient is similar to the one for pseudo-bonds but is not significant. Actual corporate bond excess return betas with respect to equity are also similar to their pseudo-bond counterparts and are significant. R^2's are a bit smaller for real corporate bonds than for pseudo-bonds, but they are not small on average. Overall, we see some strong similarities between the behavior of excess returns of corporate and pseudo-bonds and their relation to excess equity returns. Although we cannot observe the market value of assets underlying corporate bonds, we do observe it for pseudo-bonds – a major advantage of our approach – and the existence of a similar alpha for pseudo-bonds when we use the underlying assets suggests that the source of the alpha is not due to the use of equity in the regression instead of assets (which may bias the results due to its non-linear relation with assets) but is more likely the result of a genuine jump risk premium that pushes up credit spreads.

Indeed, Panels D and E of Table 5 show the same results as in Panel A and B, but based on simulations of the lognormal Merton model where we allow volatility and mean asset return to vary over time. As can be seen, when we run the same regressions based on simulated excess returns using the Merton model, the regressions alphas are much smaller and not significantly different from zero (even though the t-stats are relatively high). Betas are again increasing with leverage, but are much smaller than under empirical observations. Intuitively, the thin tails of the normal distribution does not generate much variation in bond prices as the underlying market value of the firm's assets changes over time, which reduces the beta. The time variation in volatility further decreases the direct relation between bond returns and asset returns for the same reason discussed above.

Table 6 reports the same excess return regressions on the two subsamples – 1996 - 2004 and 2005 - 2013. The results are generally similar to the overall sample, but we notice that the alphas of pseudo-bonds are especially high during the second subperiod that includes the financial crisis. Indeed, in the first subperiod, pseudo-bonds' alphas are smaller and not significantly different from zero for both cases in which assets (Panel A) and equity (Panel B) are used as explanatory variables. Instead, Panels C and D reveal very high alphas in the second subperiod for both cases in which assets and equity excess returns are the independent variables. In light of Proposition 2, the increase in a likelihood of a jump in the underlying

assets and a corresponding demand by investors for an added risk premium to compensate for tail risk may have driven up the jump risk premium α_B in equation (6) in the second subperiod.

Interestingly, actual corporate bonds returns exhibit similar effects as our pseudo-bonds during the same two subperiods. Panels E and F document that the alphas in real corporate bonds are generally not significant in the first subperiod, but are large and statistically significant during the second subperiod (except again for Aaa/Aa bonds). Under Merton's interpretation of corporate bonds as short put options (plus riskless debt) and in agreement with our findings for pseudo-bonds, the significant portfolio alpha is apparently the result of an increase in the premium that investors are willing to pay to cover significant downside tail events.

4.3. Short-horizon Pseudo-Bonds

In previous sections we focused on pseudo-bonds and real corporate bonds with maturities of around two years. This choice of a relatively short maturity for our benchmark case is dictated by options data availability and, specifically, the lack of data on long-term options. Our results, however, are conservative given that the known deficiencies of the Merton model occur primarily at shorter debt maturities. Indeed, the lognormal assumption of asset dynamics in equation (1) implies that the probability that assets travel far over a short period becomes negligible as maturity shortens. In consequence, if the leverage ratio is below 100%, the probability of default converges to zero as maturity shrinks to zero, and, hence, credit spreads also converge to zero. In the data, however, credit spreads are relatively large at the very short maturities.

In this section we examine the term structure of credit spreads of pseudo-bonds. Unfortunately, we are hampered by two data limitations. First, relatively highly rated bonds (*i.e.*, Aaa/Aa and A/Baa) have negligible historical default probabilities for short time horizons (30 and 90 days). As a result, there is not enough granularity in available option strike prices to differentiate the default probabilities of Aaa/Aa pseudo-bonds from A/Baa pseudo-bonds. For such short maturities, we therefore bunch together all pseudo-bonds in just one credit rating bin, which we call the investment-grade (IG) credit rating category. The second data issue is that for very short maturities, we do not have reliable corporate bond data. We thus rely on average commercial paper rates, which are instead available for investment grade issuers. In consequence, we are unable to compute credit spreads for corporate bonds below investment grade at very short maturities.

Panel A of Table 7 reports the term structure of credit spreads of pseudo-bonds across credit ratings. Evidently, pseudo-bonds display high credit spreads across maturities even for highly rated bonds. For example, investment-grade bonds have credit spreads of 78bps, 64bps, and 79bps at the 30-, 90-, and 183-day maturities, respectively. In addition, the term structure of credit spreads is mildly U-shaped across maturities, with higher credit spreads for very short or long maturities and lower spreads for intermediate maturities.

Panel B of Table 7 reports similar results for corporate bonds. For comparison with pseudo-bonds, we also include the average credit spreads for investment-grade bonds. Like pseudo-bonds, highly rated corporate bonds display substantial credit spreads at the short maturity and a mild U-shape across maturities. The magnitudes of the credit spreads, moreover, are similar to the pseudo-bonds. For lower credit ratings we do not have short-horizon credit spreads, as mentioned, but the term structure displays a rising curve from six months to two years. The magnitudes are comparable to the pseudo-bonds, except that very low-rated bonds (Caa-) have much higher credit spreads than their pseudo-bond counterparts.

Panel C of Table 7 displays the implied credit spreads from the simulated Merton model, which are far away from the empirical credit spreads, especially at low time horizons.

Table A2 in the Appendix shows that pseudo-bond and real corporate bond returns (as opposed to credit spreads) over short time horizons display similar properties as those documented in Table 5 for the longer-dated two-year horizon.

4.4. Individual Firms

An important potential concern about the way we constructed our pseudo firm is that its assets are systematic in nature, given that they only comprise shares of the S&P 500 portfolio of firms. Therefore, a legitimate concern is that the size of the pseudo-bond credit spreads may be due the specific nature of the assets held by our pseudo firm. In this section we address this concern by creating additional pseudo firms whose only assets are shares of individual firms in the S&P500 index. Specifically, for each company in the S&P500 index, we can form a pseudo firm whose only assets are given by shares of that company. The fictitious firm purchases such assets by issuing a zero-coupon bond and equity. As was the case for our hypothetical SPX-based firm, the value of the defaultable zero-coupon bond issued by each such pseudo firm is economically equivalent to the value of a safe risk-free zero-coupon bond minus the value of a European put option on the pseudo firm's stock.

Given data on Treasuries and individual company equity put options, we can perform the same analysis that we did for the pseudo firm whose sole asset was the SPX.

Two important difficulties arise when we use individual firms for our analysis. First, individual firms' listed equity options are typically American and not European, whereas the original Merton model assumes that the underlying put option is European. Because of an early exercise premium, American options have higher prices than European options. Given that a defaultable bond is short a put option, using American options instead of European options may bias the implied credit spread upwards. Because the practical construction of pseudo-bonds using our method requires deep out-of-the-money options, however, such bias is likely small, given that the early exercise premium is very small for out-of-the-money options. Our results below thus use American options instead of European options. However, to verify that the early exercise premium has a negligible impact on our empirical results, we also use the implied volatilities provided by the data vendor (OptionMetrics) to convert American option prices into corresponding European options prices through the Black and Scholes formula. We then use the converted European option prices for all of our calculations. The results of this robustness check are in the Appendix.

The second difficulty stems from the computation of model-free default probabilities and dealing with survivorship bias. To understand the issue, consider the same procedure described in Section 2.3. but applied to individual firms in the S&P500 index. For each stock at time t we would consider the idiosyncratic shocks of their equity and use the histogram of those shocks to back out implied default probabilities. Clearly, we are conditioning on firms that at t are part of the index, and as such, to firms that have "survived" and done sufficiently well to be included in the index. This procedure will skew the shock distribution to the right. To avoid survivorship bias, we thus proceed differently in the case of individual firms. For every t, we consider the full cross-section of firms underlying the SPX index before t (thus including those that would later drop out of the index). We then use the empirical distribution of these idiosyncratic shocks for individual firms to obtain the default probabilities for each bond of each individual pseudo-firm. We use those individual default probabilities to assign a credit rating to each pseudo-bond every month.

Panel A of Table 8 reports historical default frequencies for the individual firms in our sample. The first column is the credit rating, and the next three columns are the historical default frequencies of actual corporate bonds of the firms in our sample along with their two-tailed confidence intervals. These numbers are reported from Table 2 for convenience. The next three columns report the *ex post* default frequencies of our pseudo-bonds at the two-year horizon, which are comparable to the *ex ante* targets. For the Aaa/Aa category,

the *ex post* default probability are slightly higher than the *ex ante* results in the data, but the noise of the estimates are largely responsible for this difference, as can be seen from the large confidence interval.[14] The last two columns report the average moneyness of the options used in each of the credit rating categories ($\overline{K/S}$) and the average time to maturity $\overline{\tau}$. We note that unlike the case for SPX index options, the average moneyness of A/Baa pseudo-bonds is lower than the average moneyness of Aaa/Aa pseudo-bonds. There are two reasons for this. First, there are many firms that have only a few traded options, and it often happens that a firm only has Aaa/Aa pseudo-bonds and nothing else. Second, the cross-sectional differences in average returns and volatility are large. Because we are sorting on probability of default and not on moneyness, cross-sectional differences in volatility and average return may break the one-to-one relationship between probability of default and moneyness. This would not be an issue if all firms had bonds in all ratings, but that is not the case in our data. As such, it is possible that Aaa/Aa bonds have higher moneyness than A/Baa bonds.

Panel B of Table 8 reports the summary statistics of the credit spreads and excess returns of pseudo-bonds in each credit rating category. The average credit spreads of pseudo-bonds calculated from individual pseudo firms are in general a bit higher than the corresponding credit spreads of pseudo-bonds computed from the SPX but are on the same order of magnitude. For example, Aaa/Aa and A/Baa-rated pseudo-bonds have credit spreads of 1.39% and 1.51%, respectively, as compared to 0.53% and 1.31% from Table 3. These credit spreads are all comparable to the real corporate bonds' credit spreads (0.62% and 1.33%, respectively, from Panel B of Table 3). In all cases, the pseudo-bond credit spreads are far higher than those implied by the lognormal Merton model. The same result holds for other credit ratings, as well.

Panel B also reports the summary statistics of the excess returns of each portfolio of pseudo-bonds by credit rating category. Clearly, the properties of excess portfolio returns of pseudo-bonds constructed from individual firms' securities are similar to those obtained based on SPX options as reported in Table 3. Specifically, the average excess return and volatility are higher for lower-rated pseudo-bonds. The Sharpe ratios, however, do not show any visible pattern, perhaps as a result of noise in the estimates. The distribution of returns still appears to be leptokurtic, as was shown for pseudo-bonds based on SPX options and actual corporate bonds.

Panel C of Table 8 reports the results of regressions of pseudo-bond excess portfolio

[14]Indeed, because of the various filters, we only have 106 observations for Aaa/Aa bonds, 199 for A/Baa bonds, and the full sample of 211 observations for the other credit ratings.

returns on their average excess returns on assets for each credit rating. Most of the returns on pseudo-bonds can be explained by the average excess returns on assets, as the portfolio alphas are mostly statically indistinguishable from zero. This result is contrast with what we observed when assets consisted solely of the SPX index, and the result may be due to the less systematic nature of jumps for individual securities than the index itself. Interestingly, however, in Panel D we see that the same regression of excess pseudo-bond returns on excess pseudo-equity returns generates a statistically significant alpha. This empirical finding suggests an important role of time-varying volatility of individual securities that breaks the correlation between pseudo-bond and pseudo-equity returns. Recall that Panel C of Table 5 reported similar results for actual corporate bonds – *i.e.*, real corporate bond alphas cannot be explained by the same corporate equity excess returns. The parallel between real corporate bonds and pseudo-bonds is striking. Yet, the results in this table suggest that the source of that alpha may be time-varying volatility. (In the next section, we delve deeper into the source of pseudo-bond and corporate-bond excess returns.)

Table A3 in the Appendix shows that similar results to those in Table 8 obtain when we use European-equivalent options as opposed to the American options for which we have actual option prices. Our results are not surprising, given that, as discussed, the early-exercise premium is typically very small for deep out-of-the-money options.

5. Inspecting the Mechanism

The previous section documents a strong similarity between the behavior of zero-coupon pseudo-bonds and real corporate bonds. This similarity suggests that the source of the credit spread puzzle may simply be the demand for insurance against tail risk that investors seem to require in the options market. In this section, we carry out additional tests on pseudo-bonds and corporate bonds to highlight further similarities, and important differences, that can help up better understand the source of the credit spread puzzle.

5.1. Asset Pricing Tests

Given the results presented in the previous section, one question is whether or not the positive alphas for both pseudo-bonds and corporate bonds may be explained by systematic risk factors. Accordingly, Table 9 reports the results of the regression of portfolio bond returns on the Fama-French (1993) factors, augmented by a term premium and a default

premium factor:

$$R^e_{i,t} = \alpha_i + \beta_i \; RMRF_t + s_i \; SMB_t + h_i \; HML_t + g_i \; TERM_t + d_i \; DEF_t + \epsilon_{i,t},$$

where $R^e_{i,t}$ is the excess return on portfolio i, $RMRF_t$ is the excess return on the value-weighted stock market portfolio, SMB_t is the size factor, HML_t is the value factor, $TERM_t$ is the return on the long-term Treasury bonds in excess of T-bill rates, and DEF_t is the return on the aggregate long-term corporate bond market portfolio from Ibbotson in excess of the return on the long-term Treasury bonds.

Panel A shows the results for pseudo-bonds based on SPX options. Even controlling for these five systematic risk proxies, the alphas are significant across credit ratings. In other words, these five factors do not explain the average excess return of pseudo-bonds. In terms of factor loadings, pseudo-bonds load significantly on the market excess returns – a result that is not too surprising given that the only asset of the pseudo firm is the SPX. Yet, Fama-French factors SMB and HML do not explain any of the variation of pseudo-bonds. In contrast, loadings on $TERM_t$ and DEF_t are mostly significant across credit ratings. The fact that the excess return on aggregate corporate bond portfolio (DEF_t) is significant in explaining pseudo-bonds computed from U.S. Treasuries and SPX put options further demonstrates the close connection between the underlying common risk premium for pseudo-bonds and corporate bonds. In other words, we would expect exactly this result if investors require a high risk premium to cover the risk of a tail event, as such a premium would impact put options and corporate bonds comparably.

Panel B shows the results for pseudo-bonds based on individual firms that make up the SPX index. The results are largely the same as in Panel A, except for the Aaa/Aa credit rating category, for which the difference is likely the result of spotty returns data for this high-rating category. Otherwise, we do find strong loadings on the market return factor $RMRF_t$, the term premium $TERM_t$ and the default premium DEF_t, especially for lower-rated pseudo-bonds.

Panel C shows that results similar to those in Panel A and Panel B also hold for actual corporate bonds, with the exception of loadings on the market portfolio, especially for highly rated bonds. The five-factor alphas are strongly significant across all credit ratings, and the main explanatory variable of corporate bond excess returns are term premium $TERM_t$ and, not surprisingly, the corporate default spread factor DEF_t. The R^2 of the regressions, however, are far smaller for actual corporate bonds than for the pseudo-bonds, perhaps due to the additional noise introduced by the lower of liquidity of lower-rated bonds.

Table 10 examines whether additional risk factors might help explain the positive es-

timated alphas in the pseudo-bond and actual corporate bond portfolios. Specifically, we run a similar regression with the Fama-French five factors, but now also include the excess return on the option portfolio that underlies the VIX index, $VIXSQ_t$, the return on a portfolio that replicates the Treasury-Eurodollar spread (*i.e.*, the return on a portfolio that is long three-month Eurodollar deposits and short three-month T-Bills), and the return on the tail-risk factor of Kelly and Jiang (2014). $VIXSQ_t$ factor captures changes in risk – or risk aversion – that affect corporate bonds, $dTED_t$ captures changes in market liquidity, and $Tail_t$ captures the time variation in tail risk. All of these factors can be considered traded portfolios, allowing us to continue interpreting alpha in the usual manner.[15]

Panels A and B document that, indeed, the volatility factor enters significantly as an explanatory variable of pseudo-bond returns, both for pseudo-bonds based on the SPX and those based on individual firms. Specifically, an increase in VIX implies lower excess returns on bonds, with more negative loadings for lower-rated bonds. Surprisingly, the TED spread liquidity proxy does not seem to have much of an effect of pseudo-bonds. One reason could be that the TED spread reflects variations in both liquidity and credit risk across corporate and government bonds, and, to the extent the TED spread is indicating credit risk over the sample period, the risk may already be reflected in other variables. Tail risk, by contrast, enters significantly for some credit ratings in Panel A for SPX pseudo-bonds but not in Panel B for pseudo-bonds created from options on individual stocks. Yet, the estimated alphas of pseudo-bonds are still strongly significant, indicating that these additional risk factors are still insufficient to explain the large excess returns (and, hence, credit spreads) of pseudo-bonds.

Panel C of Table 10 shows that actual excess returns on corporate bonds are also affected by the volatility factor (with the proper sign), but the factor loadings are mostly insignificant. The liquidity and tail risk factors are also not statistically significantly in the regressions. As is the case for pseudo-bonds, the estimated alphas remain positive and strongly significant. So, once again we see the result that pseudo-bonds and actual bonds exhibit a similar credit spread puzzle, even when controlling for various proxies of systematic risk.

5.2. The Liquidity of Pseudo-Bonds

The previous sections document a close connection between pseudo-bonds and real corporate bonds for the relation between credit spreads and alphas. We also showed some differences

[15]The VIX index is the squared root of the value of a portfolio of options. Thus, $VIXSQ = VIX^2$ is effectively the value of a traded portfolio, and thus we can compute an excess return.

in these relations, such as the differences in some of the loadings in Tables 9 and 10. In this section we document that one such difference is that corporate bonds and pseudo-bonds have different liquidity risk, which may help explain the low R^2 in the earlier regressions.

In lieu of the TED spread as a proxy for market liquidity (as used in the previous section), we now use the Roll (1984) measure of illiquidity. The market illiquidity measure for pseudo-bond i in month t is computed as

$$Illiquidity_t = 2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Bid\to Ask}, \Delta p_{i,t,d+1}^{Ask\to Bid})}$$

Panel A and B of Table 11 reports the credit spreads, the average monthly returns in excess of T-bills, and the Roll illiquidity measure of the pseudo-bonds based on the SPX options and individual firms' options, respectively. The bid-ask spread for pseudo-bond i in month t is computed by $(B_{i,t}^{Ask} - B_{i,t}^{Bid})/B_{i,t}^{Mid}$. The portfolio bid-ask spread is the kernel-weighted average of pseudo-bonds, where the kernel is the same as the one used for returns. We compute the Roll measure for all pseudo-bonds that have more than 10 return observations in a month. The portfolio-level Roll measure is computed by the kernel-weighted average of the pseudo-bonds for which we can compute the Roll measure.

Panel C shows the same statistics for the corporate bonds. The Roll measure for corporate bond i in month t is computed by

$$Illiquidity_t = 2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Transaction}, \Delta p_{i,t,d+1}^{Transaction})}$$

using the daily price observations. We compute the Roll measure for all corporate bonds that have more than 10 return observations in a month. As in credit spreads and excess returns, the Roll measure for a portfolio is the value-weighted average of the corporate bonds for which we can compute the Roll measure.

Comparing Panel A to Panel B, we see that the liquidity of pseudo-bonds based on SPX options is far higher than the one of pseudo-bonds based on individual firms' options. Both the bid-ask spreads and the Roll (1984) illiquidity measure of the SPX-based pseudo-bonds are about one fifth of the same quantities computed for pseudo-bonds from individual firms' options. This is of course not surprising, as index options are far more liquid instruments than individual firms' options.

Comparing Panels A and B to Panel C, it appears that pseudo-bonds based on SPX options have far lower average execution costs than real corporate bonds, except for Aaa/Aa

bonds for which transaction costs are roughly comparable.[16] Instead, pseudo-bonds based on individual firms' options have illiquidity measures that are closer to the ones computed for real corporate bonds, with the exception of the lower rated bonds, for which corporate bonds still show far higher execution costs (lower liquidity).

All these results are qualitatively intuitive, as our SPX pseudo-bonds are formed from a combination of very liquid U.S. Treasury securities and options. Although we use deep out-of-the-money options that are relatively less liquid than comparable at-the-money options, such options are still relatively more liquid than corporate bonds. Instead, individual firms' options are less liquid that index-based options, and it is interesting to find indeed comparable execution costs as for real corporate bonds. Even if both pseudo-bonds obtained from individual firms' options and real corporate bonds are marred by illiquidity compared to our SPX-based pseudo-bonds, it is also interesting that corporate bond excess returns are not sensitive to illiquidity measures, such as changes in the TED spread.[17]

6. Applications

In this final section we provide a few applications of our model-free approach. In one application we consider the impact of the frequency of credit rating changes on average credit spreads and excess returns of bond portfolios that are sorted on credit ratings. This application is important as it speaks about the bias that can occur if credit rating agencies are not prompt in revising their credit ratings. A second application discussed the impact of a firm's capital structure on its credit spreads.

6.1. The Frequency of Credit Rating Revisions and Bond Returns

In our approach, we assign a credit rating to each of our pseudo-bonds every month. We then sort bonds on those credit rating and form portfolios. In reality, of course, credit rating agencies do not examine corporate credit ratings every month. Given the apparent strong reliance that many investors place on published ratings, an important question is how the frequency of credit rating assessments may impact *ex post* average credit spreads and excess return. To examine this question, in this section we relax the assumption of monthly credit rating assignments and assume instead that credit ratings are assessed at a lower (and

[16] Interestingly, Aaa/Aa bonds have the highest R^2 in our Tables 9 and 10, and have loadings on $TERM$, DEF, $dVIXSQ$ and $dTED$ that are significant and with the intuitive sign.

[17] We also used the Pastor and Stambaugh (2003) factor and found similar results to those reported here.

exogenous) frequency – specifically, every three, six, and 12 months. We still use monthly frequencies to compute average credit spreads and bond returns, but our allocation of bonds into ratings categories now occurs less often.

Table 12 reports the average credit ratings, and summary statistics of pseudo-bond returns using these three new (and lower-frequency) credit rating assignment intervals. As we can see, the average credit spread across credit ratings are very similar to the case in which credit ratings are changed at the monthly frequency. The only noticeable difference is at the very lowest credit rating (Caa-) for which the average credit spread moves from 5.15% when the frequency is monthly (Table 3), to 5.29%, 7.04% and 8.26% when frequency is quarterly, semi-annual, and annual, respectively. This empirical result is likely due to the convexity that exists between credit spreads and leverage (K/A) – *i.e.*, time variation in market values of underlying assets A_t over longer periods generate an increase in the average credit spread, which is more pronounced for pseudo-bonds closer to at-the- money (high K/A). That explains why this happens for lower credit ratings, but not for higher credit ratings. Indeed, in a recent paper, Federhutter and Schaefer (2014) argue that part or all of the credit spread puzzle may be due to a bias in the estimation of credit spreads across credit ratings. As is apparent from our empirical results, however, such an effect would be small for our pseudo-bonds.

Table 12 also shows that average excess returns of pseudo-bond returns are smaller the more infrequent the credit-rating assignment. Again, this effect may be due to a convexity effect – *i.e.*, over a longer period, the beta of pseudo-bond returns varies by a larger amount. Because the beta of options is convex in leverage K/A and because pseudo-bonds are based on short options, the beta of pseudo-bonds is concave in K/A, and thus induces a lower average return the more A varies. Interestingly, the *ex post* Sharpe ratio is now monotonically declining as we consider lower credit ratings. The reason, again, is that the convexity effect is stronger for options that are closer to the money.

6.2. Credit Spreads across the Capital Structure

Our model-free approach can also be used to investigate issues related to a firm's capital structure, such as the differential credit spreads of senior versus junior claims. Indeed, a firm with asset value A_t may issue senior claims with face value K_t^S and junior claims with face value K_t^J. Senior debt holders receive the payoff of K_t^S if $A_T > K_t^S$ and of A_T if $A_T < K_t^S$, exactly as before. Junior debt holders, however, receive a full payoff if $A_T > K_t^S + K_t^J$, only $A_T - K_t^S$ if $K_t^S < A_T < K_t^S + K_t^J$, and zero otherwise. So, whereas senior debt holders have

an exposure equivalent to risk-free debt minus a put option on the firm with a strike price of K_t^S, junior debt holders are long a safe bond with face value $K_t^S + K_t^J$, short a put with the same strike price and long another put with strike price K_t^S. We can use traded option prices to evaluate the credit spreads of junior securities accordingly.[18]

In order to provide a pseudo credit rating to our bonds, for every month t we first sort pseudo-bonds on the SPX index options into the rating-based portfolios as in Table 2. Because for every t there are multiple bonds in each credit rating class, we then compute the average price of the pseudo-bonds (denoted $B_{r,t}$ where r is the credit rating) and the average strike price (denoted $K_{r,t}$) for each portfolio. Then the price of the pseudo junior bond with the rating $r2$, issued by the firm with the senior rating $r1$ is $B_{r2,t}^J = B_{r2,t} - B_{r1,t}$, whereas the face value of the junior bond is given by $K_{r2,t}^J = K_{r2,t} - K_{r1,t}$. We finally compute the continuously compounded yield as $y^{cc,t} = -log(B_{r2,t}^J/K_{r2,t}^J)/\tau$, which we convert into a semi-annual compounding basis to derive yield spreads. The return on the resulting pseudo-bonds is given by $R_{i,t+1}^J = w_t^J R_{r2,t+1} + (1 - w_t^J)R_{r1,t+1}$, where $w_t^J \equiv B_{r2,t}/B_{r2,t}^J \geq 1$.

Panel A of Table 13 reports the results. Comparing this table with the Table 3, which reports credit spreads for pseudo-bonds and corporate bonds on a stand-alone basis, we see that for each credit rating, the credit spreads of pseudo junior bonds are substantially higher than stand-alone bonds with the same credit rating. For instance, consider a pseudo firm that issues Aaa/Aa bonds as well as some junior bonds. We see that a A/Baa pseudo junior bond has a credit spread of 2.18% while a A/Baa stand-alone pseudo-bond has a credit spread of 1.31%, almost a 1% difference. Similarly, a Caa- junior pseudo-bond issued by an Aaa/Aa firm has a credit spread of 9.87% as compared to a credit spread of 5.15% for stand-alone bonds, an almost 4.5% difference. Similar results obtain if the firm issues, say, A/Baa bonds and additional junior bonds.

The source of the difference is clear. Credit ratings are based on the default probability of each bond, and our pseudo-bonds have the same default probability whether they are junior or stand alone. But junior bonds have a much higher loss-given-default. For example, given a probability of default, it is unlikely that a stand-alone A/Baa bond would lose all of its value even if a default occurs, as this would require a very large decrease in asset value A_T at maturity. By contrast, it is relatively likely that a junior bond with the same probability of default will lose most or all of its value in case of default, as one only needs a very large downward realization of A_T below the threshold K_t^S for such a result to occur. As such, even

[18]Coval et. al. (2012) also use options on the S&P 500 to extract implied credit spreads for junior CDO tranches. Our methodology, however, relies on the projection of default probabilities as illustrated in Section 3. and compares credit spreads with stand-alone pseudo-bonds.

if the default probability is the same, the credit spreads of junior bonds are much higher due to the higher loss-given-default.

A similar difference can be observed in actual corporate bonds. Panel B of Table 13 shows credit spreads for actual junior corporate bonds. Unfortunately, we do not have a large sample of firms that issue both senior and junior bonds available with times to maturity close to two years. Nevertheless, we can identify a few firms that issue senior Aaa/Aa and relatively more junior A/Baa bonds. The credit spreads of the more senior bonds is 2.16%, which is higher than the 1.33% credit spreads of A/Baa corporate bonds in Table 3. The increase in credit spreads of junior bonds, moreover, is comparable to the relation described above for pseudo-bonds.

So, our methodology can be successfully applied to study the differential credit spreads across the capital structure of a single firm without relying on a parametric model and using only observed data and the basic Merton (1974) insight.

7. Discussion and Conclusions

In this paper we introduce a model-free methodology to demonstrate how we can used traded options to quantify the implications of the Merton (1974) model for the valuation of defaultable debt. The main insight of the Merton model is that the value of defaultable debt can be computed as the value of risk-free zero-coupon debt minus a the value of a put option on the firm's assets with a strike price equal to the face value of debt and with the same maturity as the debt. By assuming hypothetical firms that purchase the underlying traded securities, such as the S&P 500 index or individual firms' stocks, we study the empirical properties of the zero-coupon pseudo-bonds issued by such firms.

The empirical results are striking. We find that credit spreads generated by such pseudo-bonds (whose values are directly observable and involve no parametric assumptions) are surprisingly comparable to the credit spreads observed for real corporate bonds, especially for bonds with high credit qualities. Such credit spreads are orders of magnitudes higher than those implied by the original Merton model, which assumed that assets are lognormally distributed. Our empirical investigation of such pseudo-bonds demonstrates numerous similarities between the properties of pseudo-bonds and the empirical properties of real corporate bonds, thus potentially calling into question elaborate theories of the credit spread puzzle that rely on agency costs, asymmetric information, learning, uncertainty, and the like. Our results instead point at a genuine risk premium required by investors to hold securities that

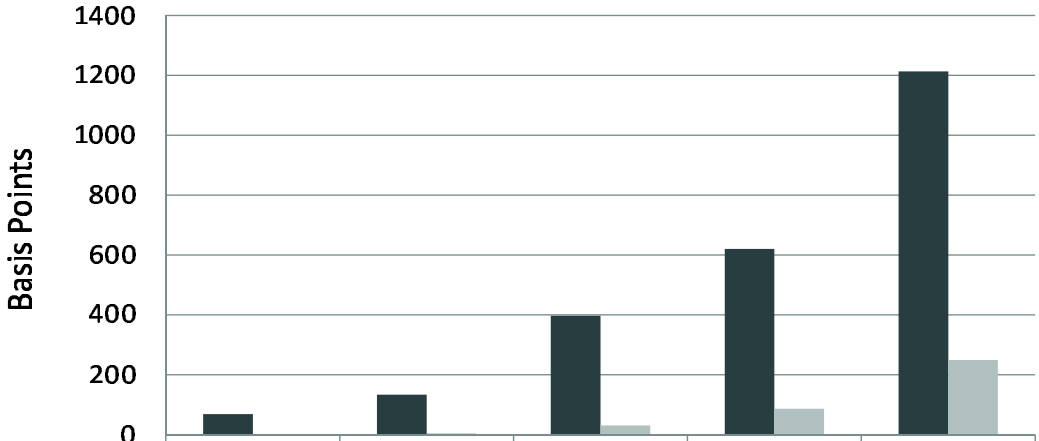
could default upon the occurrence of tail events.

A potential criticism of our approach is that our results are driven by the special nature of the assets of our pseudo firms, namely, stock indices or individual stocks, which may be too volatile and prone to market crashes or run up compared to the real assets of other firms. In fact, we believe the opposite is true, and that the observability of the market value of assets with their true volatility is a virtue of our approach rather than a limitation.

One issue hampering the existing credit spread literature – and a reason why earlier literature focused on "models" for the dynamics of assets – is exactly the difficulty to measure the *market value* of assets. Indeed, recall that stocks are just claims to future dividends, which are a relatively smooth and not too volatile (e.g. Shiller (1981)). In spite of the low volatility of dividends, stocks are highly volatile. As is well known from the work of Campbell and Shiller (1988), Vuolteenaho (2002), and others (see e.g. Cochrane (2005, 2008)), the main reason for the high volatility of market values compared to future dividends is the variation discount rates. rather than expected future cash flows. It is only logical to the conclude that a similar channel – the discount rate channel – affects the market value of firm's assets, and thus that such unobservable market values of assets is in fact highly volatile.

In this paper we focused only on firms whose asset values are only given by equity of other firms, such as the S&P 500 index or individual stocks. Our procedure can be applied to any type of traded security. For instance, a pseudo firm may purchase foreign currencies by issuing zero coupon bonds and equity, whose market value can then be analyzed by using currency options. Other types of assets of our pseudo firm could be Treasury bonds, or commodities, whose pseudo-bonds could be analyzed by using Treasury bond options or commodity options. In this case, one would likely need to use options on futures, and some approximations would be required, but this could be a fruitful avenue of future research. Indeed, it would be interesting to investigate how different pseudo-bonds depend on the type of the underlying asset value, and whether some "anomalies" in the underlying (e.g. the carry trade anomaly in currency markets) translate into particular dynamics of pseudo-bonds. Ultimately, this investigation allows us to better understand what drives corporate bond returns, and our methodology offers a model-free laboratory to exploit Merton's original insight about the value of corporate securities.

Figure 1: The Credit Spread Puzzle

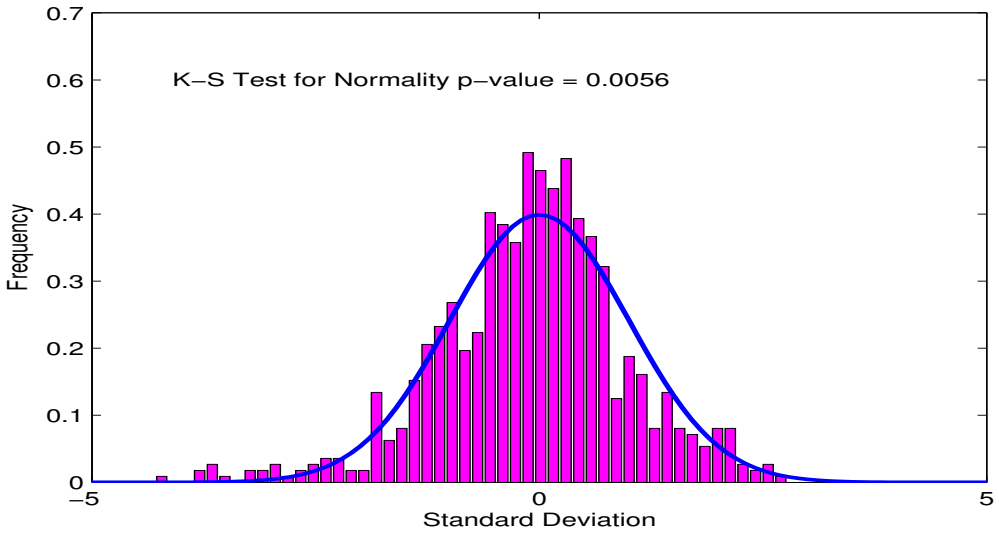


	Aaa/Aa	A/Baa	Ba	B	Caa-
Corporate Bonds	68	133	397	620	1213
Merton Model	0	4	30	86	249

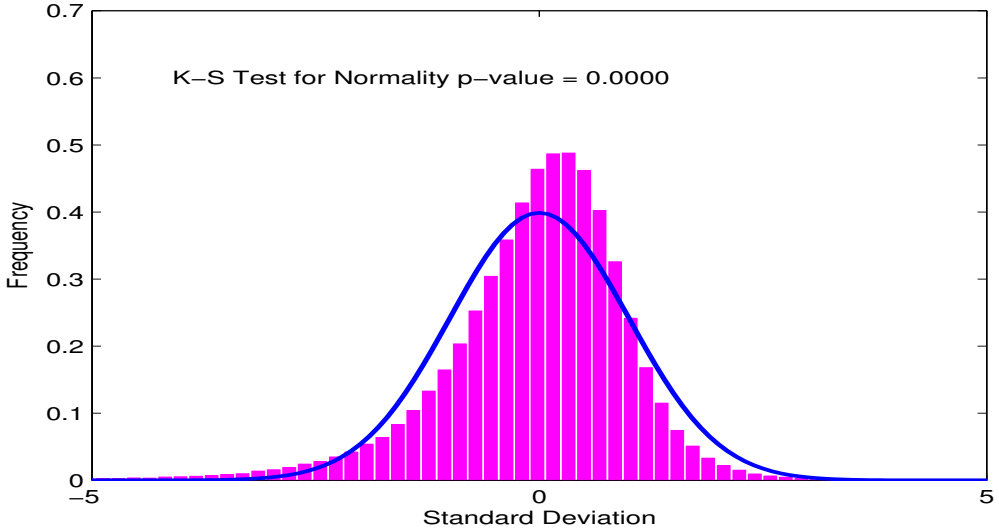
Notes: This figure shows the credit spread of non-callable corporate bonds with approximately two years to maturity. Corporate bond data are obtained from merging the Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE and DataStream. The sample is monthly between 1996 to 2013. The credit spread is computed as the difference between the semi-annual yield-to-maturity and the corresponding Treasury yield. The gray bars show the credit spread of two year zero-coupon defaultable bonds of the lognormal Merton model calibrated to match true default frequencies.

Figure 2: Normalized Monthly Shocks to two-year Pseudo-Bonds

Panel A: S&P500 Index as Assets



Panel B: Individual Firms as Assets



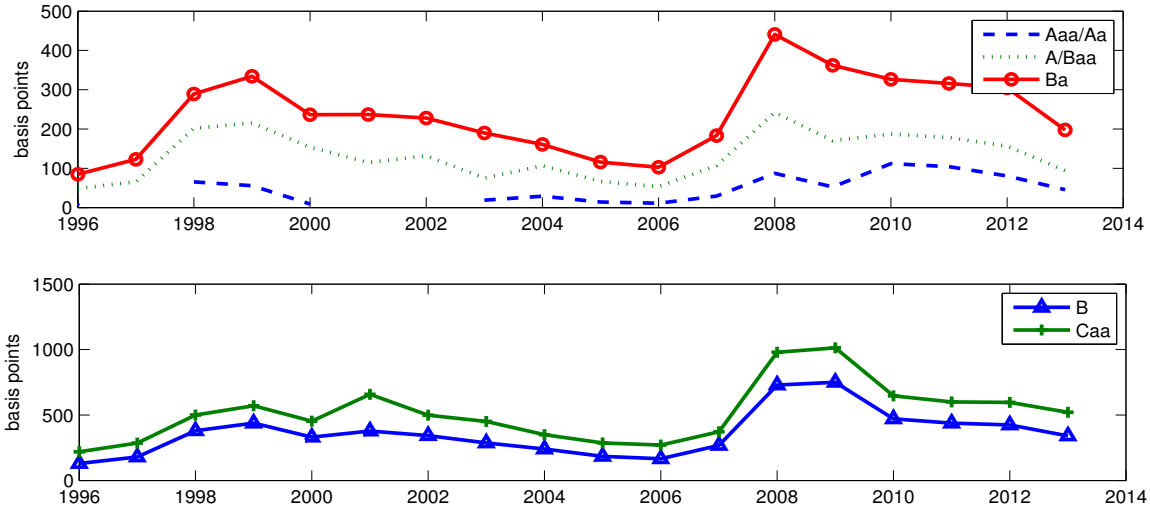
Notes: Histograms of residuals computed as

$$\epsilon^i_{t,t+\tau} = \frac{\log\left(A^i_{t+\tau}/A^i_t\right) - \left(\mu_{i,t,\tau} - \frac{1}{2}\sigma^2_{i,t,\tau}\right)}{\sigma_{i,t,\tau}}$$

In Panel A, A^i_t is the S&P 500 index, $\mu_{i,t,\tau}$ is computed from a predictive regression of future two year returns using the dividend yield as predictors, and $\sigma_{i,t,\tau}$ is obtained from fitting a GARCH(1,1) model to monthly stock returns. All computations are made on an expanding window.

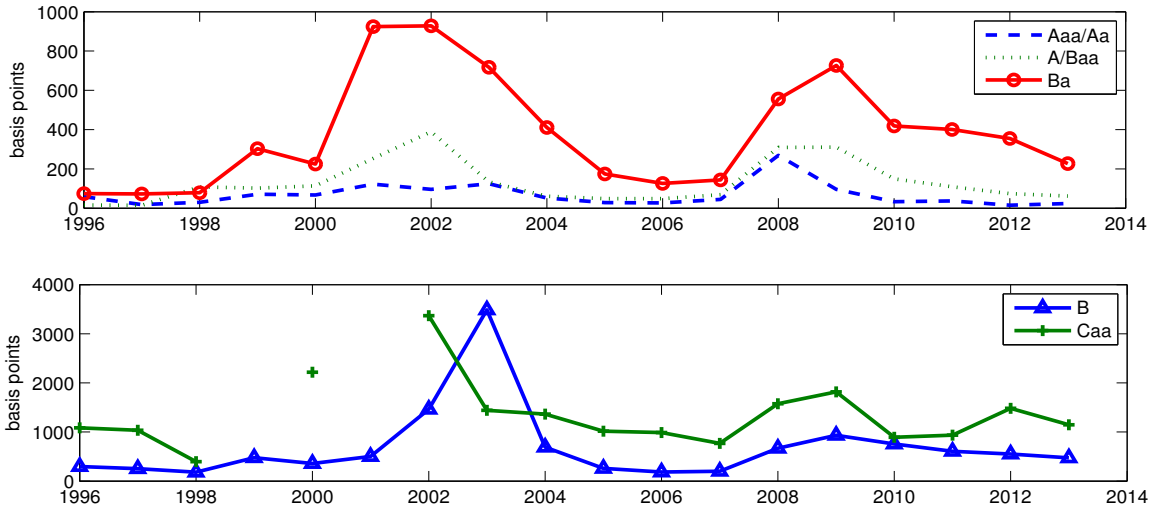
In Panel B, A^i_t are the individual stocks in the S&P 500 index, where $\mu_{i,t,\tau}$ is the average two-year stock return until t, and $\sigma_{i,t,\tau}$ is the realized volatility the previous year. For every t, all the stocks in the S&P 500 index are used to compute shocks before t to avoid survivorship bias.

Figure 3: Credit Spreads of two-year Pseudo-bonds



Notes: Credit spreads of two year Pseudo-bonds. Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity) during booms and recessions. The *ex ante* default probabilities of pseudo-bonds are computed by inverting the empirical distribution of the residuals from a simple GARCH(1,1) model of asset returns with expected growth obtained from predictive regressions.

Figure 4: Credit Spreads of two-year Corporate Bonds



Notes: Credit spreads of two year corporate bonds. Corporate bond data are from the Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE and DataStream. The sample is monthly between 1996 to 2013. The credit spread is computed as the difference between the semi-annual yield-to-maturity and the corresponding Treasury yield.

Table 1: Corporate Bonds' Historical Default Rates: 1970 — 2013

This table reports the historical cumulative default rates (in percent) of corporate bonds in our sample of firms from 1970 - 2013 and compares them with Moody's default frequencies, when available. The "Global" sample is an international sample of firms. The "US" sample only focuses on US firms. Booms and recessions are determined by NBER business cycle dates, and default rates are computed using US firms.

Moody's		Our Sample			
Rating	Global	Global	US	Boom	Recession
		Horizon: 30 days			
Aaa-Aa	-	0.00	0.00	0.00	0.00
A	-	0.00	0.00	0.00	0.01
Baa	-	0.00	0.00	0.00	0.01
Ba	-	0.04	0.05	0.04	0.11
B	-	0.19	0.22	0.19	0.43
Caa-C	-	1.91	1.89	1.61	3.47
		Horizon: 91 days			
Aaa-Aa	-	0.00	0.00	0.00	0.01
A	-	0.01	0.01	0.00	0.03
Baa	-	0.02	0.02	0.01	0.04
Ba	-	0.17	0.19	0.16	0.38
B	-	0.67	0.75	0.65	1.48
Caa-C	-	4.99	4.90	4.07	9.51
		Horizon: 183 days			
Aaa-Aa	-	0.00	0.00	0.00	0.03
A	-	0.02	0.01	0.01	0.05
Baa	-	0.05	0.05	0.04	0.12
Ba	-	0.42	0.47	0.40	0.91
B	-	1.55	1.69	1.47	3.33
Caa-C	-	9.04	8.88	7.25	17.73
		Horizon: 365 days			
Aaa-Aa	0.01	0.01	0.01	0.00	0.05
A	0.06	0.06	0.04	0.02	0.13
Baa	0.17	0.16	0.16	0.13	0.34
Ba	1.11	1.08	1.19	1.08	1.91
B	3.90	3.78	4.01	3.57	7.31
Caa-C	15.89	15.46	15.37	12.63	29.49
		Horizon: 730 days			
Aaa-Aa	0.04	0.04	0.03	0.02	0.05
A	0.20	0.19	0.16	0.14	0.25
Baa	0.50	0.47	0.47	0.43	0.66
Ba	3.07	2.94	3.23	3.15	3.76
B	9.27	8.72	9.16	8.67	12.81
Caa-C	27.00	25.13	25.18	21.93	41.37

Table 2: Default Frequencies of Two-Year Corporate Bonds and Pseudo-Bonds

Panel A of this table reports *ex post* default frequencies of corporate bonds with Moody's credit ratings reported in the first column. The mean is the aggregate average, and confidence intervals (C.I.) are the 2.5% and 97.5% bands of the computed frequencies. The last two columns report default frequencies during NBER booms and recessions, respectively. Panel B reports the results of our credit rating system for pseudo-bonds. Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity) during booms and recessions. The *ex ante* default probabilities of pseudo-bonds are computed by inverting the empirical distribution of the residuals from a simple GARCH(1,1) model of asset returns with expected growth obtained from predictive regressions. The first two columns of Panel B reports the *ex ante* average default probabilities for bonds in each pseudo credit rating category. The next three columns show the actual *ex post* default frequency of the pseudo-bonds across the pseudo credit ratings, and their confidence intervals. The *ex post* default frequency is computed as the fraction of times the two-year return (excluding dividends) on S&P500 index falls below the given moneyness of the pseudo-bonds in each portfolio. The last two columns report the average moneyness of the options $\overline{K/S}$, and the average maturity $\overline{\tau}$, in days. The sample is 1970 to 2013.

Panel A: Corporate Bonds

Credit	Historical Default Frequencies				
Rating	Mean	C.I.(2.5%)	C.I.(97.5%)	Boom	Recession
Aaa/Aa	0.03	0.02	0.03	0.02	0.05
A/Baa	0.31	0.30	0.32	0.28	0.47
Ba	3.23	2.84	3.63	3.15	3.76
B	9.16	5.90	12.42	8.67	12.81
Caa-	25.18	0.00	82.93	21.93	41.37

Panel B: Pseudo-Bonds

Credit	*Ex ante* Default Probability		*Ex post* Default Frequency				
Rating	Boom	Recession	Mean	C.I.(2.5%)	C.I.(97.5%)	$\overline{K/S}$	$\overline{\tau}$
Aaa/Aa	0.02	0.07	0.00	0.00	0.00	0.43	586
A/Baa	0.99	1.46	1.14	0.00	2.94	0.60	583
Ba	3.55	4.88	3.41	0.00	6.94	0.72	622
B	9.71	18.45	10.23	0.74	19.72	0.83	643
Caa-	23.57	44.43	21.02	7.06	34.99	0.93	649

Table 3: Two-Year Pseudo and Corporate Bonds: 1996 - 2013

Credit spreads and summary statistics of pseudo-bonds (Panel A), corporate bonds (Panel B), and the lognormal Merton model (Panel C). Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity). The default probability for pseudo-bonds are computed by inverting the empirical distribution of residuals from a simple GARCH model of asset returns with expected growth obtained from predictive regressions. Corporate bonds are non-callable corporate bonds with time to maturity between 1.5 and 2.5 years. The lognormal Merton model's statistics are based on Monte Carlo simulations to replicate the time-variation in volatility and predictability. The sample period is January 1996 to August 2013.

Credit Rating	Prob. Of Default	Avg K/S	Credit Spread	Monthly Returns in Excess of T-bill (%)				
				Mean	Std Ratio	Sharpe	Skew Kurtosis	Excess
Panel A: Pseudo-Bonds								
Aaa/Aa	0.03	0.43	53	0.14	0.65	0.22	0.37	5.57
A/Baa	0.31	0.60	131	0.26	0.86	0.30	0.05	4.59
Ba	3.23	0.72	236	0.28	1.41	0.20	-2.07	15.08
B	9.16	0.83	360	0.34	1.80	0.19	-1.26	7.79
Caa-	25.18	0.93	515	0.36	2.31	0.16	-1.18	6.09
Panel B: Corporate Bonds								
Aaa/Aa	0.03		68	0.11	0.88	0.12	-1.01	26.34
A/Baa	0.31		133	0.11	1.39	0.08	-7.19	78.35
Ba	3.23		397	0.58	2.22	0.26	0.04	17.96
B	9.16		620	0.57	2.99	0.19	-3.00	28.31
Caa-	25.18		1213	0.83	3.96	0.21	0.93	7.21
Panel C: Lognormal Merton Model								
Aaa/Aa	0.03	0.52	0	0.07	0.48	0.15	0.38	1.54
A/Baa	0.31	0.60	4	0.07	0.48	0.15	0.39	1.46
Ba	3.23	0.72	30	0.05	0.60	0.08	-0.16	0.92
B	9.16	0.81	86	0.04	0.92	0.04	-0.51	1.61
Caa-	25.18	0.92	249	0.02	1.64	0.01	-0.43	1.78

Table 4: Two-Year Pseudo and Corporate Bonds: Subsamples

Credit spreads and summary statistics of pseudo-bonds (Panel A and B), and corporate bonds (Panel C and D). Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity). The default probability for pseudo-bonds are computed by inverting the empirical distribution of residuals from a simple GARCH(1,1) model of asset returns with expected growth obtained from predictive regressions. Corporate bonds are non-callable corporate bonds with time to maturity between 1.5 and 2.5 years.

Credit Rating	Prob. Of Default	Avg K/S	Credit Spread	Monthly Returns in Excess of T-bill (%)				
				Mean	Std	Sharpe Ratio	Skew	Ex. Kurt
Panel A: Pseudo-Bonds: January 1996 - December 2004								
Aaa/Aa	0.03	0.45	38	0.13	0.51	0.25	3.28	13.89
A/Baa	0.31	0.63	124	0.25	0.81	0.31	-0.56	7.70
Ba	3.23	0.73	209	0.31	1.11	0.28	-0.72	4.15
B	9.16	0.82	301	0.33	1.44	0.23	-0.76	3.17
Caa-	25.18	0.92	443	0.36	1.88	0.19	-0.70	1.96
Panel B: Pseudo-Bonds: January 2005 - August 2013								
Aaa/Aa	0.03	0.42	61	0.15	0.70	0.21	-0.19	3.92
A/Baa	0.31	0.58	139	0.27	0.91	0.30	0.50	2.31
Ba	3.23	0.71	264	0.24	1.67	0.14	-2.32	14.41
B	9.16	0.84	423	0.35	2.13	0.16	-1.35	7.21
Caa-	25.18	0.95	590	0.37	2.70	0.14	-1.29	5.89
Panel C: Corporate Bonds: January 1996 - December 2004								
Aaa/Aa	0.03		71	0.11	0.56	0.19	-0.29	1.78
A/Baa	0.31		132	0.00	1.85	0.00	-5.97	47.25
Ba	3.23		446	0.60	2.91	0.21	-0.12	11.13
B	9.16		749	0.53	4.68	0.11	-2.17	11.30
Caa-	25.18		1292	0.64	5.36	0.12	2.07	7.74
Panel D: Corporate Bonds: January 2005 - August 2013								
Aaa/Aa	0.03		65	0.11	1.11	0.10	-0.97	19.88
A/Baa	0.31		134	0.22	0.64	0.34	0.70	8.95
Ba	3.23		352	0.56	1.35	0.42	1.27	19.55
B	9.16		516	0.60	1.22	0.49	1.49	7.94
Caa-	25.18		1182	0.89	3.48	0.26	-0.33	2.80

Table 5: Returns on Two-Year Pseudo-Bonds and Corporate Bonds

This table reports the results of the regression specification

$$R^e_{B,t} = \alpha + \beta\, R^e_{i,t} + \epsilon_t$$

where $R^e_{B,t}$ is the excess return of pseudo-bonds (Panels A and B), corporate bonds (Panel C), and simulated bonds from the Merton model (Panel D and E). The explanatory variable $R^e_{i,t}$ is the excess return on assets ($i = A$, Panel A and D) or equity ($i = E$, Panels B, C, and E). In all cases, bonds are sorted monthly into credit rating portfolios, and portfolio returns in excess of the U.S. Treasury bill rate are computed over the following month. The sample is January 1996 to August 2013.

Credit Rating	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
			Panel A: Pseudo-Bonds on Assets				
Aaa/Aa	0.14	(3.50)	0.12	(2.65)	0.07	(4.04)	0.19
A/Baa	0.26	(4.33)	0.13	(2.31)	0.17	(8.88)	0.53
Ba	0.28	(2.80)	0.16	(2.60)	0.27	(13.44)	0.68
B	0.34	(2.83)	0.18	(2.62)	0.37	(18.64)	0.77
Caa-	0.36	(2.25)	0.18	(2.62)	0.48	(23.32)	0.83
			Panel B: Pseudo-Bonds on Equities				
Aaa/Aa	0.14	(3.50)	0.13	(2.75)	0.03	(3.41)	0.14
A/Baa	0.26	(4.33)	0.16	(2.64)	0.07	(6.82)	0.41
Ba	0.28	(2.80)	0.22	(2.83)	0.09	(9.06)	0.52
B	0.34	(2.83)	0.28	(2.93)	0.10	(10.30)	0.55
Caa-	0.36	(2.25)	0.34	(2.89)	0.10	(11.27)	0.57
			Panel C: Corporate Bonds on Equities				
Aaa/Aa	0.11	(1.76)	0.11	(1.03)	0.02	(0.67)	0.02
A/Baa	0.11	(1.12)	0.19	(3.11)	0.05	(2.91)	0.15
Ba	0.58	(3.69)	0.44	(4.49)	0.09	(3.57)	0.28
B	0.57	(2.43)	0.59	(3.85)	0.05	(3.59)	0.11
Caa-	0.83	(2.32)	0.60	(2.16)	0.14	(5.42)	0.40
			Panel D: Lognormal Merton Model Bonds on Assets				
Aaa/Aa	0.07	(2.33)	0.08	(1.85)	0.01	(0.70)	0.00
A/Baa	0.07	(2.33)	0.07	(1.78)	0.01	(1.76)	0.01
Ba	0.05	(1.25)	0.07	(1.75)	0.07	(7.24)	0.24
B	0.04	(0.67)	0.07	(1.76)	0.16	(9.77)	0.52
Caa-	0.02	(0.18)	0.09	(1.63)	0.34	(11.13)	0.74
			Panel E: Lognormal Merton Model Bonds on Equities				
Aaa/Aa	0.07	(2.33)	0.07	(1.85)	0.00	(-0.13)	0.00
A/Baa	0.07	(2.33)	0.07	(1.77)	0.00	(0.84)	0.00
Ba	0.05	(1.25)	0.06	(1.70)	0.02	(6.30)	0.17
B	0.04	(0.67)	0.06	(1.55)	0.03	(9.26)	0.40
Caa-	0.02	(0.18)	0.05	(0.91)	0.05	(7.54)	0.54

Table 6: Returns on Two-Year Pseudo-Bonds and Corporate Bonds. Subsamples

This table reports the results of the regression specification

$$R^e_{B,t} = \alpha + \beta\, R^e_{i,t} + \epsilon_t; \qquad i = A,\ E$$

where $R^e_{B,t}$ is the excess return of pseudo-bonds (Panels A -D), or corporate bonds (Panel E and F). The explanatory variable $R^e_{i,t}$ is the excess return on assets (Panels A and B) or equity (Panels C - F). Bonds are sorted monthly into credit rating portfolios, and portfolio returns in excess of the U.S. Treasury bill rate are computed over the following month.

Credit Rating	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Panel A: Pseudo-Bonds on Assets: January 1996 - December 2004							
Aaa/Aa	0.13	(3.25)	0.09	(1.62)	0.06	(2.40)	0.20
A/Baa	0.25	(4.17)	0.07	(0.78)	0.19	(5.53)	0.63
Ba	0.31	(3.88)	0.16	(1.70)	0.26	(8.67)	0.73
B	0.33	(3.30)	0.14	(1.32)	0.33	(9.35)	0.77
Caa-	0.36	(2.77)	0.20	(1.91)	0.41	(12.66)	0.84
Panel B: Pseudo-Bonds on Equities: January 1996 - December 2004							
Aaa/Aa	0.13	(3.25)	0.10	(1.64)	0.03	(2.48)	0.17
A/Baa	0.25	(4.17)	0.11	(1.09)	0.08	(4.60)	0.55
Ba	0.31	(3.88)	0.19	(1.67)	0.10	(6.19)	0.64
B	0.33	(3.30)	0.17	(1.25)	0.10	(6.03)	0.65
Caa-	0.36	(2.77)	0.26	(1.58)	0.10	(6.23)	0.66
Panel C: Pseudo-Bonds on Assets: January 2005 - August 2013							
Aaa/Aa	0.15	(3.00)	0.13	(2.17)	0.07	(3.30)	0.19
A/Baa	0.27	(4.50)	0.16	(2.28)	0.17	(7.50)	0.48
Ba	0.24	(2.18)	0.16	(2.00)	0.27	(10.28)	0.66
B	0.35	(2.33)	0.19	(2.23)	0.40	(15.55)	0.77
Caa-	0.37	(1.95)	0.17	(1.95)	0.53	(20.16)	0.85
Panel D: Pseudo-Bonds on Equities: January 2005 - August 2013							
Aaa/Aa	0.15	(3.00)	0.15	(2.27)	0.04	(2.59)	0.13
A/Baa	0.27	(4.50)	0.19	(2.47)	0.07	(5.45)	0.34
Ba	0.24	(2.18)	0.23	(2.32)	0.09	(6.93)	0.47
B	0.35	(2.33)	0.34	(2.66)	0.10	(8.48)	0.51
Caa-	0.37	(1.95)	0.37	(2.43)	0.10	(9.43)	0.55
Panel E: Corporate Bonds on Equities: January 1996 - December 2004							
Aaa/Aa	0.11	(1.94)	0.13	(1.09)	0.01	(0.51)	0.01
A/Baa	0.00	(0.00)	0.26	(1.68)	0.00	(-0.13)	0.00
Ba	0.60	(2.01)	0.21	(0.92)	0.15	(2.63)	0.22
B	0.53	(0.87)	1.03	(1.59)	-0.01	(-0.26)	0.00
Caa-	0.64	(0.63)	0.69	(1.05)	0.22	(3.85)	0.64
Panel F: Corporate Bonds on Equities: January 2005 - August 2013							
Aaa/Aa	0.11	(0.99)	0.11	(0.87)	0.02	(0.64)	0.02
A/Baa	0.22	(3.42)	0.19	(2.95)	0.06	(3.77)	0.23
Ba	0.56	(4.26)	0.49	(4.91)	0.08	(2.96)	0.33
B	0.60	(4.94)	0.51	(5.15)	0.06	(4.28)	0.34
Caa-	0.89	(2.49)	0.64	(2.07)	0.12	(5.88)	0.32

Table 7: The Term Structure of Credit Spreads

This table reports the term structure of credit spreads for pseudo-bonds (Panel A), corporate bonds (Panel B), and the lognormal Merton model (Panel C). Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity). The pseudo-bonds default probability is computed by inverting the empirical distribution of residuals from a simple GARCH model of asset returns with expected growth obtained from predictive regressions. For very short maturity there is not enough granularity in strike prices to compute pseudo-bonds for high credit ratings and thus we only report "investment grade" (IG) pseudo-bonds. Corporate bonds' credit spreads for maturities between 30 and 91 days are based on commercial paper rates. Corporate bonds' credit spreads for maturity between 183 and 730 days are based non-callable corporate bonds. The Merton model's statistics are based on Monte Carlo simulations to replicate the time-variation in volatility and in predictability. Credit spreads are in basis points. The sample is January 1996 to August 2013.

Credit	Days to Maturity				
Rating	30	91	183	365	730
			Panel A: Pseudo-Bonds		
IG	78	64	69	76	109
Aaa/Aa			51	43	53
A/Baa			107	98	131
Ba	165	128	169	186	236
B	287	261	287	313	360
Caa-	501	493	472	464	515
			Panel B: Corporate Bonds		
IG	62	60	83	127	123
Aaa/Aa	32	30	42	68	68
A/Baa	69	67	92	139	133
Ba			232	329	397
B			276	517	620
Caa-			1225	1264	1213
			Panel C: Lognormal Merton Model		
IG	0	0	0	0	0
Aaa/Aa	0	0	0	0	0
A/Baa	0	0	0	1	4
Ba	1	2	5	11	30
B	4	10	19	39	86
Caa-	41	77	113	166	249

Table 8: Assets as Common Stock of Individual Firms in the S&P500 Index

This table reports our empirical results when pseudo-firms have assets that comprise shares of individual stocks in the S&P 500 index. For each credit rating, the first three columns report the target default frequencies of real corporate bonds, and the confidence intervals. The next three columns report the *ex post* default frequencies of our pseudo-bonds, and their confidence interval. The *ex post* default frequency is computed as the fraction of times the two-year return of individual stocks fall below the average moneyness for each credit rating between 1970 and 2013. The credit rating of each pseudo-bond is assigned every month according to its *ex ante* default probability over the next two years. The latter is computed non-parametrically for each firm and for each time t by exploiting the empirical distribution of normalized shocks of all the firms in the S&P500 index prior to t, to avoid survivorship bias. Confidence intervals use standard errors that are corrected for the series correlation induced by overlapping observations. The last two columns report the average moneyness $\overline{K/S}$ and the average maturity $\overline{\tau}$ of the pseudo-bonds.

Panel B reports summary statistics of the pseudo-bond portfolios. Column 5 reports the equal weighted average credit spread of pseudo-bonds in each credit rating category, while the next several columns report summary statistics of portfolio bonds' excess returns. For each credit rating, Panel C reports the time-series regression of the pseudo-bond portfolio excess returns on the average excess returns of pseudo-assets (i.e. stocks of underlying individual firms). For each credit rating, Panel D reports the time-series regression of the pseudo-bond portfolio excess returns on the average excess returns of pseudo-equity (i.e. call options of the underlying individual firms).

Panel A: Summary Statistics

	Target Probability of Default			*Ex post* Probability of Default				
	Historical Defaults 1970-2013			Stock Returns 1970-2013			$\overline{K/S}$	$\overline{\tau}$
	Target PD	C.I. (2.5%)	C.I. (97.5%)	PD	C.I. (2.5%)	C.I. (97.5%)		
Aaa/Aa	0.03	0.02	0.03	0.19	0.00	0.42	0.41	661
A/Baa	0.31	0.30	0.32	0.74	0.00	1.52	0.35	603
Ba	3.23	2.84	3.63	3.81	0.78	6.84	0.44	625
B	9.16	5.90	12.42	8.63	3.67	13.60	0.58	651
Caa-	25.18	0.00	82.93	22.26	15.96	28.56	0.79	675

Panel B: Average Credit Spreads and Monthly Returns' Summary Statistics

	Prob. of Default	Credit Spread	Monthly Returns in Excess of T-bill (%)				
			Mean	Std	SR	Skew	Ex. Kurt
Aaa/Aa	0.03	139	0.02	1.39	0.01	-4.17	31.38
A/Baa	0.31	151	0.16	0.93	0.17	0.01	3.78
Ba	3.23	201	0.22	1.08	0.21	-0.85	8.53
B	9.16	344	0.25	1.53	0.17	-1.83	10.22
Caa-	25.18	669	0.48	2.11	0.23	-0.93	3.41

Panel C: Regression of Pseudo-Bonds Excess Returns on Assets's Excess Returns

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	0.02	(0.20)	-0.07	(-0.51)	0.11	(3.10)	0.27
A/Baa	0.16	(2.67)	0.10	(1.90)	0.07	(8.33)	0.35
Ba	0.22	(3.14)	0.12	(2.43)	0.13	(9.72)	0.60
B	0.25	(2.27)	0.07	(0.98)	0.24	(10.53)	0.68
Caa-	0.48	(3.43)	0.09	(1.27)	0.40	(18.90)	0.79

Panel D: Regression of Pseudo-Bonds Excess Returns on Pseudo-Equitiy' Excess Returns

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	0.02	(0.20)	0.02	(0.20)	0.01	(0.45)	0.01
A/Baa	0.16	(2.67)	0.15	(2.31)	0.03	(1.93)	0.16
Ba	0.22	(3.14)	0.27	(4.88)	0.06	(5.69)	0.33
B	0.25	(2.27)	0.26	(4.03)	0.13	(9.90)	0.61
Caa-	0.48	(3.43)	0.41	(4.75)	0.18	(15.45)	0.67

Table 9: Time Series Regression on Fama French Five Factors

This table reports the result of the following time-series regression for each bond portfolio:

$$R^e_{i,t} = \alpha_i + \beta_i RMRF_t + s_i SMB_t + h_i HML_t + g_i TERM_t + d_i DEF_t + \epsilon_{i,t},$$

where $R^e_{i,t}$ is the excess return on portfolio i, $RMRF_t$ is the excess return on the value-weighted stock market portfolio, SMB_t is the size factor of Fama and French (1993), HML_t is the value factor, $TERM_t$ is the return on the long-term Treasury bonds in excess of T-bill rates, DEF_t is the return on the aggregate long-term corporate bond market portfolio from Ibbotson in excess of the return on the long-term Treasury bonds. $\bar{R}^2$ is adjusted R-squared. The sample is monthly from January 1996 to August 2013.

	α_i	$RMRF_t$	SMB_t	HML_t	$TERM_t$	DEF_t	$\bar{R}^2$
Panel A: Pseudo-Bonds (S&P500 Index Options)							
Aaa/Aa	0.17	0.09	-0.03	0.01	0.03	-0.02	0.26
	(2.58)	(4.06)	(-1.24)	(0.91)	(1.95)	(-0.50)	
A/Baa	0.25	0.11	0.00	-0.01	0.04	0.12	0.48
	(4.07)	(8.25)	(-0.28)	(-0.63)	(2.49)	(3.12)	
Ba	0.22	0.23	0.00	0.03	0.03	0.09	0.62
	(2.81)	(6.37)	(-0.25)	(0.97)	(1.62)	(2.23)	
B	0.29	0.31	-0.01	0.05	0.06	0.17	0.75
	(3.54)	(9.65)	(-0.49)	(1.91)	(3.01)	(3.60)	
Caa/C	0.23	0.42	-0.01	0.08	0.05	0.19	0.82
	(2.73)	(12.36)	(-0.59)	(2.80)	(2.52)	(3.53)	
Panel B: Pseudo-Bonds (Individual Stock Options)							
Aaa/Aa	-0.10	0.19	0.06	0.22	0.04	-0.25	0.18
	(-0.39)	(2.44)	(0.88)	(1.53)	(0.94)	(-1.60)	
A/Baa	0.21	0.09	-0.05	0.04	0.05	0.07	0.24
	(2.84)	(4.26)	(-2.10)	(1.63)	(2.14)	(1.50)	
Ba	0.25	0.13	0.06	0.00	0.06	0.10	0.51
	(3.48)	(5.47)	(2.63)	(0.15)	(2.91)	(2.64)	
B	0.24	0.23	0.05	0.06	0.07	0.18	0.69
	(2.90)	(6.78)	(3.15)	(1.84)	(3.02)	(3.78)	
Caa/C	0.37	0.36	0.06	0.11	0.06	0.24	0.81
	(4.19)	(13.68)	(3.14)	(3.71)	(2.46)	(4.78)	
Panel C: Corporate Bonds							
Aaa/Aa	0.49	-0.06	-0.03	-0.03	0.11	0.25	0.37
	(4.88)	(-2.14)	(-1.76)	(-1.61)	(4.69)	(3.03)	
A/Baa	0.33	0.04	0.02	0.01	0.12	0.21	0.09
	(2.61)	(1.12)	(0.49)	(0.43)	(2.77)	(2.62)	
Ba	0.72	0.04	0.07	0.16	0.07	0.12	0.08
	(3.59)	(0.66)	(1.25)	(1.63)	(1.72)	(1.93)	
B	1.01	0.05	-0.11	0.12	0.12	0.21	0.01
	(3.29)	(0.84)	(-0.90)	(1.26)	(1.69)	(1.77)	
Caa/C	1.13	0.30	0.16	0.14	0.03	0.03	0.15
	(1.76)	(3.05)	(1.06)	(1.08)	(0.31)	(0.11)	

Table 10: Time Series Regression on Risk Factors

This table reports the result of the following time-series regression for each bond portfolio:

$$R^e_{i,t} = \alpha_i + \beta_i\ RMRF_t + c_i\ TERM_t + d_i\ DEF_t + e_i\ dVIXSQ_t + f_i\ dTED_t + g_i\ Tail_t + \epsilon_{i,t},$$

where $R^e_{i,t}$ is the excess return on portfolio i, $RMRF_t$ is the excess return on the value-weighted stock market portfolio, $TERM_t$ is the return on the long-term Treasury bonds in excess of T-bill rates, DEF_t is the return on the aggregate long-term corporate bond market portfolio from Ibbotson in excess of the return on the long-term Treasury bonds, $dVIXSQ_t$ is the return on the square of the VIX index, in excess of risk free rate, and $dTED_t$ is the change in the TED spread. $Tail_t$ is the "tail" risk factor of Jiang and Kelly (2014). $\bar{R}^2$ is adjusted R-squared. The sample is monthly from January 1996 to August 2013.

	α_i	$RMRF_t$	$TERM_t$	DEF_t	$dVIXSQ_t$	$dTED_t$	$Tail$	$\bar{R}^2$
Panel A: Pseudo-Bonds (S&P500 Index Options)								
Aaa/Aa	0.19	0.07	0.04	0.01	-0.07	0.39	0.01	0.26
	(2.90)	(3.73)	(2.17)	(0.22)	(-0.60)	(1.95)	(0.55)	
A/Baa	0.28	0.09	0.03	0.09	-0.53	-0.20	0.02	0.52
	(4.95)	(7.39)	(2.31)	(2.48)	(-3.50)	(-0.82)	(2.53)	
Ba	0.31	0.18	0.03	0.08	-0.78	0.47	0.02	0.65
	(4.41)	(7.10)	(1.49)	(2.13)	(-4.07)	(1.12)	(1.92)	
B	0.38	0.25	0.06	0.15	-0.85	0.46	0.03	0.76
	(5.31)	(9.95)	(2.78)	(3.16)	(-4.16)	(1.13)	(2.22)	
Caa/C	0.34	0.36	0.05	0.18	-0.83	0.63	0.03	0.82
	(4.24)	(12.04)	(2.28)	(3.26)	(-3.50)	(1.44)	(1.79)	
Panel B: Pseudo-Bonds (Individual Stock Options)								
Aaa/Aa	0.03	0.16	0.04	-0.05	0.28	0.81	0.05	0.10
	(0.12)	(1.97)	(1.16)	(-0.40)	(0.66)	(1.44)	(0.82)	
A/Baa	0.25	0.06	0.05	0.06	-0.37	0.14	0.03	0.22
	(3.31)	(2.20)	(2.31)	(1.36)	(-1.55)	(0.44)	(1.25)	
Ba	0.29	0.12	0.05	0.08	-0.39	-0.19	-0.02	0.49
	(4.17)	(5.86)	(2.45)	(2.33)	(-2.29)	(-0.55)	(-1.32)	
B	0.35	0.18	0.07	0.18	-0.78	0.26	-0.02	0.70
	(4.42)	(6.84)	(2.68)	(4.18)	(-3.92)	(0.64)	(-1.35)	
Caa/C	0.51	0.29	0.06	0.24	-0.95	0.37	-0.01	0.80
	(5.75)	(10.75)	(2.29)	(4.40)	(-4.60)	(1.05)	(-0.64)	
Panel C: Corporate Bonds								
Aaa/Aa	0.33	-0.05	0.08	0.13	-0.52	-1.28	0.02	0.41
	(4.36)	(-2.37)	(4.19)	(2.54)	(-2.24)	(-3.02)	(1.72)	
A/Baa	0.27	0.05	0.10	0.14	0.22	-0.72	0.00	0.1
	(2.44)	(1.01)	(3.19)	(4.44)	(0.41)	(-0.92)	(-0.14)	
Ba	0.78	0.03	0.07	0.17	-0.75	0.28	0.01	0.04
	(4.31)	(0.44)	(2.08)	(3.42)	(-1.89)	(0.40)	(0.11)	
B	0.78	0.03	0.12	0.26	-0.17	0.35	0.19	0.03
	(3.03)	(0.70)	(2.48)	(2.82)	(-0.43)	(0.66)	(1.54)	
Caa/C	0.86	0.23	0.14	0.42	-1.02	2.23	-0.44	0.2
	(2.01)	(3.19)	(1.72)	(3.60)	(-1.23)	(1.97)	(-2.21)	

Table 11: The Liquidity of Pseudo-Bonds and Corporate Bonds

Panels A and B show the credit spreads, the average monthly returns in excess of T-bills and illiquidity measures of the pseudo-bonds based on options on the SPX and individual stocks, respectively. The bid-ask spread for pseudo-bond i in month t is computed by $(B_{i,t}^{Ask} - B_{i,t}^{Bid})/B_{i,t}^{Mid}$. The portfolio bid-ask spread is the kernel-weighted average of pseudo-bonds, where the kernel is the same as the one used for returns. The Roll (1984) measure for pseudo-bond i in month t is computed by $2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Bid\to Ask}, \Delta p_{i,t,d+1}^{Ask\to Bid})}$ using the daily price observations. We compute the Roll measure for all pseudo-bonds that have more than 10 return observations in a month. The portfolio-level Roll measure is computed by the kernel-weighted average of the pseudo-bonds for which we can compute the Roll measure.

Panel C shows the same statistics for the corporate bonds. The Roll measure for corporate bond i in month t is computed by $2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Transaction}, \Delta p_{i,t,d+1}^{Transaction})}$ using the daily price observations. We compute the Roll measure for all corporate bonds that have more than 10 return observations in a month. As in credit spreads and excess returns, the Roll measure for a portfolio is the value-weighted average of the corporate bonds for which we can compute the Roll measure.

Credit Rating	Credit Spread (bps)	Mean Returns (%)	Bid-Ask Spread (%)	Roll Measure (%)
Panel A: Pseudo-Bonds (S&P 500 options)				
Aaa/Aa	53	0.14	0.25	0.16
A/Baa	131	0.26	0.25	0.17
Ba	236	0.28	0.28	0.24
B	360	0.34	0.28	0.28
Caa-	515	0.36	0.28	0.35
Panel B: Pseudo-Bonds (Individual Firms)				
Aaa/Aa	139	0.02	1.33	0.59
A/Baa	151	0.16	1.42	1.39
Ba	201	0.22	1.54	1.27
B	344	0.25	1.68	1.21
Caa-	669	0.48	1.75	1.23
Panel B: Corporate Bonds				
Aaa/Aa	68	0.11		0.51
A/Baa	133	0.11		1.03
Ba	397	0.58		1.78
B	620	0.57		2.04
Caa-	1213	0.83		3.00

Table 12: Sorting Frequency and Pseudo-Bond Returns

Credit spreads and summary statistics of pseudo-bonds (Panel A), corporate bonds (Panel B), and lognormal Merton model (Panel C). Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity). The pseudo-bonds default probability is computed by inverting the empirical distribution of residuals from a simple GARCH model of asset returns with expected growth obtained from predictive regressions. The sample is January 1996 to August 2013.

Credit Rating	Prob. Of Default	Avg K/S	Credit Spread	Monthly Returns in Excess of T-bill (%)				
				Mean	Std	Sharpe Ratio	Skew	Ex. Kurt
Panel A: Sort Every 3 Months								
Aaa/Aa	0.03	0.43	54	0.12	0.61	0.20	0.25	3.75
A/Baa	0.31	0.60	132	0.18	1.11	0.16	-3.83	37.10
Ba	3.23	0.73	246	0.25	1.50	0.17	-2.39	18.98
B	9.16	0.83	366	0.35	1.91	0.18	-1.81	13.07
Caa-	25.18	0.93	529	0.36	2.41	0.15	-1.23	7.12
Panel B: Sort Every 6 Months								
Aaa/Aa	0.03	0.43	56	0.11	0.62	0.18	0.26	4.09
A/Baa	0.31	0.60	127	0.16	1.10	0.15	-4.12	40.41
Ba	3.23	0.72	244	0.21	1.52	0.14	-2.53	18.62
B	9.16	0.83	374	0.28	1.95	0.14	-1.93	12.25
Caa-	25.18	0.93	704	0.30	2.48	0.12	-1.38	6.97
Panel C: Sort Every 12 Months								
Aaa/Aa	0.03	0.43	54	0.10	0.51	0.20	2.00	10.05
A/Baa	0.31	0.60	117	0.19	0.72	0.26	0.95	7.25
Ba	3.23	0.72	273	0.12	1.61	0.07	-2.46	17.30
B	9.16	0.82	362	0.14	1.98	0.07	-1.93	13.01
Caa-	25.18	0.92	826	0.17	2.62	0.06	-1.78	10.42

Table 13: Two-Year Junior Bonds: January 1996 - August 2013

Panel A shows the pseudo- junior bonds issued by the firm with a certain senior credit rating. To construct these pseudo-bonds, we first sort pseudo-bonds on the S&P500 index options into the rating-based portfolios as in Table 2. We then compute the average price of the pseudo-bonds (denoted $B_{r,t}$ for credit rating r) and the average strike price (denoted $K_{r,t}$) for each portfolio. Then the price of the pseudo- junior bond with the rating $r2$, issued by the firm with the senior rating $r1$ is $B^J_{r2,t} = B_{r2,t} - B_{r1,t}$, while the face value of the junior bond is given by $K^J_{r2,t} = K_{r2,t} - K_{r1,t}$. We compute the continuous-compounding yield by $y^{cc,t} = -log(B^J_{r2,t}/K^J_{r2,t})/\tau$, and convert it into the semi-annual compounding basis to derive yield spreads. The return on the pseudo-bonds is given by $R^J_{i,t+1} = w^J_t R_{r2,t+1} + (1-w^J_t)R_{r1,t+1}$, where $w^J_t \equiv B_{r2,t}/B^J_{r2,t} \geq 1$.

Panel B shows the corporate junior bonds issued by the firm with a certain senior rating. We identify the pairs of the bonds issued by the same firm but with the different credit ratings by comparing the bonds with the same first 6-digit CUSIP. If a firm has bonds with more than 2 credit ratings, we treat the bond with the highest rating as senior bonds, and the rest as junior bonds. To deal with the smaller sample size, we use all the bonds with the maturity between 1.5 years and 2.5 years to obtain 2-year bond returns and spreads.

Credit Rating Senior	Credit Rating Junior	Prob. Of Default	Credit Spread Junior	Monthly Returns in Excess of T-bill (%)				
				Mean	Std	Sharpe Ratio	Skew	Ex. Kurt
Panel A: Pseudo-Bonds								
Aaa/Aa	A/Baa	0.31	218	0.39	1.43	0.27	0.15	3.43
	Ba	3.23	405	0.35	2.51	0.14	-3.27	23.05
	B	9.16	643	0.54	3.01	0.18	-2.19	12.94
	Caa/C	25.18	987	0.69	3.66	0.19	-1.70	8.69
A/Baa	Ba	3.23	432	0.63	2.69	0.23	-1.46	9.54
	B	9.16	881	0.84	3.46	0.24	-1.17	5.47
	Caa/C	25.18	1490	0.94	4.79	0.20	-1.13	3.70
Panel B: Corporate Bonds								
Aaa/Aa	A/Baa	0.31	216	0.91	5.40	0.17	5.67	35.97
A/Baa	Ba	3.23	360	0.40	3.00	0.13	2.33	20.83

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Appendix

This appendix contains the proofs and additional tables, referred to in the main body of the paper. [Proofs TBA]

Table A1: Default Frequencies of Short-horizon Corporate Bonds and Pseudo-Bonds

The left-hand-side of this table reports *ex post* default frequencies of corporate bonds with Moody's credit ratings reported in the first column across maturities. The mean is the aggregate average, and confidence intervals (C.I.) are the 2.5% and 97.5% bands of the computed frequencies. Columns 5 and 6 report default frequencies during NBER booms and recessions, respectively. The righ-hand-side of this table reports the results of our credit rating methodology for pseudo-bonds. Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity) during booms and recession. The pseudo-bonds *ex ante* default probability is computed by inverting the empirical distribution of the residuals from a simple GARCH model of asset returns with expected growth obtained from predictive regressions. The first two columns on the right-hand-side of the table report the *ex ante* average default probabilities for bonds in booms and recessions, respectively, for each pseudo credit rating. The next three columns show the actual *ex post* default frequency of the pseudo-bonds across the pseudo credit ratings, and their confidence intervals. The *ex post* default frequency is computed as the fraction of times the S&P500 return (exclusing dividends) drop below the portfolio moneyness in the sample. The last two columns collect the average leverage K/A of pseudo-bonds, and their average time to maturity (days). The sample is 1970 to 2013.

	Corporate Bonds					Pseudo-Bonds						
	Historical Default Frequencies					*Ex ante* Def. Prob.		*Ex post* Default Frequency			$\overline{K/S}$	$\overline{\tau}$
	Mean	C.I. (2.5%)	C.I. (97.5%)	Boom	Bust	Boom	Bust	Mean	C.I. (2.5%)	C.I. (97.5%)		
Target Maturity: 30 days												
IG	0.00	0.00	0.01	0.00	0.01	0.01	0.02	0.19	0.00	0.57	0.74	55
Ba	0.05	0.00	0.12	0.04	0.11	0.10	0.19	0.38	0.00	0.91	0.80	45
B	0.22	0.00	0.44	0.19	0.43	0.33	0.97	1.33	0.33	2.32	0.85	39
Caa-	1.89	0.00	3.84	1.61	3.47	1.59	3.79	2.65	1.25	4.05	0.90	39
Target Maturity: 91 days												
IG	0.01	0.00	0.02	0.01	0.03	0.01	0.08	0.00	0.00	0.00	0.65	109
Ba	0.19	0.11	0.27	0.16	0.38	0.22	0.73	0.57	0.00	1.22	0.73	97
B	0.75	0.50	1.00	0.65	1.48	1.17	3.06	1.89	0.00	3.79	0.81	82
Caa-	4.90	0.00	10.64	4.07	9.51	4.22	9.99	7.58	3.76	11.39	0.88	76
Target Maturity: 183 days												
Aaa/Aa	0.00	0.00	0.01	0.00	0.03	0.04	0.05	0.19	0.00	0.56	0.57	194
A/Baa	0.03	0.02	0.05	0.02	0.09	0.16	0.40	1.70	0.00	4.08	0.67	183
Ba	0.47	0.39	0.55	0.40	0.91	0.47	1.43	2.08	0.00	4.78	0.72	186
B	1.69	1.25	2.12	1.47	3.33	2.32	6.36	2.84	0.00	6.07	0.79	180
Caa-	8.88	0.00	22.46	7.25	17.73	7.50	18.28	9.28	3.20	15.36	0.86	179
Target Maturity: 365 days												
Aaa/Aa	0.01	0.00	0.02	0.00	0.05	0.01	0.06	0.19	0.00	0.56	0.47	353
A/Baa	0.10	0.09	0.11	0.08	0.24	0.30	0.81	3.41	0.00	7.44	0.59	339
Ba	1.19	1.08	1.31	1.08	1.91	1.35	2.74	3.98	0.00	8.48	0.70	349
B	4.01	2.88	5.14	3.57	7.31	4.99	11.13	9.47	1.91	17.03	0.79	344
Caa-	15.37	0.00	44.28	12.63	29.49	13.18	29.36	14.77	4.50	25.04	0.86	345

Table A2: Credit Spreads and Returns of Short-Horizon Pseudo and Corporate Bonds

Credit spreads and summary statistics of short-term pseudo-bonds (Panel A to D), and corporate bonds (Panel E and F). Pseudo-bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index. Pseudo- credit ratings of pseudo-bonds are assigned based on the pseudo-bonds *ex ante* default probability (i.e. the probability the put option is in the money at maturity). The pseudo-bonds default probability is computed by inverting the empirical distribution of residuals from a simple GARCH model of asset returns with expected growth obtained from predictive regressions. Corporate bonds are non-callable corporate bonds with time to maturity close to the one reported in the Panel's heading.

Credit Rating	Prob. Of Default	Avg K/S	Credit Spread	Monthly Returns in Excess of T-bill (%)				
				Mean	Std	Sharpe Ratio	Skew	Ex. Kurt
			Panel A: 30 Days Pseudo-Bonds					
IG	0.00	0.74	78	0.05	0.13	0.41	1.23	6.55
Ba	0.05	0.80	165	0.09	0.32	0.29	-1.94	25.72
B	0.22	0.85	287	0.11	0.70	0.16	-8.26	98.68
Caa-	1.89	0.90	501	0.22	0.91	0.24	-5.02	54.09
			Panel B: 91 Days Pseudo-Bonds					
IG	0.01	0.65	64	0.10	0.18	0.53	0.45	15.38
Ba	0.19	0.73	128	0.13	0.32	0.41	0.51	16.60
B	0.75	0.81	261	0.19	0.66	0.28	-2.77	23.43
Caa-	4.90	0.88	493	0.35	0.79	0.44	-0.09	5.92
			Panel C: 183 Days Pseudo-Bonds					
Aaa/Aa	0.00	0.57	51	0.07	0.29	0.24	-2.18	25.85
A/Baa	0.03	0.67	107	0.13	0.45	0.28	-0.67	18.10
Ba	0.47	0.72	169	0.14	0.81	0.17	-4.07	39.95
B	1.69	0.79	287	0.22	1.00	0.22	-2.42	16.94
Caa-	8.88	0.86	472	0.29	1.45	0.20	-2.32	14.85
			Panel D: 365 Days Pseudo-Bonds					
Aaa/Aa	0.01	0.47	43	0.07	0.43	0.17	1.16	15.41
A/Baa	0.10	0.59	98	0.16	0.61	0.26	0.98	14.69
Ba	1.19	0.70	186	0.19	1.01	0.19	-2.30	18.18
B	4.01	0.79	313	0.26	1.29	0.21	-1.20	7.05
Caa-	15.37	0.86	464	0.31	1.77	0.18	-1.54	8.69
			Panel E: 183 Days Corporate Bonds					
Aaa/Aa	0.00		42	0.01	0.85	0.01	-4.21	34.16
A/Baa	0.03		92	0.18	0.47	0.39	4.46	32.19
Ba	0.47		232	0.31	0.95	0.32	-2.46	15.90
B	1.69		276	0.27	1.71	0.16	-3.30	18.49
Caa-	8.88		1225	0.71	3.10	0.23	1.79	10.79
			Panel F: 365 Days Corporate Bonds					
Aaa/Aa	0.01		68	0.18	0.60	0.30	2.96	17.63
A/Baa	0.10		139	0.19	0.69	0.27	-0.31	20.75
Ba	1.19		329	0.44	0.85	0.52	2.10	9.74
B	4.01		517	0.75	2.30	0.32	3.94	31.20
Caa-	15.37		1264	1.20	3.62	0.33	1.03	6.21

Table A3: Assets as Shares of Individual Firms in the S&P500: Equivalent European Options

This table is the equivalent of Table 8, except that pseudo-bonds are computed out of European equivalent put options. European-equivalent put options are obtained from the implied volatilities reported from OptionsMetrics. Panel A reports summary statistics of the pseudo-bond portfolios. Column 5 reports the equal weighted average credit spread of pseudo-bonds in each credit rating category, while the next several columns report summary statistics of portfolio bond returns. For each credit rating, Panel B reports the time-series regression of the pseudo-bond portfolio excess returns on the average excess returns of pseudo-assets (i.e. stocks of underlying individual firms). For each credit rating, Panel C reports the time-series regression of the pseudo-bond portfolio excess returns on the average excess returns of pseudo-equity (i.e. call options of the underlying individual firms).

Panel A: Average Credit Spreads and Monthly Returns' Summary Statistics

	Prob. of Default	Credit Spread	Monthly Returns in Excess of T-bill (%)				
			Mean	Std	SR	Skew	Ex. Kurt
Aaa/Aa	0.03	125	-0.05	1.29	-0.04	-3.50	22.03
A/Baa	0.31	155	0.14	0.97	0.14	-0.07	3.24
Ba	3.23	204	0.19	1.12	0.17	-0.67	7.49
B	9.16	340	0.19	1.55	0.12	-1.65	8.10
Caa-	25.18	643	0.32	2.17	0.15	-0.87	2.49

Panel C: Regression of Pseudo-Bonds Excess Returns on Assets's Excess Returns

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	-0.05	(-0.56)	-0.12	(-1.16)	0.10	(3.80)	0.24
A/Baa	0.14	(2.00)	0.09	(1.49)	0.07	(7.09)	0.32
Ba	0.19	(2.38)	0.09	(1.45)	0.14	(8.43)	0.61
B	0.19	(1.73)	-0.01	(-0.07)	0.24	(8.12)	0.65
Caa-	0.32	(2.13)	-0.06	(-0.55)	0.39	(12.05)	0.73

Panel D: Regression of Pseudo-Bonds Excess Returns on Pseudo Equitiy' Excess Returns

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	-0.05	(-0.56)	-0.04	(-0.35)	0.01	(0.35)	0.01
A/Baa	0.14	(2.00)	0.13	(1.92)	0.03	(1.91)	0.15
Ba	0.19	(2.38)	0.24	(4.19)	0.07	(6.39)	0.35
B	0.19	(1.73)	0.17	(2.51)	0.13	(9.95)	0.58
Caa-	0.32	(2.13)	0.17	(1.65)	0.16	(12.53)	0.53