Option-Based Credit Spreads

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Abstract

Theoretically, corporate debt is economically equivalent to safe debt minus a put option on the firm's assets. We empirically show that indeed portfolios of long Treasuries and short traded put options ("pseudo bonds") closely match the properties of traded corporate bonds. Pseudo bonds display a credit spread puzzle that is stronger at short horizons, unexplained by standard risk factors, and unlikely to be solely due to illiquidity. Our option-based approach offers a novel, model-free benchmark for credit risk analysis, which we use to run empirical experiments on credit spread biases, the impact of asset uncertainty, and bank-related rollover risk.

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1. Introduction

The main insight of Merton (1974) is that the debt issued by a firm is economically equivalent to risk-free debt minus a put option on the assets owned by the firm. Despite its theoretical appeal, the original Merton model assumes assets are lognormally distributed and produces implied credit spreads that are far smaller than estimates of credit spreads derived from actual, traded corporate bonds. A significant literature has emerged over the last several decades that aims to explain this "credit spread puzzle" and the sources of differences between theoretical credit spreads implied by the lognormal Merton model and spreads on actual traded bonds. Even with the insights from that literature, the practical applicability of the lognormal Merton model remains limited.[1]

In this paper we propose a model-free methodology to provide empirical content to Merton's conceptual insight. In particular, we consider hypothetical firms that purchase actual traded assets financed by issuing equity and zero-coupon bonds. The market values of such zero-coupon bonds are equal to default-free debt minus put options on the traded assets purchased by the firms. Using *observed* prices of traded put options and Treasuries, we can extract the attributes of such "pseudo bonds" issued by our hypothetical firms. We can thus analyze the empirical properties of corporate credit spreads in a new light, and show how our model-free methodology can be used to run data-based experiments for the analysis of credit risk in a controlled environment.

More specifically, we consider two types of assets held by our hypothetical firm – namely, (*i*) the S&P 500 ("SPX") index; and (*ii*) shares of individual stocks that comprise the S&P 500 index. When our hypothetical firm purchases the SPX, the pseudo bonds issued by this firm ("SPX pseudo bonds") consist of risk-free Treasuries and short SPX put options. When the hypothetical firm instead purchases shares of an individual stock such as Apple, Inc., the pseudo bonds issued by that firm ("single-stock pseudo bonds") consist of risk-free Treasuries and short put options on Apple shares. We thus use market prices of both Treasuries and equity put options to compute observed market values of the pseudo bonds in both cases, and analyze their properties.

The implications of our empirical analysis of pseudo bonds are striking. First, credit spreads of pseudo bonds are increasing in hypothetical issuers' leverage and *ex ante* default

[1] We distinguish between Merton's *insight* that corporate debt can be viewed as risk-free debt and a short put option – an insight that requires no assumptions about the distribution of underlying assets owned by the hypothetical firm – and the Merton (1974) *model* for the valuation of risky corporate debt – which assumes underlying asset values are lognormally distributed and thus uses the Black, Scholes, and Merton formula for the valuation of corporate debt.

probabilities. This is intuitive. The surprising result is about magnitudes, as pseudo bonds' credit spreads are close to those of real corporate bonds and far larger than those implied by the lognormal Merton model. As is the case for actual corporate bonds, the credit spread puzzle thus is also pronounced in pseudo bond credit spreads. For example, the credit spreads of two-year SPX pseudo bonds corresponding to the default probabilities for Aaa/Aa and A/Baa bonds are 0.54% and 1.31%, respectively. Those spreads are very similar to the average credit spreads observed for actual Aaa/Aa and A/Baa corporate bonds – *i.e.,* 0.53% and 1.28%, respectively. For high-yield ("HY") debt, SPX pseudo bonds have relatively large credit spreads – *i.e.*, between 2.37% for Ba-rated bonds and 5.17% for Caa-rated bonds. Although these credit spreads are smaller than spreads on real corporate bonds (3.74% for Ba-rated bonds and 13.45% for Caa- rated bonds, respectively), they 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.

Second, our empirical results hold not only for medium-term bonds (two years to maturity in our implementation) but also for short-term pseudo bonds. For example, investment-grade ("IG") SPX pseudo bonds with 30 and 91 days to maturity have average credit spreads of 0.77% and 0.64%, respectively, as compared to average credit spreads of 0.62% and 0.60% for actual IG bonds and zero spreads implied by the lognormal Merton model. This result is especially important because the majority of extensions to the original Merton model typically cannot explain observed short-term credit spreads.

Third, transactional illiquidity of corporate bonds does not seem to be the main source of the large observed credit spreads. We measure transactional illiquidity using the Roll (1984) bid-ask bounce measure (*see, e.g.,* Bao, Pan, and Wang (2011)) and find that it is much lower for pseudo bonds than real corporate bonds. Because pseudo bonds display large credit spreads, it seems unlikely they are stemming from illiquidity.

Finally, like actual corporate bonds and in contrast with the lognormal Merton model, monthly returns on portfolios of pseudo bonds exhibit different Sharpe ratios across credit ratings. Similar to real corporate bonds, moreover, our pseudo bonds mostly exhibit a substantial alpha that emerges when we regress excess pseudo bond returns on excess returns of the hypothetical firm's pseudo equity (*i.e.,* traded call options). In addition, for both corporate and pseudo bonds, excess returns are not fully explained by a variety of standard risk factors.

Our empirical findings have numerous implications. First, they suggest that the observed large credit spreads are unlikely to be the result of the different timing of default and/or the payoff structure of coupon-bearing corporate bonds vis-a-vis the zero-coupon bonds of Merton's conceptual insight. For instance, it is unlikely that early default (*e.g.*, Black and Cox (1976)) or large bankruptcy costs (*e.g.*, Leland (1994)) are the main reason behind large credit spreads. The reason is that the payoff of our pseudo bonds exactly matches the payoff of a bond underlying Merton's original insight (*i.e.*, the minimum between the bond's face value and the value of the firm's assets). Yet, empirical credit spreads of our pseudo bonds are comparable to those of real corporate bonds.

Second, our empirical findings also suggest that the credit spread puzzle is unlikely to be solely attributable to theories of corporate behavior such as optimal default (*e.g.,* Leland and Toft (1996)), agency costs (*e.g.,* Leland (1998), Gamba, Aranda, and Saretto (2013)), strategic default (*e.g.,* Anderson and Sundaresan (1996)), asymmetric information, uncertainty and learning (*e.g.,* Duffie and Lando (2001) and David (2008)), corporate investment behavior (*e.g.,* Kuehn and Schmid (2014)), and the like. The reason is that our firm is a very simple one in which the asset value is observable, information is symmetric, managerial frictions do not exist (because there is nothing to be managed), and the leverage and default boundary are set mechanically. Yet, our pseudo bonds display properties that are surprisingly close – qualitatively and quantitatively – to those of real corporate bonds. Rather, our results provide an indirect argument that the underlying source of the large credit spread should be investigated in the dynamics of risk or investors' risk preferences (as in the long-run-risk models of Bhamra, Kuehn, and Strebulaev (2010) and Chen (2012) or the habit models of Chen, Collin-Dufresne, and Goldstein (2009)), as discount rate shocks simultaneously affect the market value of assets and the discount rate applied to value bonds.

The explanation for the credit spread puzzle in our data also seems to be related to the notorious "put option overpricing puzzle" in the equity options literature – *i.e.,* the well-established result that equity put options are relatively overpriced *vis-a-vis* the theoretical prices implied by the Black-Scholes formula and lognormal distribution. The credit spread puzzle thus is plausibly due to an additional insurance premium that investors require to hold securities that are subject to tail risk.

We next illustrate how our option-based approach for pseudo bond valuation can be used as a benchmark to study data-based experiments for the analysis of credit risk that are difficult or impossible to implement in the real world. We provide examples of three such experiments. Our first experiment concerns the potential bias that may be introduced in average credit spreads and average returns by the frequency of revisions in credit rating assignments, an important question given the apparent reliance of investors on credit ratings in their investment decisions. We show that if credit ratings are assigned at quarterly, semi-annual, or annual frequencies, average credit spreads for highly rated bonds do not change significantly, whereas average spreads on lower-rated bonds increase by as much as 60%. In contrast, average pseudo bond excess returns fall (by as much as 50% for lower-rated bonds) as the frequency of credit rating assignments declines. Different convexity effects result in varying impacts on average bond yields and returns.

In the second application of our option-based approach to pseudo bond valuation, we investigate the impact of asset value uncertainty on credit spreads. This relation is typically hard to estimate using real corporate bonds given the endogeneity of credit ratings – *i.e.*, firms with more uncertain assets should have lower credit ratings – and the difficulty of measuring the uncertainty of underlying asset values (which are generally unobservable). Our methodology overcomes both hurdles. We find that, even taking into account the endogeneity of credit ratings, higher uncertainty typically translates into higher credit spreads and lower leverage. The impact of uncertainty on credit spreads is large and similar in magnitude to the differential *across* credit ratings. Indeed, our empirical exercise demonstrates significant heterogeneity across pseudo bonds even conditioning on the same credit rating.

In the third application of our option-based approach to credit risk analysis, we study the rollover risk of a hypothetical pseudo bank that extends loans to groups of individual pseudo firms. Because the pseudo bank has an asset portfolio comprised solely of a portfolio of pseudo bonds, we use empirical returns on single-stock pseudo bonds to compute the empirical distribution of the assets of our pseudo bank. Assuming that the bank finances the purchase of those bonds by issuing equity and only short-term debt, we analyze the rollover risk of the pseudo bank and compute the minimum capital required for the pseudo bank to avoid a default. Our empirical results suggest that common shocks to the individual firms' assets are amplified by the leveraged nature of the loans, leading to negatively skewed and leptokurtic return distributions of our pseudo bank's assets. Such fat-tailed distributions require higher levels of capital to support than would be needed for a loan portfolio with closer to normally distributed returns.

Our paper is clearly related to the large literature that sprang from both the insight and valuation model of Merton (1974). We do not attempt an exhaustive survey here, but instead refer readers to Lando (2004), Jarrow (2009) and Sundaresan (2013).[2] In addition, Huang and Huang (2012) discuss the deficiencies of the Merton model and elaborate on the credit spread puzzle by showing that numerous structural models calibrated to match true

[2] In addition to the academic literature, numerous variants of the Merton mode are used in the industry and by practitioners to evaluate the credit risk of individual firms (*e.g.,* Moody's KMV model) or of portfolios of credits (*e.g.,* CreditMetrics).

default probabilities generate credit spreads that are still too small compared to the data. Most of these models, moreover, have implications only for very long-term debt and do not explain short-term credit spreads. High short-term credit spreads are instead obtained by Zhou (2001) in a model that incorporates jumps in asset values and by Duffie and Lando (2001) in a model of optimal default with uncertainty about the true value of assets. The approaches of all of these papers, however, are different from ours. We do not use any parametric model, but instead go straight to the data to evaluate the empirical relevance of Merton's insight without imposing the additional distributional restrictions of Merton's valuation model.

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&P 100 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 out-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 approach differs as we directly test the empirical implications of Merton (1974) insight using traded options. Finally, our approach is related to Coval, Jurek, and Stafford (2009) who study the valuation of collateralized debt obligations ("CDOs") and use traded SPX options 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 SPX-based tranches are smaller than the spreads on corresponding CDO tranches. Although we also use options and the insight from the Merton model to study bonds, we focus on the empirical implications of Merton's insight and show that option-based credit spreads are very much in line with observed corporate credit spreads.[3]

The paper is organized as follows. Section 2. describes our approach for estimating option-based credit spreads. Section 3. describes the data and summarizes our main empirical results about credit spreads. Section 4. analyzes the properties of portfolios of pseudo bonds, whose excess returns are then investigated in Section 5. Section 6. offers some additional applications of our methodology, and Section 7. concludes. Appendices A and B contain a summary of the original lognormal Merton model and an extension to incorporate jumps and stochastic volatility, respectively. Appendices C through E present our supplemental results.

[3]Our paper is also related to the literature that compares corporate bonds to "synthetic" corporate bonds, as given by risk free bonds plus credit default swaps (*e.g.* Duffie (1999), Longstaff, Mithal and Neis (2005)). Such synthetic bonds, however, do not facilitate the same kind of analysis that we undertake here that uses options on the underlying assets of the firm that issues the corporate debt.

2. Option-Based Credit Spreads

Our model-free, option-based approach for the analysis of credit risk is based on Merton's (1974) insight that the value of a pseudo bond issued by a hypothetical firm can be viewed as the observable price of a risk-free Treasury minus the observable price of a put option on the assets held by the hypothetical firm. As noted earlier, the prices (and credit spreads) of these pseudo bonds are model-free and, in particular, depend only on observed market prices and not on any explicit distributional assumptions about the value of the assets owned by the hypothetical securities issuer.

Specifically, consider a hypothetical firm i that finances the purchase of its assets by issuing equity and zero-coupon debt. The firm is passive and engages in no discretionary investment or financing decisions. The only assets purchased by the firm are traded securities, which could include traded equity indices, individual stocks, foreign currencies, fixed income securities, and the like. In this paper, we consider two specific types of traded securities that our hypothetical firm may hold: the SPX index, and shares of individual firms in the SPX index.

We begin with a description of our approach using the SPX index as the sole underlying asset owned by the hypothetical securities issuer. Let $A_{i,t}$ be the market value of the SPX index that is purchased by hypothetical firm i at time t. Let $K_{i,t}$ denote the face value of zero-coupon debt issued by firm i at time t, and let $t+\tau$ be the debt's maturity. We assume for simplicity that the firm cannot become insolvent prior to the $t+\tau$ debt maturity date.[4] If on that date $t+\tau$, the assets of the firm are worth $A_{i,t+\tau} > K_{i,t}$, then debt holders receive the face value of debt $K_{i,t}$. Alternatively, the value of the firm's assets are inadequate to repay debt holders fully, in which case the firm defaults, debt holders take over the firm and liquidate its assets, and debt holders receive the market value of the firm's assets $A_{i,t+\tau}$. The payoff to debt holders at time $t+\tau$ is then

$$\text{Bond Payoff at } t+\tau = \min(K_{i,t}, A_{i,t+\tau}) = K_{i,t} - \max(K_{i,t} - A_{i,t+\tau}, 0) \qquad (1)$$

The value at t of a τ-period zero-coupon defaultable bond is given by the value of risk-free debt minus the value of a European put option on the assets of the firm expiring on date $t+\tau$ with a strike price equal to the face value of the bond, $K_{i,t}$. Because the firm's assets are comprised solely of the SPX portfolio, the put option in this case is an option on the

[4] In the United States, a firm is "insolvent" under the U.S. bankruptcy code in any of three situations: (i) it cannot pay its bills when they are due; (ii) it is inadequately capitalized; or (iii) the market value of its assets is less than the face value of its total outstanding debt at *or before* the dates on which the debt matures. (*See* Heaton (2007).) Following Merton (1974), we assume here that insolvency can only occur in situation (i) on the maturity date of the debt.

SPX index, which has an observable price. Thus, the value of debt is given by:

$$\widehat{B}_t\left(t+\tau, K_{i,t}\right) = K_{i,t}\widehat{Z}_t(t+\tau) - \widehat{P}_t^{SPX}(t+\tau, K_{i,t}) \tag{2}$$

where a "hat" indicates that the price is directly observable. We rely on the Treasury and SPX put option data to compute the empirical properties of our pseudo bonds $\widehat{B}_t(t+\tau, K_{i,t})$. We refer to the ratio $L_{i,t} = K_{i,t}/A_{i,t}$ as firm i's market leverage ratio, given by the face value of its debt divided by the market value of its assets.

We also consider the case in which our hypothetical firm purchases shares of individual stocks (instead of the SPX index), and finances that purchase by issuing a zero-coupon bond and equity. For concreteness, suppose that our hypothetical firm i purchases Apple shares at time t and issues zero-coupon debt with face value $K_{i,t}$ and maturity $t+\tau$. Then, the value of the zero coupon bond at time t is given by

$$\widehat{B}_t\left(t+\tau, K_{i,t}\right) = K_{i,t}\widehat{Z}_t(t+\tau) - \widehat{P}_t^{Apple}(t+\tau, K_{i,t}) \tag{3}$$

where $\widehat{P}_t^{Apple}(t+\tau, K_{i,t})$ is the value of a European put option on Apple stock maturing on date $t+\tau$ and with strike price $K_{i,t}$. In practice, traded put options on individual stocks are American-style (unlike SPX index options, which are European). Because we work with deep out-of-the-money options, however, the early exercise premium on American options is extremely small, and we approximate the prices of European options on individual shares with their traded American counterparts. (As a robustness check, we also performed all of our calculations using European option price equivalents based on implied volatilities of American options. We did not find any significant impact on our results, thereby confirming the reasonableness of our assumption that American and European put prices can be treated as comparable for the deep out-of-the-money options that we examine. Results are in the Appendix.)

We compute the credit spread on the pseudo bond issued by hypothetical firm i at time t with time to maturity τ relative to Treasury bonds as $\widehat{cs}_{i,t}(\tau) = \widehat{y}_{i,t}(\tau) - \widehat{r}_t(\tau)$, where $\widehat{y}_{i,t}(\tau)$ and $\widehat{r}_t(\tau)$ are the semi-annually compounded zero-coupon yields for the pseudo bonds and the Treasury bond, respectively. We refer to these credit spreads as *option-based credit spreads*, as they are fictitious credit spreads of fictitious pseudo bonds issued by a fictitious firm to purchase traded assets A_t, such as the SPX or individual stocks. We also note that there is no relation between the pseudo bonds issued by a pseudo firm that purchases, say, Apple shares, and the true corporate bonds issued by Apple Inc. These are different securities with different default probabilities. As will become clear in the next section, true bonds from Apple could be rated Aaa, whereas bonds issued by the pseudo firm holding Apple stock may be assigned a Caa- rating depending on our choice of face value $K_{i,t}$. Actual Apple bonds, moreover, are backed by different underlying assets (*e.g.*, real factories, patents, intangibles, etc.), whereas our pseudo firm has only Apple shares – a traded security – as its assets.

So far we have assumed that options with the exact desired target maturity τ actually exist. In reality, at every given time t only certain maturities $\hat{\tau}_{i,t}$ are available. For this reason, we take the Gaussian kernel-weighted average of all bonds with the same rating, where the weighting function has the following specific form:

$$w_{i,t} \propto \frac{1}{\sqrt{2\pi}s} \exp\left(-\frac{1}{2}\frac{(\hat{\tau}_{i,t} - \tau)^2}{s^2}\right)$$

where $s = 30$ days. We use expressions (2) and (3) with $\hat{\tau}_{i,t}$ instead of τ for all computations.

2.1. Ex Ante Default Probabilities

Before we discuss the empirical properties of the pseudo bonds constructed in the previous section, we assign *ex ante* default probabilities to each pseudo bond. Specifically, at every time t and for each bond with maturity τ and face value $K_{i,t}$, we want to compute

$$p_t(L_{i,t}) = \Pr\left[A_{i,t+\tau} < K_{i,t} \,|\mathcal{F}_t\right] \tag{4}$$

where $\mathcal{F}_t$ denotes the information available at time t. (Recall that $L_{i,t} = K_{i,t}/A_{i,t}$).

To avoid making explicit distributional assumptions about asset returns and to keep our approach as model-free as possible, we use the empirical distribution of underlying asset values to compute $p_t(L_{i,t})$. Nevertheless, we need to take into account any time-varying market conditions, which could have a substantial impact on default probabilities for a given current market leverage ratio $L_{i,t}$.

When hypothetical firm i's assets consist solely of the SPX, the market value of the firm's assets at time t is $A_{i,t} = SPX$. Dropping the subscript i for notational simplicity, let log asset growth for this firm be given by:

$$\ln\left(\frac{A_{t+\tau}}{A_t}\right) = \mu_{t,\tau} - \frac{1}{2}\sigma_{t,\tau}^2 + \sigma_{t,\tau}\varepsilon_{t+\tau} \tag{5}$$

where $\varepsilon_{t+\tau}$ are standardized unexpected asset 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 log asset growth $\ln(A_{t+\tau}/A_t)$ has an expected component and a volatility scaling parameter $\sigma_{t,\tau}$.

A structural assumption is required to estimate $\mu_{t,\tau}$ and $\sigma_{t,\tau}$. Accordingly, we estimate $\mu_{t,\tau}$ by running return forecasting regressions (excluding dividends) using the dividend-price ratio for τ horizons, and $\sigma_{t,\tau}$ by fitting a GARCH(1,1) process based on monthly asset returns.[5] Given estimates of $\mu_{t,\tau}$ and $\sigma_{t,\tau}$, we collect the (overlapping) history of shocks

$$\varepsilon_{t+\tau} = \frac{\ln\left(A_{t+\tau}/A_t\right) - \left(\mu_{t,\tau} - \frac{1}{2}\sigma_{t,\tau}^2\right)}{\sigma_{t,\tau}}$$

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

In particular, we rewrite the probability $p_t(L_{i,t})$ in (4) as follows:

$$p_t(L_{i,t}) = \Pr\left[\varepsilon_{t+\tau} < X_{i,t} \middle| \mathcal{F}_t\right] \qquad \text{where} \qquad X_{i,t} = \frac{\ln\left(L_{i,t}\right) - \left(\mu_{t,\tau} - \frac{1}{2}\sigma_{t,\tau}^2\right)}{\sigma_{t,\tau}} \tag{6}$$

Thus, we can estimate such probabilities simply as:

$$\widehat{p}_t(L_{i,t}) = \frac{n(\varepsilon_{s+\tau} < X_{i,t})}{n(\varepsilon_{s+\tau})} \quad \text{for all} \quad s+\tau < t. \tag{7}$$

where $n(x)$ counts the number of events x. We perform these computations on expanding windows, so that at any time t we only use information available at time t to predict the default probability of a pseudo bond with market leverage ratio $L_{i,t}$ and maturity $t+\tau$. The empirical distribution of shocks $\varepsilon_{t+\tau}$ thus determines these default probabilities. If these shocks are not normally distributed, then our default probabilities will be different from those implied by the lognormal Merton model. Panel A of Figure A1 in Appendix E presents the histogram of shocks $\{\varepsilon_{t+\tau}\}$ for maturity $\tau = 2$. The Kolmogorov-Smirnov test rejects normality at 1% confidence level.

When hypothetical firm i's assets $A_{i,t}$ consist of shares of an individual stock included in the SPX, a difficulty arises in dealing with survivorship bias in our computations of empirical default probabilities. Specifically, consider the same procedure described above for the hypothetical firm holding the SPX index but now applied to hypothetical firms holding shares of individual SPX constituents as assets. For each such stock at time t, we would consider the idiosyncratic shocks of its stock returns and use the histogram of those shocks to back out implied default probabilities. Clearly, these computations would be performed *conditional on* the firm being part of the SPX index at t (*i.e.*, conditional on firms that have "survived" and done sufficiently well to remain or be included in the index). This procedure would skew the distribution of shocks to the right.

To avoid survivorship bias in the case of individual pseudo firms, for every t we consider the full cross-section of all firms underlying the SPX index before t (including those that

[5] Specifically, we use monthly returns to estimate $\sigma_{t,1}^2$ and compute $\sigma_{t,\tau}^2$ for $\tau > 1$ from the properties of the fitted GARCH(1,1) model.

dropped out of the index). For each firm i and $s < t$, we use its previous-year return volatility and unconditional average return (before s) to compute its normalized return shock. We then use the full empirical distribution of all these normalized shocks across firms i for all $s < t$ to obtain the default probabilities for each bond issued by each pseudo firm j as of time t. As before, for each firm j we scale the shocks by their unconditional means and previous-year volatilities. Panel B of Figure A1 in Appendix E shows the histogram of resulting normalized shocks. Like the shocks in Panel A computed for SPX index, the shocks display fat tails and the Kolmogorov-Smirnov test rejects normality at 1% confidence level.

3. The Credit Spreads of Pseudo Bonds

In this section we discuss the main properties of pseudo bonds' credit spreads, and compare them against two benchmarks: the credit spreads of real corporate bonds, and credit spreads implied by the original lognormal Merton model. The latter is a standard benchmark in the "credit spread literature" discussed in the introduction. (Appendix A briefly reviews the lognormal Merton model.) We begin by first describing the data we use.

3.1. Data

We use the OptionMetrics Ivy database for daily prices on SPX index options and options on individual stocks from January 4, 1996, through August 31, 2013. For SPX options, we generally follow Constantinides, Jackwerth and Savov (2013) to filter the data in order to minimize the effects of quotation errors. For individual equity options, we apply generally the same filters as Frazzini and Pedersen (2012). Stock prices are from the Center for Research in Security Prices ("CRSP").

We construct the panel data of corporate bond prices from the Lehman Brothers Fixed Income Database, TRACE, the Mergent FISD/NAIC Database, and DataStream, prioritized in this order when there are overlaps among the four databases. We exclude junior bonds and all bonds with floating-rate coupons and embedded options (*e.g.,* callable bonds) from our data set.

Risk-free rates and commercial paper rates (used to compute short-term credit spreads) are from the Federal Reserve Economic Data ("FRED") database.

A more detailed description of the data is contained in Appendix C.

3.2. Empirical Results

We focus in this section on credit spreads of two-year pseudo bonds. The procedure illustrated in Sections 2. and 2.1. implies that for every month t and for every pseudo bond i, we can compute a credit spread $\widehat{cs}_{i,t}$ and an *ex ante* default probability $\widehat{p}_{i,t}$. Panel A of Figure 1 plots average credit spreads of two-year pseudo bonds against their estimated *ex ante* default probabilities, both for the SPX pseudo bonds (diamonds) and for single-stock pseudo bonds (circles). The averages are taken over unit bins for default probabilities ranging from zero to 30%. For comparison, the figure also plots average credit spreads for real corporate bonds (triangles) relative to their own default probabilities, where the latter are based on Moody's default frequencies corresponding to the bonds' actual credit ratings.

The credit spreads of pseudo bonds match the credit spreads of real corporate bonds quite well, especially for default probabilities below 15%. Indeed, for default probabilities between 0 and 1%, the average credit spreads are around 0.74% for SPX pseudo bonds and 1.78% for single-stock pseudo bonds. These credit spreads are approximately the same as the average credit spreads observed on real corporate bonds (1.2%) for comparable default probabilities. As the probability of default increases, the credit spreads of both SPX and single-stock pseudo bonds increase, reaching 3.4% and 5.7%, respectively, for default probabilities in the [10%,11%] bin, and 8% and 10.1%, respectively, for default probabilities in the [29%,30%] bin. Corporate bond spreads also increase as default probabilities increase, reaching 5.3% for default probabilities in the range from 10% to 11% and 18% for default probabilities around 27%. (The data on corporate bonds are sparse at such high default probabilities, and we thus compute averages on a coarser interval centered at 27%.)

Panel A of Figure 1 also reports the credit spreads implied by the lognormal Merton (1974) model. In essence, Merton (1974) assumes that the value of assets on the debt maturity date $t+\tau$ are lognormally distributed – *see* Appendix A. As such, the values of put options are given by the Black, Scholes, and Merton formula. The credit spreads implied by the Merton (1974) model are shown in the figure as the dotted dashed line. As is apparent, there is gulf between the credit spreads of both pseudo bonds and real bonds and those implied by the lognormal Merton model.[6]

Panel B of Figure 1 again shows the credit spreads for pseudo bonds, real bonds, and those implied by the Merton (1974) model, except that spreads are now plotted against book

[6] Appendix A also describes the methodology employed to compute credit spreads implied by the Merton valuation model. In a nutshell, average credit spreads are simulated in order to take into account discretization bias and stochastic volatility.

leverage. For pseudo bonds and the lognormal Merton model, book leverage is defined as "Face Value of Debt / (Face Value of Debt plus Market Equity)," where "Market Equity" is the value of the corresponding call option. We use this definition instead of the more natural "market leverage ($= K/A$)" because it is the analogous definition we can use for real corporate bonds, for which book leverage is "Book Value of Debt / (Book Value of Debt plus Market Equity)." As is evident, Panel B shows that pseudo bonds' average credit spreads increase substantially with leverage. For instance, as leverage passes from around 30% to around 90% credit spreads increase from 0.5% and 2.30% for SPX and single-stock pseudo bonds, respectively, to 10.8% and 13.3%, respectively. Credit spreads on real corporate bonds also generally increase with leverage, and are mostly sandwiched between the credit spreads of single-stock pseudo bonds and the credit spreads of SPX pseudo bonds, except for very high leverage ratios, where real bond credit spreads are lower than pseudo bonds' credit spreads.

Figure 2 presents plots similar to those in Figure 1, but, in this case, we divide the sample into booms (left panels) and recessions (right panels). Credit spreads of pseudo bonds are relatively high in both samples. During recessions, the credit spreads of real bonds increase significantly, but they also become much more noisy, as we do not have many observations over which to compute averages.

3.3. Implications

The credit spreads of pseudo bonds shown in Figures 1 and 2 are large and comparable to credit spreads of real corporate bonds. In the terminology of the existing literature, our pseudo bonds thus display a similar "credit spread puzzle" as is observed in actual corporate bond spreads – *i.e.*, credit spreads implied by the lognormal Merton (1974) model do not match the observed empirical credit spreads of pseudo bonds.

How can we interpret our results? First, given that our pseudo bonds are based solely on observed market prices of U.S. Treasuries and equity put options, our empirical results are model-free. Our results thus do not rely on theories of corporate behavior that relate credit spreads to issues like corporate governance, funding constraints, investments, uncertainty about default threshold, and the like. The reason is simply that such theories do not apply to our pseudo firms. Because our pseudo bonds are just simple zero-coupon bonds with the same payoff structure as in the original distribution-free Merton insight (*i.e.* $\min(K, A_{i,t+\tau})$), moreover, our empirical results cannot be explained by different characteristics between actual bonds (*e.g.,* coupon-paying) and the zero-coupon bonds underlying the original Merton insight in terms of their payoffs at maturity or the timing of the firm's default. Explanations of the credit spread puzzle that are based on the potential for early default or the existence of bankruptcy costs, for instance, do not apply in our setting.[7]

One possible explanation of our results is that the *ex ante* default probabilities for our pseudo firms are too low compared to their real probabilities of default, and that we underestimate implicit risk in our pseudo bonds in consequence. We can check this potential explanation by testing whether *ex post* default frequencies are similar to *ex ante* probabilities. Figure 3 carries out this test using data from 1970 to 2013.[8] Panel A shows that for SPX pseudo bonds, point estimates of *ex post* default frequencies (the circles in the figure) are different from *ex ante* probabilities (the 45 degree line) and are higher for low default probabilities and lower for high default probabilities. But the confidence bands are very wide, and, as such, we cannot reject the hypothesis that *ex ante* and *ex post* probabilities are the same. These wide confidence intervals underscore an important point about SPX pseudo bonds. Namely, because we construct pseudo bonds from a *single* fictitious firm that has only SPX shares as assets, we do not have a cross-section of firms over which to average defaults. We only have one time series of assets (*i.e.*, the SPX) for our firm, and the difference across pseudo bond default frequencies thus only reflects different leverage ratios of that single fictitious firm and not different firms with different assets. So, the mean *ex post* default rate is noisy, and the confidence intervals are large.[9]

Panel B of Figure 3 shows that the average *ex post* frequencies of default for single-stock pseudo bonds (the circles in the figure) are very close to the *ex ante* default probabilities (the 45 degree line). The confidence intervals are relatively tight, moreover, thanks to the diversification across the 500 firms in the SPX index, and they comfortably include the *ex ante* default probabilities. Overall, the evidence suggests that our *ex ante* default probabilities are not too low (especially for pseudo bonds issued by firms holding individual stocks) and that too-low default probabilities are not an explanation for the large observed

[7] Indeed, as in Merton's original insight, our pseudo bond's payoff is $\min(K, A_{t+\tau})$. Bankruptcy costs of $\kappa\%$ would lead to the modified payoff of $\min(K, A_{t+\tau}) - \kappa A_{t+\tau} 1_{A_{t+\tau}<K}$. For a given probability of default $\widehat{p}_t(\tau) = \Pr(A_{t+\tau} < K)$, the additional bankruptcy cost will further increase the credit spread. To be conservative and to avoid adding parameters to our model-free approach, we just assume $\kappa = 0$.

[8] We note that we do not need options to compute *ex post* default frequencies of pseudo bonds, as default at $t + \tau$ only depends on whether $A_{t+\tau} < K_{i,t}$. Thus, for every month t and given estimates of $\mu_{t,\tau}$ and $\sigma_{t,\tau}$, for each probability p on the $x-$axis of Figure 3 we back out the threshold $K_{i,t}$ so that the *ex ante* probability $\widehat{p}_{i,t}(\tau) = p$. We then compute the *ex post* average frequencies with which default occurs at time $t+\tau$. The sample 1970 to 2013 is chosen to match the Moody's sample, used in Section 4.1. to assign credit ratings to pseudo bonds.

[9] Intuitively, out of our 44-year SPX sample we only have 22 independent observations over which we can compute default frequencies for two-year pseudo bonds. At this frequency, just one observation is sufficient to generate over a 2% *average* default frequency, but with large standard errors.

credit spreads on our pseudo bonds.

Instead, our results are consistent with the large literature documenting that equity put options (especially out-of-the-money puts) are overpriced compared to the Black-Scholes-Merton lognormal model. Our results so far do not shed any light on whether that overpricing is rational (*i.e.,* risk-based) or behavioral (*i.e.*, overpaying for insurance). The novelty of our approach, rather, is to document that such overpricing of put options is consistent with observed spreads on actual corporate bonds. 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) that corporate securities can be viewed as a portfolio of safe bonds plus a short put is quite accurate even if the exact specification in the Merton valuation model (*i.e.*, lognormally distributed assets) is not.

4. Pseudo Bond Portfolios

In this section we dig deeper into the sources of the large observed credit spreads relative to the lognormal Merton model by analyzing portfolios of pseudo bonds. The monthly sorting of bonds into portfolios helps reduce idiosyncratic noise and allows us to examine the implications of specific characteristics of our pseudo bond issuers (*e.g.*,, leverage and default probabilities) and to allow such characteristics to remain approximately constant over time. We follow the literature and form monthly portfolios of pseudo bonds grouped by credit rating. As such, we begin this section by describing our methodology for assigning pseudo bonds to pseudo credit rating categories.

4.1. Pseudo Credit Ratings

We use the *ex ante* default probabilities $\widehat{p}_{i,t}$ computed in Section 2.1. to assign each bond to a credit rating category.[10] Our goal is to construct portfolios of pseudo bonds that match the realized default frequencies of actual corporate bonds. To that end, we employ a large dataset of corporate defaults spanning the 44-year period from 1970 to 2013 obtained from Moody's Default Risk Service. For each credit rating assigned by Moody's to our universe of firms,

[10]We use nomenclature from Moody's Investors Service to describe the credit ratings we assign to our pseudo bonds. Nevertheless, our credit ratings are not intended to match the ratings that actually would be assigned by Moody's or any other rating agency to such bonds (if they existed) based on their own criteria. We rely solely on the methodology described herein – and not rating agency criteria – for this mapping exercise.

we estimate *ex post* default frequencies at various horizons from 30 days up to two years. We use our own estimates rather than the Moody's default frequencies for three 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 analyze default frequencies at horizons of below one year, which are not provided by Moody's. Third, the lack of sufficient granularity of option strike prices sometimes prevents us from differentiating pseudo bonds with extremely low default probabilities. We thus group IG bonds into two categories – Aaa/Aa and A/Baa – which we use to compute category-level default frequencies.[11] Appendix D further discusses the construction of these data. For reference, Table A1 in Appendix E shows that our annual estimates of default frequencies are very close to Moody's estimates, and further reports their disaggregation into different maturities and over the business cycle.

Panel A of Table 1 presents the default frequencies estimated from Moody's dataset on corporate defaults for the credit ratings reported in the first column. In particular, the second column reports the estimated default frequencies, and the third and fourth columns report the default frequencies in booms and recessions. The last two columns report the break points in booms and recessions that we use to assign the pseudo bonds to credit rating bins. These break points are just the middle points of the corresponding default probabilities in columns three and four.[12] So, for every month t, we compare the probability of each bond i, $\widehat{p}_{i,t}(\tau)$ to the corresponding thresholds in the last column, depending on whether month t is a boom or recession, and obtain a classification into a credit rating category.

Panels B and C of Table 1 report the results of our credit rating classification methodology for pseudo bonds based on the SPX and individual stocks, respectively. In both panels, for each credit rating in the first column, the second and the third columns show the weighted average *ex ante* default probabilities for pseudo bonds in each rating category. According to the procedure, these probabilities should be close to the historical default frequencies reported in columns three and four of Panel A, and they are. As in Figure 3, we can also test whether *ex post* default frequencies are close to the *ex ante* default probabilities. As in Section 3.3., columns four to six of Panels B and C of Table 1 confirm that this is indeed the case; we cannot reject that *ex ante* and *ex post* default probabilities are equivalent.

[11] Even with this slightly coarser definition of credit ratings, the Aaa/Aa category has 69 and 148 months of missing observations for pseudo bonds based on the SPX and individual stocks, respectively (out of 212 months in our sample). The A/Baa category has six and eleven months of missing observations for pseudo bonds based on the SPX and individual stocks, respectively.

[12] To avoid overpopulation of Caa- category and keep its default probability close to the target from Moody's data, we exogenously set the upper limit equal to 1.5 times Moody's default probabilities in columns three and four.

The second-to-last column in Panels B and C of Table 1 reports the average moneyness of the options ($\overline{K/A}$). As is evident, the options used for highly rated pseudo bonds are deeply out-of-the-money to be consistent with a low probability of default. As noted and further discussed in the next section, we sometimes lack sufficient data to compute a default rate for the Aaa/Aa category at all because options so far out-of-the-money are excluded by our minimum liquidity filters (*see* Appendix C).

The last column of Panels B and C report the average maturities $\overline{\tau}$ of the options used by credit rating category. Across the two panels, these averages are between 580 and 671 days (1.59 and 1.84 years). Times to maturities thus are a bit smaller than the two-year (730-day) target mainly due to lack of data in the early part of the historical sample. Even so, the lower average maturity biases the empirical results against us, given that shorter maturities imply lower probabilities for the put options to end up in-the-money at maturity. Notwithstanding the shorter average maturity, we continue to refer to our pseudo bonds as two-year bonds for simplicity.

4.2. Pseudo Bond Credit Spreads by Credit Rating

We first verify that the results in Figures 1 and 2 hold for our portfolios of pseudo bonds sorted by pseudo credit ratings. Column two of Table 2, Panels A and B, show the sizable credit spreads of two-year pseudo bonds, which are similar to the spreads on real corporate bonds shown in Panel C, especially for high credit ratings. The empirical credit spreads for both pseudo bonds and real corporate bonds are far higher than the credit spreads implied by the lognormal Merton model, whose values are reported in Panel D of Table 2. Table A3 in Appendix E indicates that the same credit spread puzzle is also apparent across the two sub-sample periods of 1996 – 2004 and 2005 – 2013.

Columns three and four of Table 2 report average credit spreads over the business cycle. Panels A and B indicate relatively large credit spreads for pseudo bonds both in booms and recessions. Similar results are observable for corporate bonds in Panel C, although average credit spreads during recessions are a bit larger than for pseudo bonds. In both cases, average credit spreads are far higher than those implied by the lognormal Merton model (as shown in Panel D).

Panels A through E of Figure 4 present graphical representations of the time series of monthly credit spreads of pseudo bonds and corporate bonds across the five credit rating categories.[13] Across credit ratings, the credit spreads for both pseudo bonds and actual corporate bonds skyrocketed during the 2008 financial crisis, and then returned to more normal levels by the end of the 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 especially Ba-rated corporate bond spreads increased substantially during this period. Nonetheless, pseudo and corporate bond spreads still show a good deal of comovement over time, as shown in the top left corner of each panel. Except for A/Baa-rated single-stock pseudo bonds, whose correlation with real corporate bonds is just 2%, the correlation between pseudo bond and corporate bond credit spreads ranges from 21% and 53%.

4.3. The Term Structure of Credit Spreads

In this section we examine the term structure of credit spreads of pseudo bonds across maturities other than the two-year vertex on which we have previously focused. Unfortunately, this exercise is hindered by two data limitations. First, higher-rated bonds in the Aaa/Aa and A/Baa categories have negligible historical default frequencies over short time horizons (*i.e.*, 30 and 91 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 combine all pseudo bonds with ratings of Baa or higher into a single IG credit rating bin. Even so, for the shortest maturity we are unable to compute reliable credit spreads for pseudo bonds based on options on individual stocks.

Second, we do not have reliable corporate bond data for maturities of less than 91 days. We rely instead on commercial paper ("CP") issued with original maturities of 270 days or less. Below-investment-grade CP, however, is not available. As such, our actual corporate bond data includes no empirical observations for 30- and 91-day corporate debt with ratings of Ba or lower.

Panels A and B of Table 3 report the term structure of credit spreads across credit ratings for SPX and single-stock pseudo bonds, respectively. Evidently, pseudo bonds display high credit spreads across maturities even for highly rated bonds. For example, Panel B shows that IG-rated SPX pseudo bonds have credit spreads of 77, 64, and 69 bps at the 30-, 91-, and 183-day maturities, respectively. Panel B shows that IG-rated single-stock pseudo bonds have credit spreads of 168, and 116 at 91- and 183-day maturities, respectively.

[13] The various panels in Figure 4 also show the extent of missing observations, both for pseudo bonds (*e.g.*, in Panels A and B) and for real corporate bonds (*e.g.*, in Panels D and E).

Panel C of Table 3 reports similar results for corporate bonds. For comparison with pseudo bonds, we also report average credit spreads for IG bonds. The magnitudes of the credit spreads are similar to the pseudo bonds, especially those based on the SPX. Although we lack data on short-dated real corporate debt, the term structure nevertheless displays the same increasing pattern that we observe for pseudo bonds for maturities from six months to two years. The magnitudes are also comparable to the pseudo bonds except for very low-rated bonds (Caa-), which have much higher credit spreads than their pseudo bond counterparts.

Panel D of Table 3 presents the implied credit spreads from the simulated Merton model. Consistent with previous results in the literature and discussed elsewhere in this paper, the simulated spreads implied by the lognormal Merton model differ dramatically from the empirical credit spreads on both actual and pseudo bonds. The effect is especially pronounced for short times to maturity, where the Merton-model-implied spreads are close to zero for all but the highest-risk credit rating category.

4.4. The Transactional Liquidity of Pseudo Bonds

In this section, we follow Bao, Pan, and Wang (2011) and consider the Roll (1984) measure of transactional liquidity. The Roll "bid-ask bounce" is a measure of transactional liquidity that reflects the degree to which traded prices bounce up and down (the logic being that large reversals indicate relatively less transactional liquidity and higher sensitivities of bid and offer prices to large orders). To quantify the bid-ask bounce, the Roll measure uses the negative autocovariance of log price changes.

Specifically, following Roll (1984), we compute the transactional market illiquidity measure for pseudo bond i in month t as

$$Illiquidity_t = \sqrt{-Cov_t(\Delta p_{i,t,d}^{Bid\to Ask}, \Delta p_{i,t,d+1}^{Ask\to Bid})} \tag{8}$$

where $\Delta p_{i,t,d}^{Bid\to Ask} \equiv \log Ask_{i,t,d} - \log Bid_{i,t,d-1}$ and $\Delta p_{i,t,d}^{Ask\to Bid} \equiv \log Bid_{i,t,d} - \log Ask_{i,t,d-1}$.[14] 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, where we again use the Gaussian kernel to compute weighted returns. In addition to the Roll measure, we

[14]This formula slightly differs from Roll (1984) formula, which is used instead in equation (9) below for pseudo bonds where we have available bid and ask prices. Thus, we can compute the round-trip liquidity execution cost without imputing a transaction to be performed at the bid or ask with 50-50 probability, which was a computational assumption adopted by Roll (1984).

also compute the bid-ask spreads, calculated as $(B_{i,t}^{Ask} - B_{i,t}^{Bid})/B_{i,t}^{Mid}$. The portfolio bid-ask spread is the kernel-weighted average across pseudo bonds.

For corporate bonds, bid and ask spreads are not available. Thus, we only compute the Roll measure. Using daily price observations, the Roll measure for corporate bond i in month t is

$$Illiquidity_t = 2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Transaction}, \Delta p_{i,t,d+1}^{Transaction})} \quad (9)$$

where $p_{i,t,d}^{Transaction}$ is the log transaction price of corporate bond i on day d. We compute the Roll measure for all corporate bonds that have more than 10 return observations in a month.[15] As in credit spreads and excess returns, the Roll measure for a portfolio is the value-weighted average of all corporate bonds for which the Roll measure can be calculated.

Table 4 shows the results. Comparing Panels A and B, we see that the liquidity of pseudo bonds based on the SPX is far higher than the liquidity of pseudo bonds based on individual stocks. Both the bid-ask spreads and the Roll (1984) illiquidity measure of the SPX pseudo bonds are about one fifth the size of those same measures computed single-stock pseudo bonds. This is not altogether surprising given that SPX options are far more liquid than most individual equity options.[16]

Comparing Panels A and B to Panel C, it appears that pseudo bonds, and especially those based on SPX options, have far greater transactional liquidity than real corporate bonds. Pseudo bonds based on individual stocks have illiquidity measures that are somewhat closer to the ones computed for real corporate bonds, except for lower-rated bonds for which corporate bonds still show far lower transactional liquidity. Interestingly, these lower-rated bonds also show the highest credit spreads compared to pseudo bonds. This difference between our benchmark option-based credit spreads and the observed credit spreads on HY 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 HY corporate bonds may be attributable to transactional illiquidity.[17]

Overall, these results suggest that transactional liquidity alone is unlikely to be the source of the credit spread puzzle, especially because SPX pseudo bonds are far more liquid than

[15]Daily transaction prices are obtained from Mergent FISD/NAIC and TRACE.

[16]Panel A of Table 4 also shows that highly rated bonds are more liquid than lower rated bonds, which may be surprising given that highly rated bonds use put options that are further out-of-the-money, and hence more illiquid. The reason for this result is that we follow Bao, Pan, and Wang (2011) and use log prices for our estimates of the Roll measure, and highly rated bonds have higher prices. Thus, highly rated bonds may have a lower "dollar" liquidity but a higher "percent" liquidity.

[17]A future study might examine this issue further by using more liquid credit default swap spreads to construct implied bond prices and returns and comparing the results to those presented here for cash bonds.

corporate bonds and yet exhibit similar credit spreads. Still, given that lower-rated corporate bonds are far more illiquid than comparable pseudo bonds, we can ascribe at least some of the difference in credit spreads for such bonds to differential transactional liquidity.

5. The Credit Spread Puzzle in Excess Returns

In this section we take a different approach to the analysis of the credit spread puzzle and focus on pseudo bond excess returns instead of credit spreads. In particular, Proposition 1 in Appendix A provides us with testable hypotheses about the behavior of pseudo bond excess returns in the Merton (1974) valuation model. We also compare our empirical results for pseudo bonds to the excess returns on actual corporate bonds.

Going back to Table 2, columns five through nine report summary statistics for monthly excess returns of pseudo bonds (Panels A and B), corporate bonds (Panel C), and the lognormal Merton model (Panel D). Highly rated pseudo bonds display lower average excess returns than lower-rated pseudo bonds. Similarly, highly rated pseudo bonds exhibit lower volatility than lower-rated pseudo bonds. Both results are qualitatively consistent with the implications of the Merton model (Proposition 1.b in Appendix A) because both average excess returns and volatility are increasing in market leverage K/A.

Sharpe ratios for pseudo bonds, however, are substantially different across credit ratings. In Panel A, for instance, the Sharpe ratio for A/Baa-rated pseudo bonds is 0.30, which is far higher than the Sharpe ratio of Caa-rated pseudo bonds (0.15). Similar differences are apparent in Panel B, with the highest Sharpe ratio evident for Caa- pseudo bonds (0.30). 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.d in Appendix A).

Panel C of Table 2 shows that actual corporate bonds also display higher excess returns and volatility for lower ratings, which is consistent with the Merton model. Similar to pseudo bonds (Panels A and B) and in contrast with the lognormal Merton model, however, real corporate bonds also have Sharpe ratios that differ across credit ratings, with the highest Sharpe ratios occurring for lower rated bonds (0.22 for B-rated bonds and 0.21 for Caa-rated bonds).

Panel D of Table 2 shows that even taking into account the influence of time-varying volatility on return series and monthly sampling of returns, the lognormal Merton model does not produce the kind of returns displayed in the first three panels. In particular, average returns and volatility estimates obtained for the lognormal Merton model with Monte Carlo simulations have much smaller magnitudes than are apparent in the data, and the simulated Sharpe ratios exhibit higher values for highly rated bonds than for lower-rated bonds.

The last two columns of Table 2 contain two other important statistics of excess bond returns – skewness and excess kurtosis.[18] For both pseudo bonds and real corporate bonds, excess returns are leptokurtic, although real corporate bonds show a higher excess kurtosis. No obvious pattern of skewness or kurtosis is visible across credit ratings, however, for both pseudo and real corporate bonds.

Table A3 in Appendix E shows the same summary statistics discussed above for the 1996–2004 and 2005–2013 subsamples and demonstrates that the credit spread puzzle in pseudo bonds appears to be a robust phenomenon across time.

5.1. Excess Bond Returns and Firm's Assets or Equity

We now examine the determinants of excess bond returns in more detail. Specifically, the second and third columns of Table 5 report average excess returns and t-statistics by rating category. According to the lognormal Merton model, the average excess return on bonds should be explained by the firm's excess return on assets (Proposition 1.b in Appendix A). Because the market values of assets for actual firms are unobservable, we cannot analyze this relation empirically using real corporate bonds. But we can conduct such an analysis on pseudo bonds, whose values are based on *observable* market values of our pseudo firm's assets. For both real corporate bonds and pseudo bonds, moreover, we can observe excess returns on *equity* and hence can perform the alternate test in Proposition 1.c (see Appendix A) and compare results for corporate and pseudo bond excess returns.

Specifically, we run the following monthly regressions and report the results in Table 5:

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

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 (*e.g.*, the SPX) and pseudo equity (*e.g.*, 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 holds only for instantaneous returns conditional on a given leverage

[18] Excess kurtosis is the kurtosis in excess of three, because the kurtosis of the normal distribution is three.

ratio. To address that issue at least in part, we rebalance our portfolios monthly so that the leverage ratio K/A is relatively constant over our unit of observation. In addition, Panel D reports results from the simulated lognormal Merton model with time-varying volatility and predictability to analyze any potential bias in the average α due to time variation in β.

Column four in Panel A shows that SPX pseudo bond returns display a significantly positive α across credit ratings when excess returns are regressed on the pseudo firm's excess return on assets. The alphas are larger for lower credit ratings, ranging from 0.12% (Aaa/Aa) to 0.17% (Caa-) per month. This result is consistent with the assets of the pseudo firm, the SPX, being subject to systematic (*i.e.,* priced) jumps and stochastic volatility – see Appendix B for a simple demonstrative model.

Columns nine to 13 of Panel A show the results when we regress pseudo bond excess returns on pseudo equity excess returns (given by returns on corresponding SPX call options). 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, which is consistent with the non-linear relation between asset values and equity.

Turning to single-stock pseudo bonds, column four in Panel B shows that in a regression of excess pseudo bond returns on excess return on assets, three out of five portfolio alphas are significantly different from zero, albeit with lower t-stats than for SPX pseudo bonds. This result is consistent with a model with jumps and stochastic volatility, so long both quantities do not have large market prices of risk, which seems natural for individual stocks. In contrast, the regression of pseudo bond excess returns on pseudo equity excess returns (given by returns on corresponding call options) show that only two alphas are significantly different from zero, and these are for intermediate credit ratings. The weaker results for the extreme categories may be due to noise in the call option data used for the regression. As discussed earlier, moreover, the top Aaa/Aa rating category has a very small sample size.

How do these results for pseudo bonds compare with real corporate bonds? As mentioned, we cannot test whether excess returns of corporate bonds can be explained by excess returns on firms assets. But we can test whether they can be explained by excess returns on firms' equity, and we present the results of those tests in columns nine through 13 of Panel C. The results are similar to those for the pseudo bond regressions shown in Panel A for SPX pseudo bonds. In particular, the corporate bond alphas (like the SPX pseudo bond alphas) are positive and increasing in credit quality. For the most highly rated Aaa/Aa corporate bonds, alpha is a relatively low 0.11% (as compared to 0.12% for pseudo bonds), but, unlike the pseudo bond alpha, is not statistically 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, on average, are not small in magnitude. Overall, we see some strong similarities between the behavior of excess returns of corporate and pseudo bonds *vis-a-vis* excess equity returns.

Panel D of Table 5 presents the same results as in Panels A and B, but in this case for simulations of excess bond returns based on the lognormal Merton model (as discussed in Section 3.2.). When we run the same regressions based on simulated excess returns using the Merton model, estimated alphas are much smaller than alphas estimated using real and pseudo bonds and are not significantly different from zero. Betas are again increasing with leverage, but are now much smaller than those estimated using the empirical observations.

Table A4 in Appendix E reports results from comparable excess return regressions on the two subsamples, 1996 – 2004 and 2005 – 2013. The results are generally similar to those for the full sample. One notable exception is that estimated alphas for both SPX pseudo bonds and real corporate bonds are especially high and significant during the second subperiod (which includes the financial crisis), whereas they are not significantly different from zero in the first subperiod. This result makes sense in light of Proposition 2 in Appendix B – *i.e.*, the increase in the likelihood of a jump in the underlying assets reflected in the second subperiod seems to result in a correspondingly higher risk premium arising from heightened tail risk that manifests in the form of a higher estimated jump risk premium (see equation (17) in Appendix B).

5.2. Asset Pricing Tests

An important question is whether or not the excess returns for both pseudo bonds and corporate bonds can be explained by priced, systematic risk factors. Accordingly, Table 6 examines whether a number of common risk factors help explain the positive estimated alphas in our pseudo bond and real corporate bond portfolios.

We run the regression

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

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,[19] $TERM_t$ is the return on the long-term Treasury bonds in

[19]We initially also included Fama-French SMB and HML factors. They did not help explain the alphas of these regressions, and so we left them out of the table for parsimony.

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 long-term Treasury bonds, $dVIXSQ_t$ is the excess return on the option portfolio that underlies the VIX index, $dTED_t$ is the return on a portfolio that replicates the Treasury-Eurodollar ("TED") spread, and $Tail_t$ is the return on the tail-risk factor of Kelly and Jiang (2014). All of these factors are constructed to mimic traded portfolios, thereby enabling us to interpret alpha as an excess return.[20]

Panel A shows the results for pseudo bonds based on the SPX pseudo firm. Even controlling for these six systematic risk proxies, the alphas are significant across credit rating categories. In other words, these six systematic factors do not fully explain the average excess return of pseudo bonds. In terms of factor loadings, pseudo bonds load significantly on the market excess return, the $TERM_t$ and the DEF_t factor, as well as the volatility factor $dVIXSQ_t$. The fact that the excess return on the 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.

Somewhat surprisingly, the TED spread liquidity proxy does not seem to have much impact on pseudo bond returns.[21] 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.[22] Tail risk, by contrast, enters significantly for some credit ratings, possibly due to the jump probability in the underlying SPX. Yet, the estimated alphas of pseudo bonds are still strongly significant, showing that there are other sources of risk not captured in the risk factors above.

Panel B documents the results for pseudo bonds created from options on individual stocks. The results are consistent with those in Panel A, except that now the tail risk factor is largely statistically insignificant. This is consistent with our earlier finding (*see* Section 5.1.) that jump risk seems to be less of a source of risk premiums for pseudo bonds based on individual stocks than the SPX. Nevertheless, the estimated alphas are strongly significant across credit ratings (except for the Aaa/Aa credit rating). As shown in Panel B of Table 5, however, the pseudo bonds in the highest rating category do not display a significant average excess return to start as the category suffers from significant noise.

[20]The VIX index is the square-root of the value of a portfolio of options. Thus, $VIXSQ = VIX^2$ is effectively the value of a traded portfolio.

[21]Using the LIBOR-OIS spread instead of the TED spread did not significantly change our results.

[22]We also used the Pastor and Stambaugh (2003) factor and found similar results.

Panel C shows the results of similar regressions for real corporate bonds. Like Panels A and B, the estimated alphas are strongly significant across all credit ratings, showing that the proposed risk factors do not explain the corporate bonds' risk premia. The main explanatory variables for corporate bond excess returns are the term premium $TERM_t$ and (not surprisingly) the corporate default risk factor DEF_t. The volatility risk factor $dVIXSQ_t$ mostly enters negatively in the regressions (as in Panels A and B) but is not significant. The R^2s of the regressions, moreover, are far smaller for actual corporate bonds than for the pseudo bonds, perhaps due to the additional noise introduced by the lower liquidity of lower-rated corporate bonds.[23]

6. Applications

The previous sections document that pseudo bonds and real corporate bonds are similar both in terms of credit spreads and excess returns. We now illustrate how our option-based methodology can be applied to the analysis of credit risk using data-based experiments that would be hard or impossible to implements in the real world. The benefit of our methodology is that our findings are extracted straight from the data without the filter of a parametric model. We offer three suggested applications for illustrative purposes, and leave more elaborate examples to future research.

6.1. Credit Spreads and the Frequency of Credit Rating Revisions

In previous sections, we assign credit ratings to each of our pseudo bonds every month. We then sort bonds on those credit ratings and form portfolios. In reality, of course, credit rating agencies do not assign corporate credit ratings at exactly a monthly frequency. Given the apparent strong reliance that many investors place on published ratings and the importance of potential clientele effects resulting from institutional portfolio constraints involving minimum credit ratings, an important question is how the frequency of credit rating assessments may impact *ex post* average credit spreads and excess returns.[24] To address this issue, we

[23]An interesting question is whether for each credit rating, our pseudo bond returns explain the real corporate bond returns. Except for the top credit rating Aaa/Aa, the slope coefficients of regressions of real excess bond return on SPX pseudo bond excess returns are significant. The R^2 of such regressions, however, are small and some of the alphas are significantly positive.

[24]Our analysis of the empirical implications of the frequency of ratings assignments is not intended to be a proscriptive commentary on how often ratings "should" be assigned or re-evaluated. Indeed, rating agencies typically assign ratings based on a variety of considerations, not all of which immediately imply a simple

now consider the implications of credit rating assessments at lower (and exogenous) frequencies – specifically, every three, six, and 12 months. We continue to compute average credit spreads and bond returns, however, at the monthly frequency.

Table 7 reports average credit ratings and summary statistics for pseudo bonds using these three new, lower-frequency credit rating assignment intervals. We can see in columns three and four that as we decrease the ratings frequency, average credit spreads become smaller during booms and substantially larger during recessions. Although a negative bias from less frequent credit rating assignments in booms and a positive bias in recessions seems intuitive, the size of these effects is surprising, especially during recessions. Still, as shown in column two, because booms last longer than recessions, the grand average credit spreads across rating categories are similar to average spreads based on a monthly rating assignments. Indeed, the only noticeable difference is at the very lowest credit rating (Caa-), for which the average credit spread moves from 5.17% at the monthly assignment frequency (Table 2) to 5.53%, 7.32% and 8.37% at the quarterly, semi-annual, and annual assignment frequencies, respectively. As first noted by David (2008), this 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 over longer periods generate increases in average credit spreads, which are more pronounced for pseudo bonds closer to at-the-money (high K/A).[25]

Table 7 also shows that average excess pseudo bond returns are smaller for less frequent credit rating assignments. Again, this effect is likely due to negative convexity – *i.e.*, bond prices are capped when asset values increase, whereas they may decrease to zero when asset values decrease. Thus, over a longer period, the variation of asset value generates a negative convexity bias in average bond returns as underlying asset values move away from the initial leverage ratio K/A that defines its credit rating at rebalancing time. The effect of this negative bias is large and affects all credit ratings, with the largest impact occurring on relatively higher-risk bonds. For instance, the average excess return for Caa- bonds decreases from 0.35% when credit ratings are assigned at the monthly frequency (Panel A, Table 2) to 0.17% when credit ratings are assigned at the annual frequency (Panel C, Table 7). Indeed, the Sharpe ratio for bonds in that category drops to just 0.06 (despite the relatively high credit spread of 8.37%).

In sum, less frequent credit rating revisions generate two convexity biases that move in opposite directions: average credit spreads increase while average returns decrease, and these

rule for frequency of evaluations.

[25]See also Feldhutter and Schaefer (2014) for a discussion of this convexity issue and its impact on estimation of credit spreads.

effects are especially large for the lowest credit rating categories.

6.2. Uncertainty about Asset Values and Credit Spreads

Our option-based approach to credit risk analysis can also be used to investigate the vexing issue of how uncertainty about asset values is related to credit spreads and bond returns (*e.g.,* Duffie and Lando (2001), Yu (2005), Polson and Korteweg (2010)). All else equal, put option values are higher for larger amounts of uncertainty about underlying asset values. In the Merton framework, bonds (which include short put options) thus have prices that are decreasing in underlying asset uncertainty.

The empirical question, however, is the extent to which higher underlying asset uncertainty gives rise to higher credit spreads across different credit ratings. The question is complicated by the fact that a bond's credit rating should already take into account (at least to some extent) uncertainty in asset values – *i.e.,* firms with more uncertain asset values should have lower credit ratings, *ceteris paribus.* Thus, it is not obvious that firms in the same credit rating category with higher underlying asset uncertainty should exhibit higher credit spreads. This endogeneity issue is hard to resolve using real corporate bond data because (*i*) natural experiments are rare in which everything stays constant except uncertainty about underlying asset values, and (*ii*) asset value uncertainty is difficult to measure. Our model-free approach allows us to overcome both issues: (*i*) we assign bonds to credit rating categories according to a specific rule that holds constant most confounding variables and allows us to focus more specifically on asset uncertainty, and (*ii*) our options-centric approach enables us to measure the uncertainty of our pseudo firms' asset values by analyzing volatilities of the assets underlying the options on which we rely.

Consider the pseudo bonds computed from individual stocks included in the SPX index. For each time t, we sort these single-stock pseudo bonds according to their pseudo credit ratings. For each credit rating category, we then sort pseudo bonds into low, medium, and high asset volatility categories. For each credit rating/volatility combination, Table 8 reports pseudo bonds' average credit spreads (Panel A), excess returns (Panel B), leverage K/A (Panel C), and underlying asset volatility (Panel D).

Panel A indicates that for all rating categories except Aaa/Aa, credit spreads for pseudo bonds with high-volatility assets are higher than spreads on pseudo bonds with low-volatility assets. The net effect of higher underlying asset uncertainty thus is indeed a higher credit spread, even after taking into account the endogenous effect that higher uncertainty translates into lower average leverage K/A to qualify for a given credit rating (Panel C). The magnitudes are large, moreover, especially for lower-rated bonds. For instance, a Ba-rated pseudo bond has 2.63% spread in the low-volatility bin but a 4.45% spread in the high-volatility bin. These magnitudes are larger than the differences in average credit spreads between A/Baa and Ba rated bonds (shown in Table 2). In contrast to other credit ratings, credit spreads for the Aaa/Aa rating category are instead decreasing in volatility (uncertainty). While this result is interesting, we recall that in this rating category the data are sparse and thus results are especially noisy. Finally, the pattern of average excess returns (Panel B) mostly mimics the pattern of credit spreads, although noise in the data at times may generate different particular patterns.

Panel C shows the intuitive fact that, conditional on individual credit ratings, high underlying asset volatility corresponds to lower leverage. Panel D provides a sense of the difference in average asset volatility within credit ratings. For instance, the difference in volatility in the Aaa/Aa rating category is relatively small because only safe assets make it into the high credit quality bin. By contrast, the difference in asset volatility for lower-rated pseudo bonds can be substantial – *e.g.*, from 25% to 46% for Caa- bonds.

6.3. Pseudo Bank Rollover Risk and Capital Requirements

As a final application of our option-based approach to the study of credit risk, we study the rollover risk and capital requirement for a hypothetical pseudo bank that lends money to the individual pseudo firms whose assets are based on the stocks of SPX constituent companies. Specifically, we consider a hypothetical bank that issues short-term debt (*e.g.,* demand deposits and CP) to finance longer-term zero-coupon commercial loans. Equivalently, the pseudo bank purchases pseudo bonds from the firms to which it extends credit. To analyze the impact of maturity transformation and rollover risk, we assume that the pseudo bank issues debt with only one month to maturity (see Figure 5 for a schematic representation of the pseudo bank). Given the empirical properties of monthly pseudo bond returns, we can then evaluate the pseudo bank's probability of default.

In particular, suppose that the pseudo bank defaults if the market value of its assets are below the face value of the bank's debt when that debt matures. For every t, default thus occurs if $A_t^{Bank} < K_{t-1}^{Bank}$, where K_{t-1}^{Bank} is the total face value of short-term debt issued by the pseudo bank in previous month $t-1$. Given that the bank's assets are only a portfolio of pseudo bonds issued by the bank's pseudo firm borrowers, we have $A_t^{Bank} = A_{t-1}^{Bank}(1+R_{t-1,t}^{Port})$, where $R_{t-1,t}^{Port}$ is the return on the portfolio of bonds between $t-1$ and t. Therefore, the requirement for one-month survival for the bank is $R^{Port}_{t-1,t} > -(1 - \frac{K^{Bank}_{t-1}}{A^{Bank}_{t-1}}) = -(1 - L_{t-1})$, where L_{t-1} is the bank's leverage ratio at $t-1$. We want to find the minimum equity capital that keeps the probability of the pseudo bank's failure at t small – *i.e.*, we want to find $\overline{L}$ such that $Pr(R^{Port}_{t-1,t} < -(1 - \overline{L})) = \alpha$ for some small probability α.

We consider three types of pseudo bond portfolios that comprise the assets of the pseudo bank. The first is an "All " portfolio consisting of a portfolio of pseudo bonds diversified by maturity and credit rating. In addition, we consider IG and HY portfolios that contain only pseudo bonds with credit ratings above (and equal to) or below Baa, respectively. Although the IG and HY portfolios are distinguished by credit quality, we assume that both portfolios are diversified across maturities. All of these pseudo bonds are issued by the individual hypothetical firms discussed in previous sections, and we assume the bank only extends one loan to each pseudo firm.

We construct our pseudo bank's loan portfolios to have approximately constant characteristics across the overall sample. We draw the maturities of our pseudo bonds from only three maturity bins – up to 273 days, 274 to 548 days, and 549 days or longer.[26] We also choose a minimum portfolio size $N = 20$ to ensure some diversification benefits for the pseudo bank. Specifically, for every month t, for each firm and rating category, we randomly choose one maturity bin per firm/borrower and select one pseudo bond as the bank's loan to that firm. Some firms may have no pseudo bonds with the selected maturity/rating combination, in which case such firms are not part of the portfolio. For the IG and HY portfolios, if the number of firms with the selected pseudo bonds is more than N, we average them and record the portfolio returns. Otherwise we have missing data for that month. For the "All" portfolio, if the number of IG firms is more than $N/2$, we randomly pick the same number of HY bonds as IG bonds and compute returns for the overall portfolio. This methodology ensures that the "All" portfolio has an equal representation of IG and HY pseudo bonds.[27] We repeat this procedure for the overall 1996 – 2013 sample period. In addition, we simulate this procedure 1,000 times to compute representative portfolios. Note that the simulation only pertains to the choice of the portfolio at any t; the portfolio return itself is not simulated and is the actual market return for the chosen pseudo bonds.

Panels A to C of Figure 6 show the return distributions of our pseudo bond portfolios. For

[26]We choose these three maturity bins because they are equally well-populated across the overall sample.

[27]This procedure avoids sample selection issues in which the "All" portfolio may end up with over-representation of HY pseudo bonds simply because there may be more such pseudo bonds available in a given month. This is likely to happen as HY pseudo bonds use put options that are less out-of-the-money than IG pseudo bonds. A drawback, however, is that there are months with no observations, and thus the empirical distributions across panels in Figure 6 are not comparable, as they may include different samples.

comparison, Panels D to E show the return distributions of the portfolios of assets underlying the pseudo bond portfolios. All distributions are all normalized to have a zero mean and unitary standard deviation for ease of comparison. Several results are apparent. First, the distributions of pseudo bonds (top row) are always more dispersed than the corresponding distributions of assets that underly the pseudo bonds (bottom row) – *i.e.*, the diversification benefit in a portfolio bonds is not as strong as for the portfolio of underlying assets inasmuch as diversification does not curtail the tails by the same amount. Second, although the difference in dispersion is mild for the IG portfolio, that difference is large for the HY portfolio. The underlying assets have a maximum negative return of about four standard deviations below the mean, whereas the underlying HY portfolio reaches seven standard deviations below the mean.

Finally, Panel C of Figure 6 shows that the "All" portfolio has some observations that are over eight standard deviations below the mean, although their frequency is smaller than the HY portfolio as a result of the mixture of HY and IG pseudo bonds to make it a more balanced portfolio. Banks diversified across credit ratings and maturities thus are especially prone to "Black Swans" (*i.e.*, low-frequency, high-severity events) even if the underlying individual asset distributions do not demonstrate such risks.

To gain further insights on the relation between the distribution of the pseudo bank's assets and the portfolio of assets underlying those pseudo bonds, Figure 7 shows the scatter-plot of the distributions contained in Figure 6. Panel A shows an interesting result for the IG portfolio. Namely, although the worst six standard deviation decline in the bank's assets (the $y-$axis) occurs for a four standard deviation decline in the underlying asset portfolio (the $x-$axis), even a four standard deviation decline in the bank's assets may occur for mild negative variations in the underlying asset portfolios. In other words, significant negative pseudo bond returns may occur, for example, as a result of large increases in volatility or a sudden reduction in liquidity even if the assets underlying the bonds themselves do not show particularly large declines.

Panel B shows that for the HY portfolio, the worst returns on pseudo bonds occur around the worst returns on underlying asset values. The seven standard deviation decline in the HY bond portfolio occurs at the same time as a four standard deviation decline in the value of underlying assets. The apparent concave relation between HY returns and underlying asset returns is attributable to leverage, but the magnitude of this effect is the interesting part of this exercise. Notably, the extreme negative realizations visible on the bottom left corner are due to just one date (*i.e.,* October 2008), and several points on the scatter plot illustrate different combination of returns across different simulated portfolios that include that date. There was no simulated HY pseudo bond portfolio that could have averted the massive decline in pseudo bond returns – and thus in the asset value of the pseudo bank – on October 2008.

Finally, Panel C shows that a balanced portfolio comprising 50% IG bonds and 50% HY bonds still shows potentially devastating eight (and more) standard deviation drops in value due to a four standard deviation drop in asset values. So, even if the pseudo bank's loan portfolio is well-diversified across credit ratings, the leverage of the pseudo bond portfolio is still sufficient to generate a potential "Black Swan" scenario that could have a devastating effect on the bank itself.

We can use the return distribution of our pseudo bank's assets to obtain the amount of equity capital required to make the probability of default "small." For example, the minimum, 99.5%, and 99% percentiles of the (non-normalized) monthly return distributions for the "All" portfolio are −11.92%, −4.27%, and −3.41% respectively. If we want to ensure zero probability of default over a monthly horizon, the minimum equity capital requirement would have to be more than 12% of assets. The same percentiles for the IG portfolio are −3.12%, −1.56%, and −1.26%, and, for the HY portfolio, −13.13%, −6.46%, and −5.44%. Based on these data, a pseudo bank that only lends to IG firms could ensure no default over a one-month time horizon by having an equity capital buffer of just 4%, whereas a pseudo bank that specializes in HY loans would need a much higher capital buffer of over 14% to absorb "maximum" possible default-related losses.

7. Conclusions and Discussion

In this paper we have introduced a model-free, option-based methodology to analyze issues related to credit risk ranging from the size of credit spreads of defaultable bonds to the source of rollover risk in banking. Our model-free methodology utilizes traded options to quantify the implications of the original Merton (1974) insight that the value of defaultable debt can be computed as the value of risk-free zero-coupon debt minus the value of a put option on the firm's assets. By imagining that hypothetical pseudo firms issue debt and equity securities to finance their purchases of underlying traded assets such as the SPX index portfolio or individual firms' stocks, we can study the empirical properties of the pseudo bonds issued by such firms.

Our empirical results are striking. We find that the credit spreads generated by pseudo bonds (whose values are directly observable and involve no parametric assumptions) are 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 bond valuation model, which assumes that the value of the assets underlying defaultable corporate debt are lognormally distributed.

Our empirical investigation of pseudo bonds also demonstrates numerous similarities between the properties of pseudo bonds and the empirical properties of real corporate bonds. These results call into question theories of the credit spread puzzle that rely on agency costs, asymmetric information, learning, uncertainty, and the like. Instead, our results indicate a genuine risk premium that investors demand to compensate for adverse outcomes that could occur following the realization of tail events in the underlying asset distribution.

We have also shown how our model-free approach to bond valuation offers a benchmark to conduct experiments for the analysis of credit risk that are grounded in the data but that would be otherwise hard or impossible to perform with real corporate bond data. For instance, we have shown the type of biases we should expect in average credit spreads and bond returns when credit ratings are not updated with sufficient regularity. We have also demonstrated how uncertainty about underlying asset values affects credit spreads once we take into account the endogenous effect of asset uncertainty on credit ratings. Finally, we presented an application to banking and capital requirements by looking at the empirical distribution of several simulated loan portfolios. Such experiments are important because they capture the full extent of the variation in debt valuations arising from discount rate movements, as opposed to just shocks to cash flows. Those variations in discount rates generate significant changes in the mark-to-market values of assets that impact the market values of debt in a systematic fashion. This has important implications for debt valuation, as well as capital requirements.

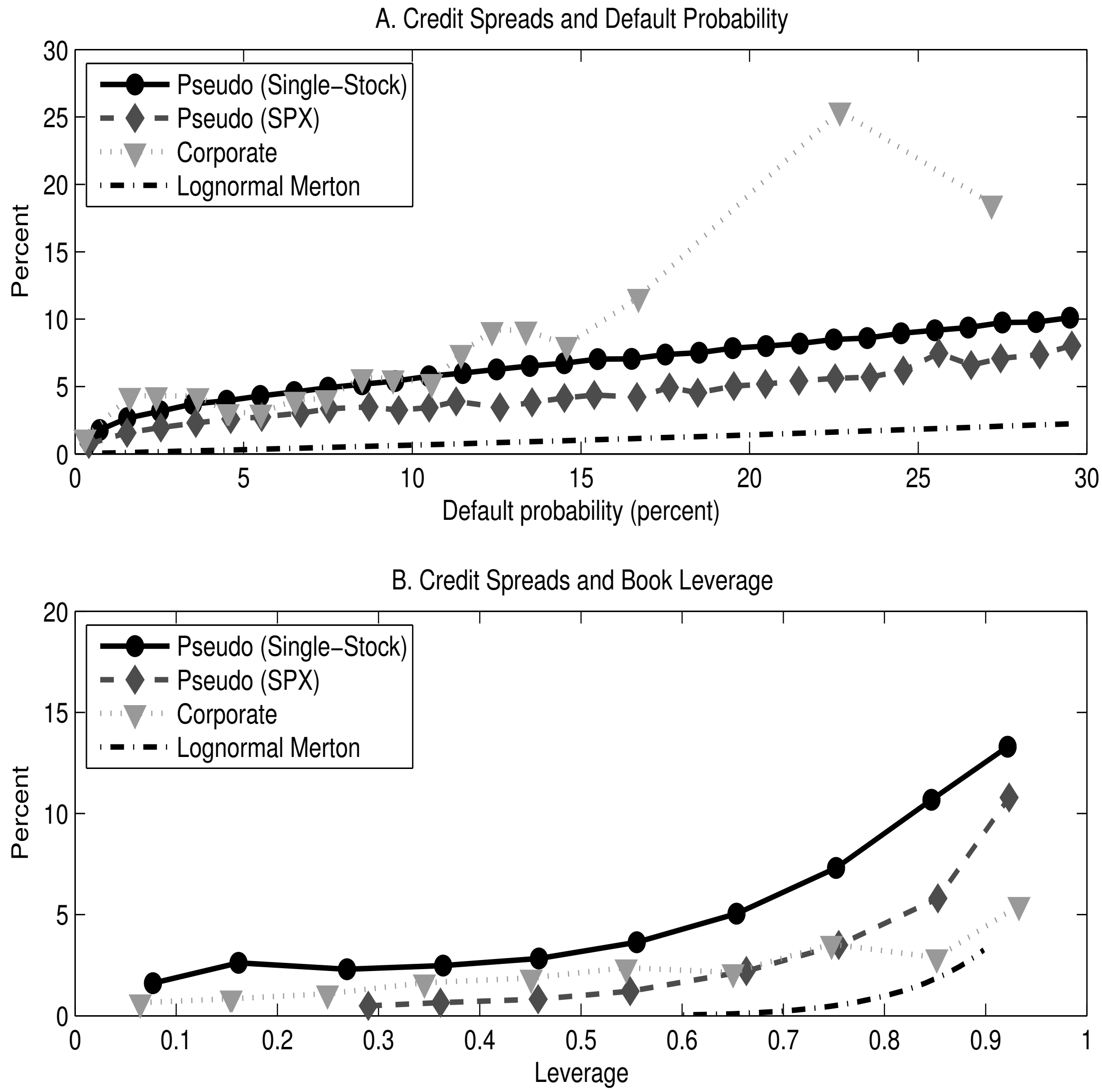
A potential criticism of our approach is that our results are driven by the special nature of the assets held by our pseudo firms, *i.e.*, stock indices or individual stocks, which may be too volatile and prone to market crashes or run-ups compared to the real assets in which other (especially non-financial) firms invest. We believe the opposite is true and that the observability of the market values and volatilities of our pseudo firms' underlying assets is a virtue of our approach rather than a limitation. Indeed, even if unobservable, the *market* values of assets underlying real firms are likely to be quite volatile and prone to crashes, as well. In fact, recall that stocks are just claims on future dividends, which are relatively smooth and not too volatile (*e.g.,* Shiller (1981)). In spite of the low volatility of dividends, stock prices themselves are highly volatile. As is well known from the work of Campbell and Shiller (1988), Vuolteenaho (2002), Cochrane (2005, 2008), and others, discount rate shocks are critical determinants of the volatility of market values. It is only logical to conclude that a similar channel – the discount rate channel – affects the market value of firms' underlying assets and thus that such unobservable market values of assets are in fact highly volatile and leptokurtic. Our empirical results offer indirect evidence that market values of actual firms' assets likely have similar empirical characteristics.

Our empirical approach can be generalized and extended in multiple directions. For instance, future research could investigate hypothetical firms with different types of traded assets, such as commodities, currencies, Treasury bonds, swaps, exchange-traded funds, and the like. As long as traded options exist on the underlying assets, our model-free approach can be used as a benchmark for investigating the relation between the risk characteristics of underlying assets (which are observable for pseudo firms) and the risk characteristics of pseudo bonds issued by those pseudo firms. Such empirical research could shed further light on the cross-sectional and time series determinants of credit spreads.

Future research might also extend our framework to deal with coupon-bearing pseudo bonds, pseudo bonds with embedded options, and the like. Indeed, one could use options with various maturities to extract assets' risk-neutral distributions and then use the risk-neutral methodology to value defaultable bonds with more realistic features than just zero-coupon bonds. One could then investigate the empirical properties of such bonds and shed additional light on related issues like optimal prepayment and redemption decisions, the design of structured hedges embedded into debt instruments, and more.

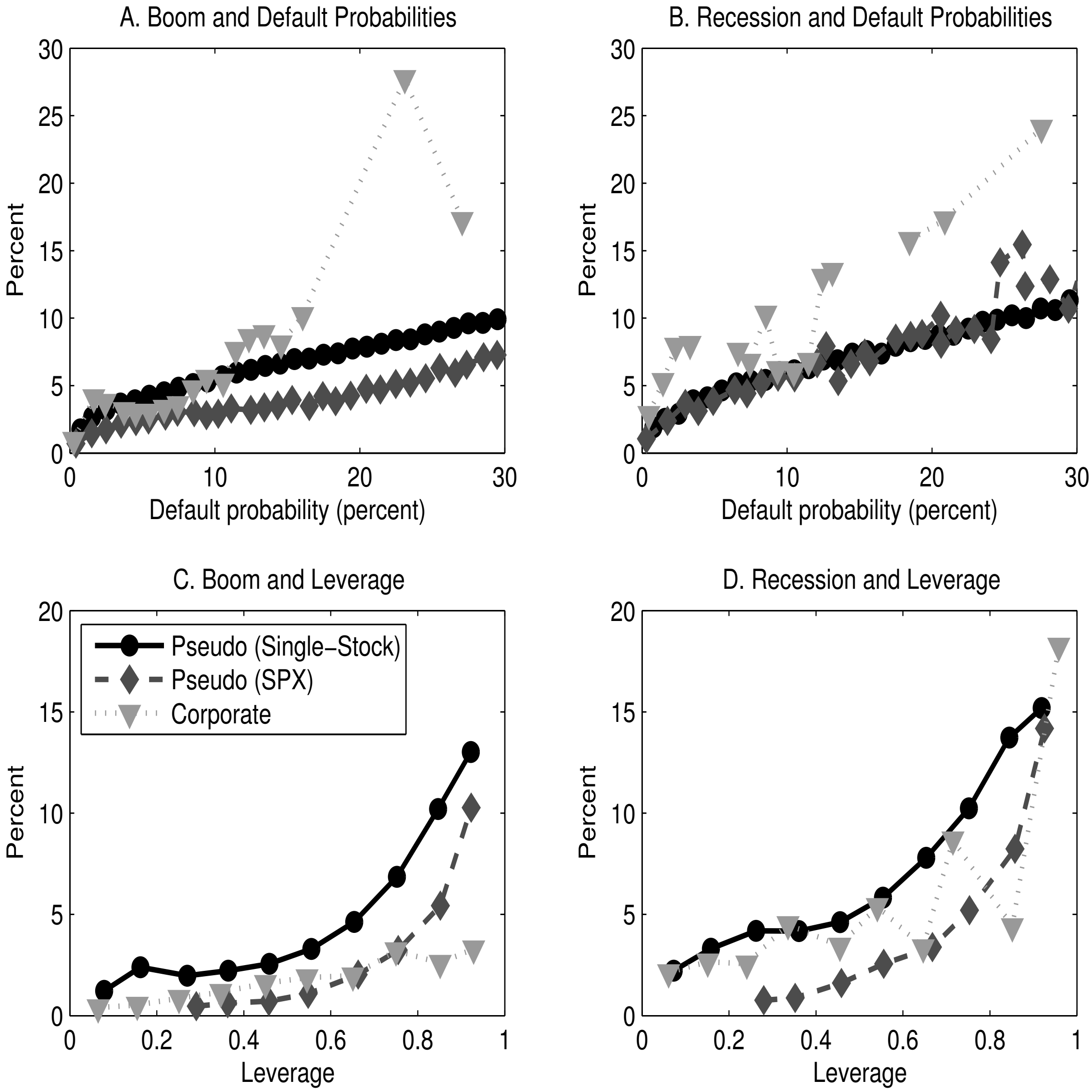
Subsequent research might also consider additional data-based experiments. For example, it would be interesting to extend our simple banking example to more elaborate cases, assess the appropriateness of various parametric modifications to the lognormal Merton model currently used in academia and industry, analyze the implications of legal and institutional issues like solvency tests (ability-to-pay vs. balance-sheet), and the like. One could also adopt our model-free methodology to investigate issues in corporate finance, such as the trade-off theory of capital structure in which the tax benefits of debt are traded for additional costs of financial distress. By using our pseudo firms as a laboratory, one could obtain implications that naturally take into account the true risk premia required by investors to hold pseudo bonds, and thus obtain quantitative implications of optimal capital structure in a controlled environment.

Figure 1: Credit Spreads of Two-Year Pseudo Bonds



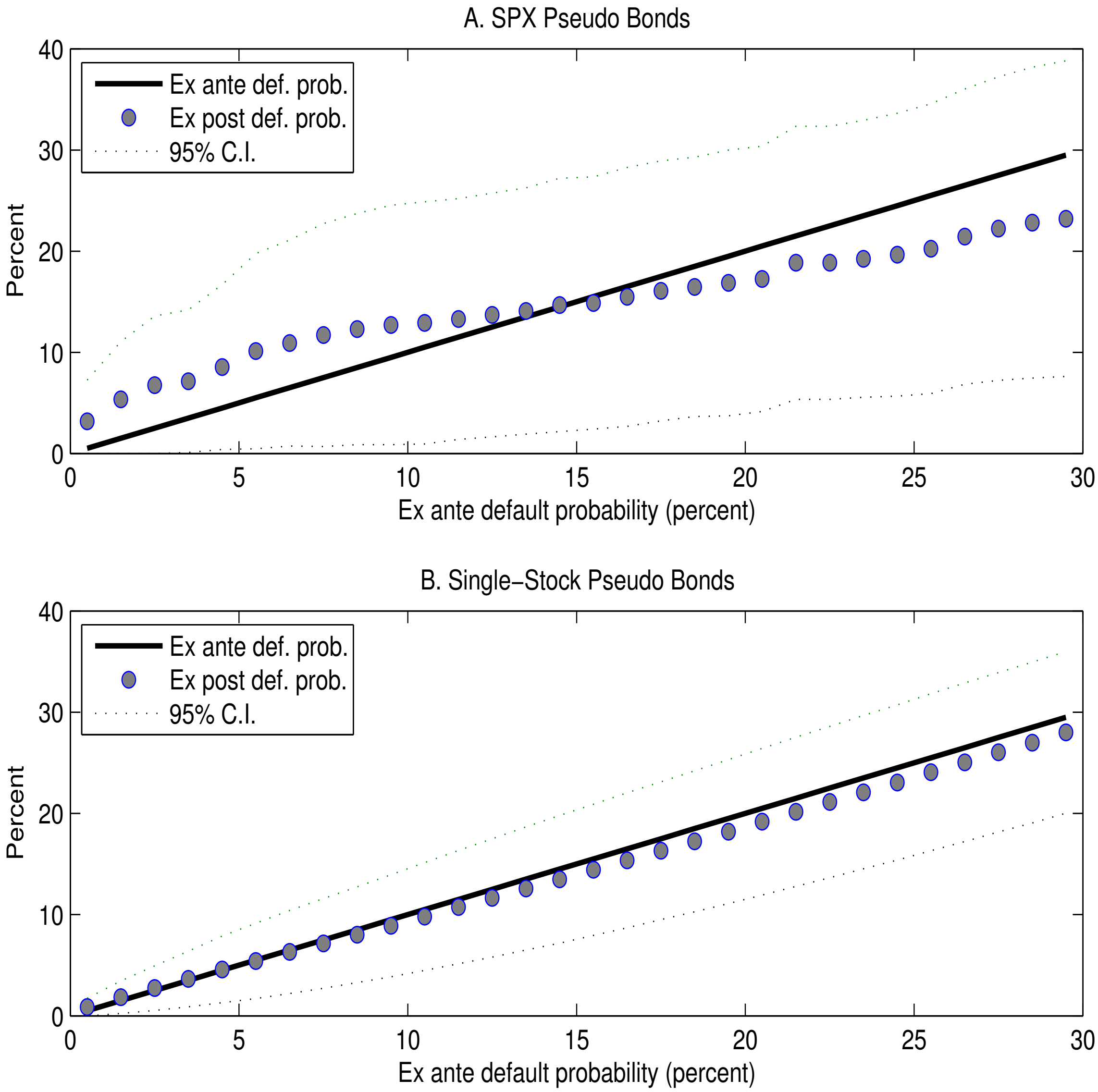
Notes: Credit spreads of single-stock pseudo bonds (circles), SPX pseudo bonds (diamond), real corporate bonds (triangles), and implied by the lognormal Merton model (dash dotted line). Panel A reports the credit spreads plotted against the probability of default. For pseudo bonds, the default probability is computed from the empirical distribution of asset returns, i.e. the SPX or individual stocks for Panel A and B, respectively. For real corporate bonds, the default probability corresponds to Moody's default frequencies for corresponding bonds credit ratings. For the Merton model, the default probability is obtained from its implied lognormal distribution. Panel B reports the credit spreads plotted against the book leverage ratio. For pseudo bonds and the Merton's model, the book leverage ratio is defined as "Face Value / (Face Value plus Equity)" for pseudo bonds, where "Equity" is the value of the corresponding call option, while for the real corporate bonds, the book leverage is defined as "Book Value of Debt / (Book Value of Debt plus Market Value of Equity)". The sample is 1996 – 2013.

Figure 2: Credit Spreads of Two-Year Pseudo Bonds over the Business Cycle



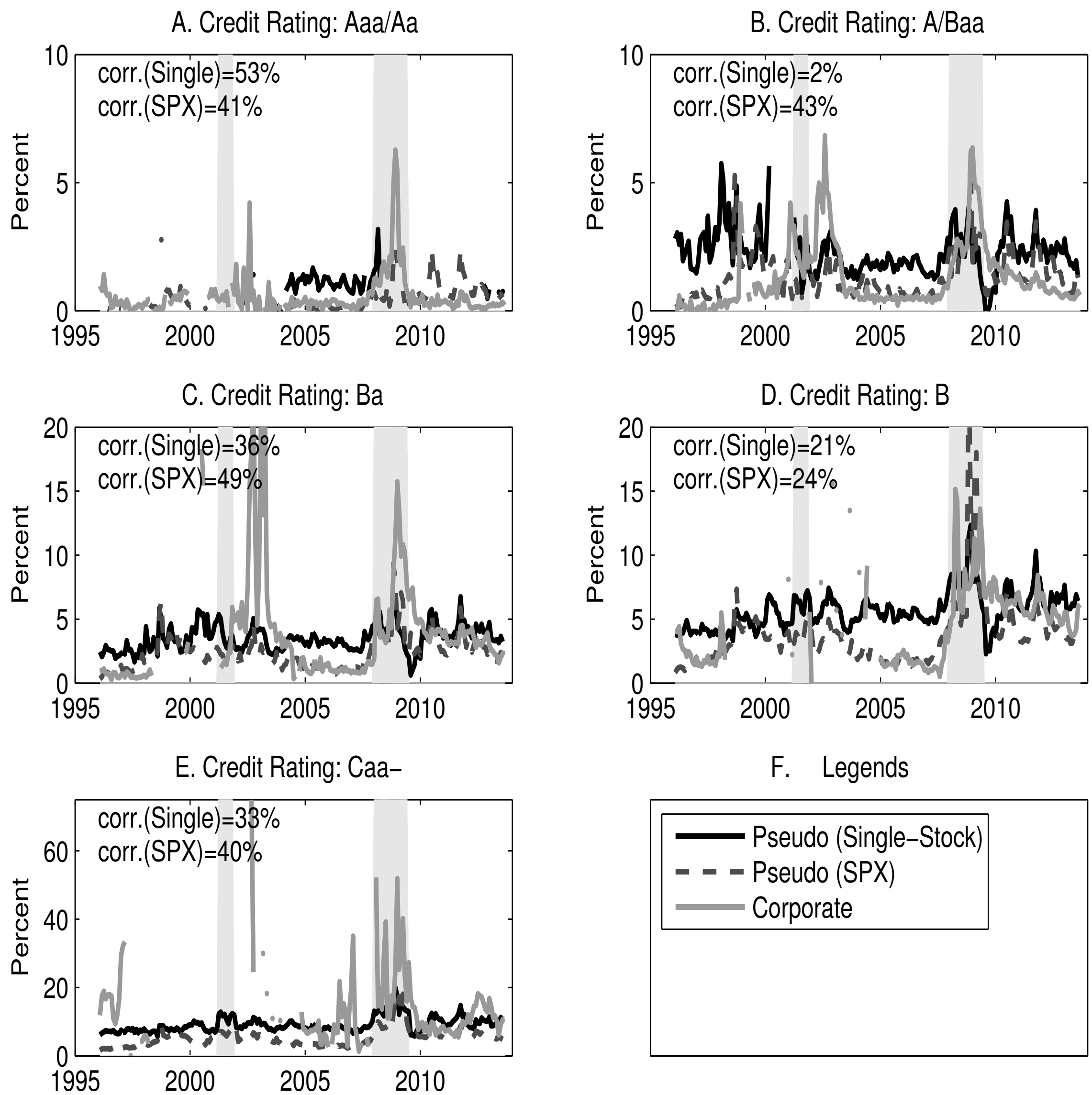
Notes: Credit spreads of single-stock pseudo bonds (circles), SPX pseudo bonds (diamond), and real corporate bonds (triangles) over the business cycle. Panels A and C report the credit spreads plotted against the probability of default during booms and recessions, respectively. For pseudo bonds, the *ex ante* default probability is computed from the empirical distribution of asset returns, i.e. the SPX or individual stocks for Panel A and B, respectively. For real corporate bonds, the default probability corresponds to Moody's default frequencies for corresponding bonds credit ratings. For the Merton model, the default probability is obtained from its implied lognormal distribution. Panels B and D report the credit spreads plotted against the book leverage ratio in booms and recessions, respectively. For pseudo bonds and the Merton's model, the book leverage ratio is defined as "Face Value / (Face Value plus Equity)" for pseudo bonds, where "Equity" is the value of the corresponding call option, while for the real corporate bonds, the book leverage is defined as "Book Value of Debt / (Book Value of Debt plus Market Value of Equity)". The sample is 1996 – 2013.

Figure 3: Ex Ante Default Probabilities versus Ex Post Default Frequencies



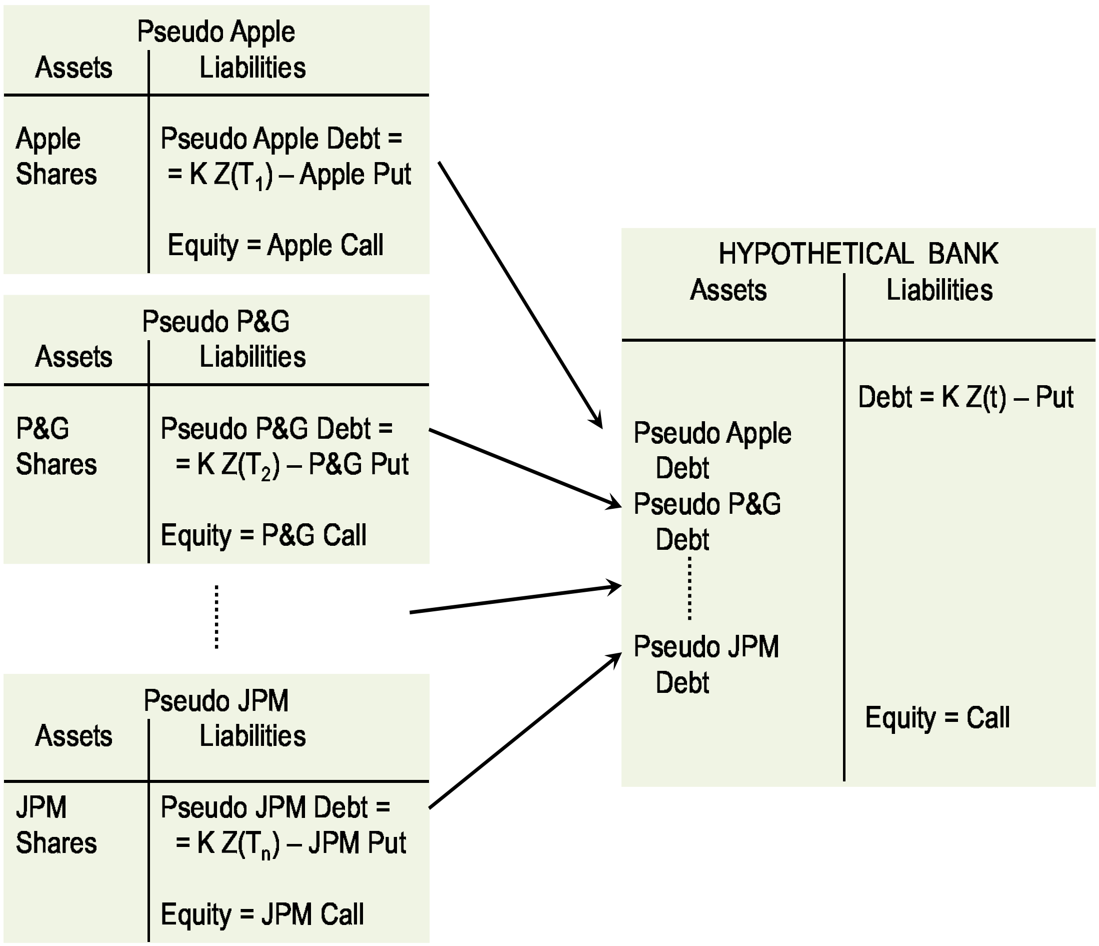
Notes: Panel A plots the estimated *ex post* default frequencies of pseudo bonds based on individual stocks (circles) together with its 95% confidence intervals (dotted lines) against the 45 degree line, which represent the ex-ante default probability for each of the pseudo firms. The sample is 1970 to 2013. Panel B plots the same quantities for SPX based pseudo bonds.

Figure 4: Credit Spreads of Two-Year Pseudo and Corporate Bonds Over Time



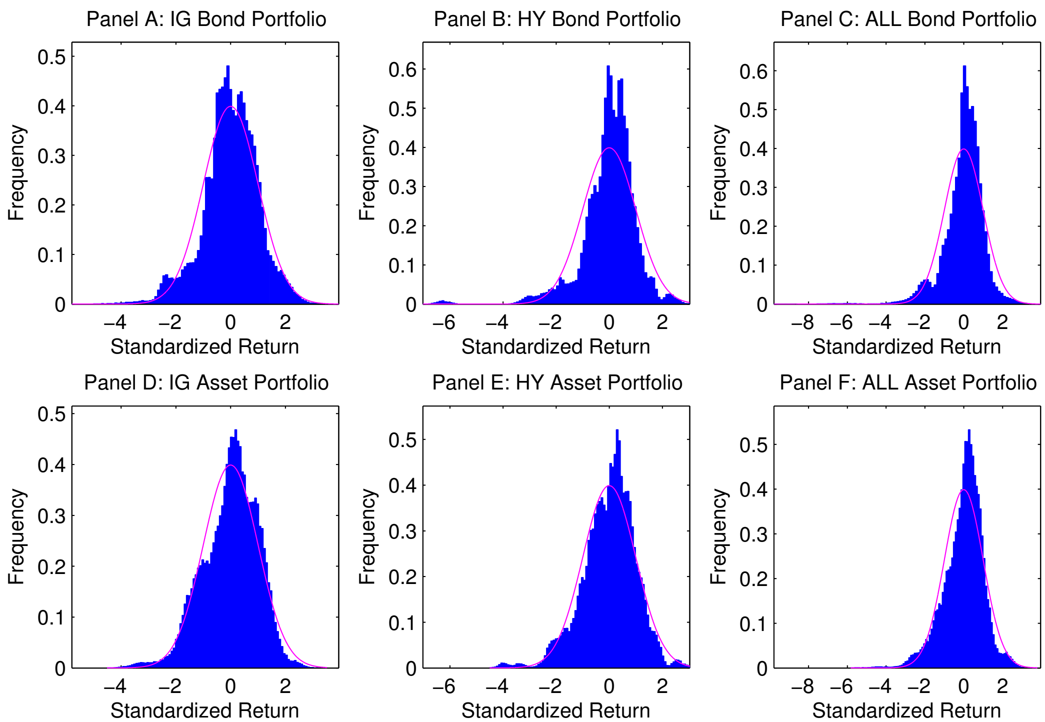
Notes: Credit spreads of two-year pseudo and corporate bonds. Pseudo bonds are constructed from a portfolio of risk free debt minus put options on individual stocks (solid black line), or risk free debt minus SPX options (dashed line). Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *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 are computed from the empirical distribution of asset returns, i.e. the SPX or individual stocks. Corporate bond data (solid grey line) are from the Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE and DataStream. Credit ratings of corporate bonds are from Moody's. The correlations in the top left corner of each panel are the empirical correlations of corporate credit spreads with pseudo bonds' credit spreads. Shaded vertical bars denote NBER-dated recessions. The sample is monthly between 1996 to 2013. All credit spreads are computed as the difference between the semi-annual yield-to-maturity and the corresponding Treasury yield.

Figure 5: The Assets of a Pseudo Bank



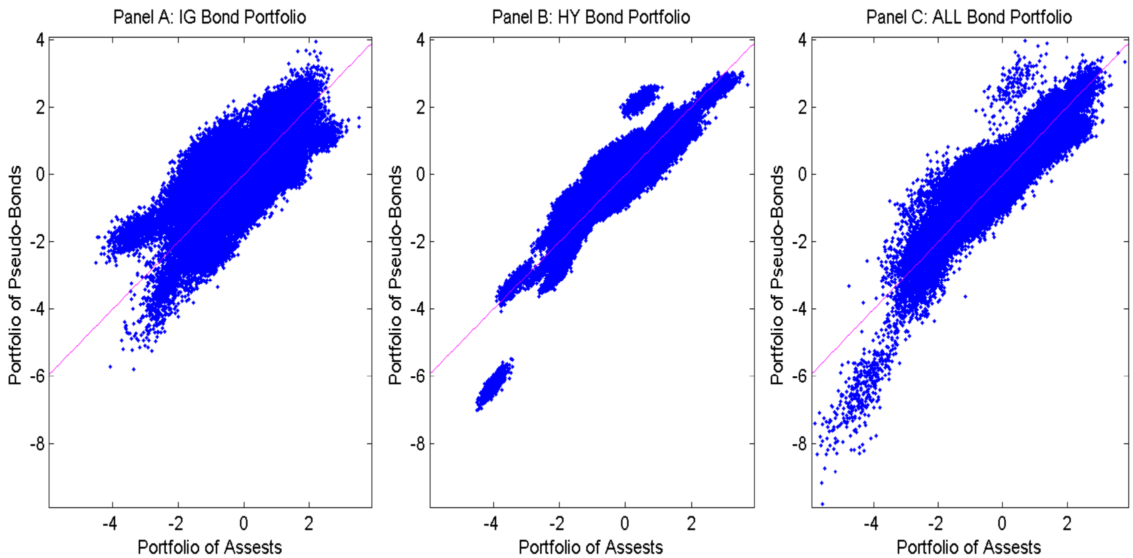
Notes: This diagram represents the assets of a fictitious pseudo bank that lends money to the pseudo firms in our sample. Pseudo firms are hypothetical firms that purchase shares of underlying traded firms, and that finance those purchases by selling equity and zero-coupon bonds. The values of these zero-coupon bonds are given by safe U.S. Treasury zero-coupon bonds minus traded put options on the underlying firms. In the figure, the pseudo bank purchases the pseudo bonds, which then form its loan asset portfolio, and finances the acquisition of its portfolio by issuing equity and short-term zero-coupon debt.

Figure 6: Return Distribution of Pseudo Bond Portfolios



Notes: Panels A, B, and C show the return distributions of random portfolios of pseudo bonds over the sample 1996 – 2013, while panel D shows the return distribution of portfolio of stocks underlying the "All Bond" portfolio. The distributions have been normalized to have zero mean and unit standard deviations. The random portfolios in each panel are constructed as follows: For every month t, we consider all potential available pseudo bonds for all the 500 firms in the S&P 500 index. We group such bonds in credit rating / maturity bins. We consider only two credit ratings: Investment Grade (i.e. Aaa/Aa and A/Baa) or High Yield (i.e. Ba, B, Caa-) and only three maturity ranges (0,273), (274,548), (549, ∞). For each firm and for each rating, we randomly choose one maturity bin per firm, when available. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. If not, we record a missing observation for the portfolio return in the month. For "All" portfolio, if the number of IG firms is more than 10, then we randomly pick the same number of HY bonds as the IG bonds, and then compute the average across all the bonds. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

Figure 7: Pseudo Bond Portfolio Returns versus Underlying Asset Portfolio Returns



Notes: Panels A, B, and C show the scatter-plot of pseudo bond portfolio returns versus underlying asset portfolio returns. The distributions have been normalized to have unit standard deviations. The random portfolios in Panel A are constructed as follows: For every month t, we consider all potential available pseudo bonds for all the 500 firms in the S&P 500 index. We group such bonds in credit rating / maturity bins. We consider only two credit ratings: Investment Grade (i.e. Aaa/Aa and A/Baa) or High Yield (i.e. Ba, B, Caa-) and only three maturity ranges (0,273), (274,548), (549, ∞). For each firm and for each rating, we randomly choose one maturity bin per firm, when available. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. If not, we record a missing observation for the portfolio return in the month. For "All" portfolio, if the number of IG firms is more than 10, then we randomly pick the same number of HY bonds as the IG bonds, and then compute the average across all the bonds. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

Table 1: Default Frequencies of Two-Year Corporate Bonds and Pseudo Bonds

Panel A of this table reports *ex post* default frequencies of corporate bonds by credit rating category (shown in the first column.) The second column is the aggregate average, while columns 3 and 4 report default frequencies during NBER booms and recessions, respectively. The last two columns report the cutoff points used to assign pseudo credit ratings to pseudo bonds, which equal the mid-points of the default frequencies in columns 3 and 4. The exception is the final cut off for Caa- ratings, that is chosen as 150% the historical default of Caa- bonds. 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 SPX put options. Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *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 from the empirical distribution of underlying asset returns, i.e. the SPX or individual stocks for Panel A and B, respectively. 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 frequencies 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 that the two-year return (excluding dividends) on SPX index falls below the given moneyness of the pseudo bonds in each portfolio. The last two columns report the average moneyness of the options $\overline{K/A}$, and the average maturity $\overline{\tau}$ in days. Panel C reports the same quantities as in Panel B, but for pseudo bonds formed from individual stocks' options. The sample is 1970 to 2013.

Panel A: Corporate Bonds

Credit Rating	Historical Default Frequencies: Mean	Boom	Recession	Pseudo Rating Cutoffs: Boom	Recession
Aaa/Aa	0.03	0.02	0.05	[0.00, 0.15)	[0.00, 0.26)
A/Baa	0.31	0.28	0.47	[0.15, 1.72)	[0.26, 2.12)
Ba	3.23	3.15	3.76	[1.72, 5.91)	[2.12, 8.29)
B	9.16	8.67	12.81	[5.91, 15.3)	[8.29, 27.1)
Caa-	25.18	21.93	41.37	[15.3, 32.9]	[27.1, 62.1]

Panel B: Pseudo Bonds (SPX)

	Ex ante Def. Prob.		*Ex post* Def. Prob.				
	Boom	Recession	Mean	C.I.(2.5%)	C.I.(97.5%)	$\overline{K/A}$	$\overline{\tau}$
Aaa/Aa	0.02	0.09	1.98	0.00	4.75	0.43	590
A/Baa	0.99	1.49	2.18	0.00	5.30	0.60	580
Ba	3.59	4.98	7.14	0.10	14.19	0.72	617
B	9.74	18.88	12.90	1.33	24.46	0.83	645
Caa-	23.77	45.41	20.04	5.57	34.51	0.93	650

Panel C: Pseudo Bonds (Single-Stock)

	Ex ante Def. Prob.		*Ex post* Def. Prob.				
	Boom	Recession	Mean	C.I.(2.5%)	C.I.(97.5%)	$\overline{K/A}$	$\overline{\tau}$
Aaa/Aa	0.11	0.21	0.16	0.00	0.35	0.45	625
A/Baa	1.21	1.58	0.63	0.00	1.29	0.53	627
Ba	4.01	5.76	3.40	0.84	5.95	0.62	643
B	10.54	17.38	8.76	4.02	13.49	0.75	659
Caa-	22.83	36.51	24.13	17.53	30.74	0.92	671

Table 2: Two-Year Pseudo and Corporate Bonds: 1996 - 2013

Credit spreads and summary statistics are shown for pseudo bonds (Panels A and B), corporate bonds (Panel C), and the lognormal Merton model (Panel D). Pseudo bonds are constructed from a portfolio of risk free debt minus put options on the SPX index (Panel A) or put options on individual stocks (Panel B). Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability, i.e. the probability the put option is in the money at maturity. The default probability is computed from the empirical distribution of asset returns, i.e. the SPX or individual stocks for Panel A and B, respectively. Corporate bonds are non-callable corporate bonds with time to maturity between 1.5 and 2.5 years. The sample period is January 1996 to August 2013. The lognormal Merton model's statistics are averages over 1,000 Monte Carlo simulations of 212 months of asset values. Simulations are designed to replicate the time-variation in volatility and predictability found in the SPX data.

Credit Rating	Credit Spreads			Monthly Returns in Excess of T-bill (%)				
	Average	Boom	Recession	Mean	Std	Sharpe Ratio	Skew	Excess Kurtosis
			Panel A: Pseudo Bonds (SPX)					
Aaa/Aa	54	51	83	0.14	0.65	0.22	0.41	5.60
A/Baa	131	121	207	0.25	0.86	0.30	0.09	4.82
Ba	237	216	375	0.27	1.41	0.19	-2.06	15.17
B	367	313	718	0.34	1.80	0.19	-1.27	7.87
Caa-	517	450	957	0.35	2.31	0.15	-1.20	6.01
			Panel B: Pseudo Bonds (Single-Stock)					
Aaa/Aa	105	100	187	0.02	0.55	0.04	-0.88	1.22
A/Baa	224	222	240	0.26	1.23	0.21	-0.57	4.70
Ba	348	339	408	0.29	1.37	0.21	-1.32	5.99
B	565	533	776	0.39	1.92	0.20	-1.68	8.13
Caa-	914	850	1332	0.74	2.45	0.30	-0.99	3.06
			Panel C: Corporate Bonds					
Aaa/Aa	53	36	166	0.10	0.88	0.11	-0.48	20.97
A/Baa	128	102	298	0.06	1.58	0.04	-7.83	81.93
Ba	374	336	588	0.37	2.55	0.14	-0.22	24.76
B	527	478	839	0.58	2.65	0.22	0.17	28.13
Caa-	1345	1145	2576	0.94	4.59	0.21	0.32	5.45
			Panel D: Lognormal Merton Model					
Aaa/Aa	0	0	1	0.07	0.48	0.15	0.37	1.55
A/Baa	4	3	10	0.07	0.48	0.14	0.31	1.50
Ba	30	26	61	0.08	0.62	0.12	-0.61	3.80
B	86	72	184	0.09	0.94	0.10	-0.92	5.15
Caa-	249	195	603	0.14	1.68	0.09	-0.52	4.03

Table 3: The Term Structure of Credit Spreads

This table reports the term structure of credit spreads for pseudo bonds (Panels A and B), corporate bonds (Panel C), and the lognormal Merton model (Panel D). Pseudo bonds are constructed from a portfolio of risk free debt minus put options on the SPX index (Panel A) or put options on individual stocks (Panel B). Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability, i.e. the probability the put option is in the money at maturity. The default probability is computed from the empirical distribution of asset returns, i.e. the SPX or individual stocks for Panel A and B, respectively. For very short maturities 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. For single-stock pseudo bonds, 30-days pseudo bonds cannot be computed due to lack of data. Corporate bonds' credit spreads for maturities between 30 and 91 days are based on commercial paper rates. Corporate bonds' credit spreads for maturities 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 (SPX)					
IG	77	64	69	75	108
Aaa/Aa			50	42	54
A/Baa			106	97	131
Ba	165	133	169	186	237
B	286	262	287	311	367
Caa-	503	495	471	469	517
Panel B: Pseudo Bonds (Single-Stock)					
IG		168	116	120	213
Aaa/Aa			84	92	105
A/Baa			118	123	224
Ba	285	183	175	201	348
B	402	308	336	435	565
Caa-	600	532	662	898	914
Panel C: Corporate Bonds					
IG	62	60	84	120	117
Aaa/Aa	32	30	24	43	53
A/Baa	69	67	98	134	128
Ba			235	341	374
B			320	610	527
Caa-			1206	1352	1345
Panel D: 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 4: The Transactional Liquidity of Pseudo Bonds and Corporate Bonds

Panels A and B show credit spreads, average monthly returns in excess of T-bills, and transactional liquidity measures of pseudo bonds based 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 $\sqrt{-Cov_t(\Delta p_{i,t,d}^{Bid\to Ask}, \Delta p_{i,t,d+1}^{Ask\to Bid})}$ 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 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 (SPX)				
Aaa/Aa	54	0.14	0.25	0.08
A/Baa	131	0.25	0.25	0.08
Ba	237	0.27	0.28	0.12
B	367	0.34	0.28	0.14
Caa-	517	0.35	0.28	0.18
Panel B: Pseudo Bonds (Single-Stock)				
Aaa/Aa	105	0.02	0.85	0.23
A/Baa	224	0.26	1.06	0.44
Ba	348	0.29	1.15	0.46
B	565	0.39	1.32	0.51
Caa-	914	0.74	1.49	0.59
Panel C: Corporate Bonds				
Aaa/Aa	53	0.10		0.51
A/Baa	128	0.06		1.05
Ba	374	0.37		1.82
B	527	0.58		1.92
Caa-	1345	0.94		3.33

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 lognormal Merton model (Panel D). The explanatory variable $R^e_{i,t}$ is the excess return on assets ($i = A$, Columns 4 to 8) or equity ($i = E$, Columns 9 to 13). In all cases, bonds are sorted monthly into credit rating categories, 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. Statistics for the lognormal Merton model in Panels D are averages of 1,000 Monte Carlo simulations of 212 months of underlying asset values. Simulations are designed to replicate the time-variation in volatility and predictability found in the data.

Credit	Average		Bonds on Assets					Bonds on Equities				
Rating	$\overline{R}$	$t(\overline{R})$	α	$t(\alpha)$	β	$t(\beta)$	R^2	α	$t(\alpha)$	β	$t(\beta)$	R^2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
					Panel A: Pseudo Bonds (SPX)							
Aaa/Aa	0.14	(2.80)	0.12	(2.61)	0.07	(4.00)	0.18	0.13	(2.67)	0.03	(3.11)	0.12
A/Baa	0.25	(4.17)	0.13	(2.38)	0.18	(8.99)	0.53	0.14	(2.15)	0.07	(7.18)	0.42
Ba	0.27	(2.70)	0.16	(2.60)	0.27	(13.41)	0.68	0.19	(2.38)	0.09	(9.14)	0.52
B	0.34	(2.83)	0.18	(2.72)	0.37	(18.16)	0.76	0.23	(2.32)	0.10	(10.30)	0.54
Caa-	0.35	(2.19)	0.17	(2.46)	0.49	(23.07)	0.83	0.23	(1.88)	0.10	(10.99)	0.56
					Panel B: Pseudo Bonds (Single-Stock)							
Aaa/Aa	0.02	(0.54)	0.01	(0.25)	0.07	(5.21)	0.26	0.02	(0.29)	0.03	(2.97)	0.13
A/Baa	0.26	(3.09)	0.11	(2.00)	0.18	(11.33)	0.65	0.19	(2.64)	0.08	(6.19)	0.45
Ba	0.29	(3.05)	0.13	(1.97)	0.25	(9.79)	0.69	0.16	(2.50)	0.11	(11.51)	0.60
B	0.39	(2.97)	0.11	(1.35)	0.37	(10.55)	0.80	0.08	(0.91)	0.15	(11.84)	0.67
Caa-	0.74	(4.41)	0.18	(1.99)	0.51	(16.79)	0.86	0.09	(0.73)	0.17	(15.40)	0.67
					Panel C: Corporate Bonds							
Aaa/Aa	0.10	(1.60)						-0.04	(-0.29)	0.03	(0.89)	0.08
A/Baa	0.06	(0.54)						0.11	(1.84)	0.07	(4.53)	0.40
Ba	0.37	(1.90)						0.38	(2.55)	0.21	(3.02)	0.52
B	0.58	(2.56)						0.63	(2.69)	0.07	(5.24)	0.17
Caa-	0.94	(1.83)						1.01	(2.14)	0.09	(2.77)	0.19
					Panel D: Lognormal Merton Model							
Aaa/Aa	0.07	(2.24)	0.07	(1.85)	0.00	(0.24)	0.00	0.07	(1.85)	0.00	(-0.68)	0.01
A/Baa	0.07	(2.08)	0.07	(1.74)	0.01	(1.43)	0.01	0.07	(1.77)	0.00	(0.38)	0.01
Ba	0.08	(1.81)	0.06	(1.61)	0.07	(5.57)	0.21	0.06	(1.63)	0.02	(4.73)	0.15
B	0.09	(1.49)	0.06	(1.44)	0.15	(7.65)	0.49	0.07	(1.41)	0.03	(7.89)	0.37
Caa-	0.14	(1.23)	0.07	(1.29)	0.33	(9.40)	0.73	0.06	(1.00)	0.05	(9.93)	0.54

Table 6: 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 and t-statistics are in parenthesis. 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 (SPX)				
Aaa/Aa	0.18	0.07	0.03	0.01	-0.07	0.39	0.01	0.25
	(2.77)	(3.63)	(1.99)	(0.35)	(-0.55)	(1.91)	(0.57)	
A/Baa	0.27	0.09	0.03	0.09	-0.50	-0.12	0.03	0.51
	(4.65)	(7.15)	(2.28)	(2.66)	(-3.31)	(-0.54)	(2.91)	
Ba	0.30	0.18	0.03	0.08	-0.76	0.52	0.02	0.65
	(4.29)	(7.14)	(1.49)	(2.24)	(-3.93)	(1.22)	(2.25)	
B	0.39	0.25	0.06	0.16	-0.86	0.46	0.03	0.77
	(5.67)	(9.94)	(3.15)	(3.38)	(-4.26)	(1.13)	(2.61)	
Caa-	0.33	0.36	0.05	0.18	-0.85	0.62	0.03	0.82
	(4.14)	(12.08)	(2.25)	(3.20)	(-3.59)	(1.44)	(1.79)	
				Panel B: Pseudo Bonds (Single-Stock)				
Aaa/Aa	0.18	0.10	0.09	-0.06	0.34	-0.37	-0.02	0.21
	(2.24)	(3.83)	(4.50)	(-0.83)	(1.68)	(-0.91)	(-1.22)	
A/Baa	0.26	0.17	0.05	0.00	-0.27	0.14	0.10	0.52
	(3.42)	(6.62)	(2.00)	(0.03)	(-1.25)	(0.53)	(2.66)	
Ba	0.32	0.18	0.04	0.08	-0.64	0.01	0.01	0.65
	(3.51)	(8.06)	(1.48)	(1.74)	(-3.45)	0.02	(0.55)	
B	0.42	0.26	0.05	0.18	-0.90	0.31	-0.01	0.75
	(4.19)	(8.74)	(1.68)	(3.59)	(-4.02)	(0.68)	(-0.33)	
Caa-	0.71	0.35	0.04	0.24	-1.02	0.64	0.02	0.79
	(6.77)	(11.37)	(1.36)	(4.16)	(-4.41)	(1.49)	(0.67)	
				Panel C: Corporate Bonds				
Aaa/Aa	0.22	-0.07	0.09	0.18	-7.77	2.19	2.17	0.35
	(3.69)	(-2.75)	(5.17)	(3.28)	(-2.72)	(2.53)	(0.57)	
A/Baa	0.31	0.04	0.10	0.19	2.10	-2.35	-2.67	0.07
	(3.34)	(0.73)	(2.21)	(2.63)	(0.40)	(-1.59)	(-0.92)	
Ba	0.49	0.13	0.11	0.11	-8.36	-2.21	-0.72	0.14
	(1.78)	(1.74)	(2.05)	(1.77)	(-1.52)	(-0.31)	(-0.07)	
B	0.75	0.00	0.10	0.18	-11.82	-2.80	-1.48	0.08
	(3.10)	(0.02)	(1.94)	(2.46)	(-1.62)	(-0.47)	(-0.18)	
Caa/C	0.86	0.47	-0.06	0.22	19.05	-10.61	3.71	0.27
	(2.16)	(3.64)	(-0.45)	(0.99)	(1.72)	(-1.00)	(0.19)	

Table 7: Sorting Frequency and Pseudo Bond Returns

Credit spreads and excess return summary statistics are shown 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 SPX put options. Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability (i.e. the probability the put option is in the money at maturity). The pseudo bond default probabilities are computed from the empirical distribution of residuals from a simple GARCH(1,1) model of asset returns with expected growth obtained from predictive regressions. The sample is January 1996 to August 2013. Credit spreads are expressed in basis points.

Credit Rating	Credit Spread			Monthly Returns in Excess of T-bill (%)				
	Average	Boom	Recession	Mean	Std	Sharpe Ratio	Skew	Excess Kurtosis
				Panel A: Sort Every 3 Months				
Aaa/Aa	57	53	91	0.11	0.69	0.16	0.07	6.16
A/Baa	132	118	228	0.18	1.12	0.16	-3.63	35.46
Ba	246	214	452	0.25	1.51	0.17	-2.31	18.33
B	385	312	880	0.35	1.94	0.18	-1.95	14.53
Caa-	553	449	1233	0.35	2.45	0.14	-1.43	8.84
				Panel B: Sort Every 6 Months				
Aaa/Aa	67	55	164	0.10	0.73	0.14	0.07	5.73
A/Baa	142	110	347	0.14	1.14	0.12	-3.77	34.96
Ba	249	204	541	0.21	1.53	0.14	-2.46	17.82
B	371	299	834	0.26	1.96	0.13	-2.08	13.68
Caa-	732	441	2623	0.30	2.53	0.12	-1.53	8.37
				Panel C: Sort Every 12 Months				
Aaa/Aa	53	39	165	0.10	0.51	0.20	2.00	10.07
A/Baa	127	93	335	0.16	0.75	0.21	0.65	6.94
Ba	273	200	707	0.12	1.61	0.07	-2.46	17.37
B	372	285	916	0.15	1.97	0.08	-1.87	12.55
Caa-	837	452	3348	0.17	2.64	0.06	-1.74	10.15

Table 8: Asset Uncertainty and Credit Spreads of Pseudo Bonds

This table shows the impact of asset volatility on pseudo bond' credit spreads and returns. The sample is the pseudo bonds of pseudo firms whose assets are the stock of individual firms that are in the S&P 500 index. Pseudo bonds are portfolios of risk-free debt minus put options on the underlying assets (i.e. stock) of individual firms. Pseudo credit ratings are assigned using a model-free methodology that computes the probability of default at maturity. For each time t, we first sort pseudo bonds according to their pseudo credit rating, and then according to the volatility of their pseudo firm's assets (individual stocks). Panel A reports the average credit spreads for each credit rating / volatility bin, and Panel B reports the corresponding average excess returns. Panels C and D report the average leverage K/A and the average asset volatility for each credit rating / volatility combination.

Credit	Volatility			Credit	Volatility		
Rating	Low	Medium	High	Rating	Low	Medium	High
Panel A: Credit Spread				Panel B: Average Excess Returns			
Aaa/Aa	114	119	96	Aaa/Aa	0.09	0.00	-0.07
A/Baa	139	257	277	A/Baa	0.20	0.32	0.23
Ba	263	341	445	Ba	0.23	0.33	0.30
B	484	537	676	B	0.37	0.40	0.43
Caa-	837	881	1027	Caa-	0.70	0.71	0.84
Panel C: Average Leverage $\overline{K/A}$				Panel D: Volatility			
Aaa/Aa	0.50	0.51	0.41	Aaa/Aa	0.18	0.21	0.25
A/Baa	0.54	0.56	0.48	A/Baa	0.22	0.28	0.37
Ba	0.67	0.63	0.57	Ba	0.24	0.32	0.42
B	0.82	0.76	0.69	B	0.25	0.33	0.45
Caa-	0.98	0.93	0.85	Caa-	0.25	0.33	0.46

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Appendix A. The Lognormal Merton Model

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

$$dA_t = \mu_A A_t dt + \sigma_A A_t dW_{A,t} \tag{10}$$

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 debt ($A_T > K$), the firm can pay its debt in full – *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 thus is

$$CF_T = K - \max(K - A_T, 0) \tag{11}$$

and the value of debt today $B_t(T,K)$ is given by

$$B_t(T,K) = K Z_t(T) - P_t(T,K) \tag{12}$$

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 European put option at t with maturity T and strike price K. From the assumptions about A_t, the value of the put option $P_t(T,K)$ can be computed and the bond prices in equation (12) analyzed.[28] The corporate bond yield under the Merton model is given by

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

The following proposition is useful to frame some of our later discussion:

Proposition 1. Under the asset dynamics in equation (10), the bond price $B_t(T,K)$ in expression (12) 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

$$\mu_B - r = \beta\,(\mu_A - r);\ \text{and}\ \sigma_B = \beta\sigma_A \tag{13}$$

with $\beta = \frac{Cov(dB/B, dA/A)}{\sigma_A^2} > 0$;

(c) The bond's expected excess return can be equivalently written as

$$\mu_B - r = \beta_E\,(\mu_E - r) \tag{14}$$

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

(d) 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 in the lognormal Merton model 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 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. Expression (14) for the bond's excess returns, moreover, is often convenient because, in analyzing real corporate bonds, we cannot observe the value of

[28]The dynamics of assets in (10) is only convenient inasmuch as it provides a closed-form solution for the value of the put option in equation (12).

the firm's assets but do observe the value of its equity. For such securities, (14) thus has an empirical counterpart.[29]

Much of the literature that has expanded the original lognormal Merton model has focused on generalizing the asset dynamics in equation (10) – *e.g.*, by adding a jump process, incorporating stochastic volatility, stochastic interest rates, and endogenous default, allowing a firm to experience insolvency prior to maturity, 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 directly. In Appendix B, we discuss one specific modification of the Merton model in which the market value of the firm's assets A_t follows a jump-diffusion process with stochastic volatility. Although we do not estimate this model, the discussion and a related Proposition 2 in Appendix B shed light on some of our empirical results.

Proof of Proposition 1. (a) Immediate from the properties of the Black and Scholes formula.

(b) From Ito's lemma:

$$dB = rKe^{-r(T-t)}dt - \left(\frac{\partial P}{\partial t} + \frac{\partial P}{\partial A}\mu_A A + \frac{1}{2}\frac{\partial^2 P}{\partial A^2}A^2\sigma_A^2\right)dt - \frac{\partial P}{\partial A}A\sigma_A dW$$

The Black and Scholes pricing Partial Differential Equation has

$$\frac{\partial P}{\partial t} + \frac{1}{2}\frac{\partial^2 P}{\partial A^2}A^2\sigma_A^2 = rP - \frac{\partial P}{\partial A}Ar$$

Substitution into the previous equation proves the claim, with

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

and where $\sigma_B = -\frac{1}{B}\frac{\partial P}{\partial A}A\sigma_A$.

The proof of part (c) follows from the same steps as in part (b) but applied to a call option.

Part (d) also follows from the excess return expression above, once we divide by σ_B the expected return equation. Q.E.D.

The results for the lognormal Merton model reported in Figure 1 and Tables 2, 2, and 3 correct for the influence of any bias generated by time-varying stock return volatility and/or the monthly sampling. In particular, all the statistics reported in the tables are averages of the same statistics computed over 1,000 Monte Carlo simulations across 212 months of asset values. Simulations are designed to replicate the GARCH(1,1) volatility and predictability found in the SPX data. For each simulation of asset values, we use the Black and Scholes model (adjusted for a continuous dividend yield) to compute put and call prices across strike prices and then construct simulated bond values from these option prices. Employing simulations that feature time-varying volatility and predictability enable us to conclude that our empirical results in Panel A are not driven by our estimation of a GARCH(1,1) model, the fitting of predicting regressions, and/or the sampling of returns at the monthly frequency.

[29]Note in this connection that we are *not* assuming that the CAPM has to hold under the lognormal Merton model. Indeed, under process (10) 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.

Appendix B. Jumps and Stochastic Volatility in the Merton Framework.

Some of the empirical results in the paper can be better understood if we examine the specific implications for relaxing the original Merton lognormality assumption and assume instead that the market value of the firm's assets A_t follows a jump-diffusion process with stochastic volatility:

$$dA_t = [\mu_A - \lambda E(J_A - 1)] A_t dt + \sigma_{A,t} A_t dW_{A,t} + (J_A - 1)A_t dQ_t \quad (15)$$
$$d\sigma_{A,t} = \mu_\sigma (\sigma_{A,t}) dt + s(\sigma_{A,t}) dW_{\sigma,t} \quad (16)$$

where dQ_t is the increment of a Poisson process with intensity λ, J_A is a random variable determining the size of the jump (*see, e.g.,* Zhou (2001)), and $\mu_\sigma(.)$ and $s(.)$ are a drift and diffusion that satisfy the usual regularity conditions. Following the analysis of Broadie, Chernov, Johannes (2009), we then obtain the following:

Proposition 2. Under the asset dynamics in Equations (15) and (16), the bond price $B_t(T, K)$ in expression (12) has a risk premium given by

$$\mu_B - r = [\alpha_B - \beta_A \alpha_A + \beta_\sigma \xi s(\sigma_{A,t})] + \beta_A (\mu_A - r) \quad (17)$$

where $\beta_A = \frac{\partial \ln(B(t,A,\sigma_A))}{\partial \ln A}$ is the loading on the "asset risk", $\beta_\sigma = \frac{\partial \ln(B(t,A,\sigma_A))}{\partial \sigma_A}$ is the loading on volatility risk, α_B and α_A are the jump risk premia on bonds and on assets, respectively, and ξ is the market price of volatility risk.

Expression (17) illustrates how the violations of Merton's lognormality assumption manifest themselves in the risk premium. Because generally $\alpha_B \neq \beta \alpha_A$, we should expect a non-zero estimated intercept in a regression of excess bond returns on excess asset returns if jumps reflect an important component of the bond's excess returns and/or volatility dynamics are priced.[30]

Proof of Proposition 2. From standard arguments, the pricing partial differential equation of $B_t = B(t, A, \sigma)$ when A follows a jump-diffusion process with stochastic volatility is

$$\begin{aligned} & \frac{\partial B}{\partial t} + \frac{1}{2}\frac{\partial^2 B}{\partial A^2} A^2 \sigma_A^2 + \frac{1}{2}\frac{\partial^2 B}{\partial \sigma_A^2} s(\sigma_A)^2 + \frac{\partial^2 B}{\partial A \partial \sigma_A} A \sigma_{A,t} s(\sigma_{A,t}) \rho_{A,\sigma} \\ = \; & rB - \frac{\partial B}{\partial A} A \{r - \lambda^* E^*[J_A - 1]\} - \frac{\partial B}{\partial \sigma_A} [\mu_\sigma(\sigma_A) - \xi s(\sigma_A)] - \lambda^* E^* [B(AJ_A, t) - B(A, t)] \end{aligned}$$

where λ^* is the risk neutral jump probability, and $E^*[]$ are the risk neutral expectations of the jump J_A, and ξ is the market price of volatility risk. From Ito's lemma, the process for B under the physical measure is

$$\begin{aligned} dB = & \left\{ \frac{\partial B}{\partial t} + \frac{\partial B}{\partial A} A [\mu_A - \lambda E(J_A - 1)] + \frac{\partial B}{\partial \sigma_A} \mu_\sigma(\sigma_A) + \frac{1}{2}\frac{\partial^2 B}{\partial A^2} \sigma_A^2 A^2 + \frac{1}{2}\frac{\partial^2 B}{\partial \sigma_{A,t}^2} s(\sigma_A)^2 \right. \\ & \left. + \frac{\partial^2 B}{\partial A \partial \sigma_{A,t}} \sigma_A A s(\sigma_{A,t}) \rho_{A,\sigma} \right\} dt + \frac{\partial B}{\partial A} \sigma_A A dW_{A,t} + \frac{\partial B}{\partial \sigma_A} s(\sigma_A) dW_{\sigma,t} \\ & + [B(AJ_A, t) - B(A, t)] dQ \end{aligned}$$

[30] As discussed in Broadie et al. (2009, Appendix B), additional alpha may result from discretization bias and the covariance between asset value and volatility.

Taking the expectation under the physical measure, and using the PDE above, we obtain

$$\begin{aligned} E[dB]/dt &= rB - \frac{\partial B}{\partial A} A\left\{r - \lambda^* E^*[J_A - 1]\right\} - \lambda^* E^*\left[B(AJ_A, t) - B(A,t)\right] \\ &\quad + \frac{\partial B}{\partial A} A\left[\mu_A - \lambda E(J_A - 1)\right] + \frac{\partial B}{\partial \sigma_A}\xi s\left(\sigma_A\right) + \lambda E\left[B(AJ_A, t) - B(A,t)\right] \end{aligned}$$

or

$$\begin{aligned} E\left[\frac{dB}{B}\right]/dt - r &= \frac{1}{B}\frac{\partial B}{\partial A} A\left[\mu_A - r - \left[\lambda E(J_A - 1) - \lambda^* E^*[J_A - 1]\right]\right] + \frac{1}{B}\frac{\partial B}{\partial \sigma_A}\xi s\left(\sigma_A\right) \\ &\quad + \lambda E\left[\frac{B(AJ_A, t)}{B} - 1\right] - \lambda^* E^*\left[\frac{B(AJ_A, t)}{B} - 1\right] \\ &= \alpha_B - \beta_A \alpha_A + \beta_\sigma \xi s\left(\sigma_A\right) + \beta_A[\mu_A - r] \end{aligned}$$

where

$$\begin{aligned} \beta_A &= \frac{1}{B}\frac{\partial B}{\partial A} A; \quad \beta_\sigma = \frac{1}{B}\frac{\partial B}{\partial \sigma_A} \\ \alpha_A &= \lambda E(J_A - 1) - \lambda^* E^*[J_A - 1] = \text{jump risk premium of assets} \\ \alpha_B &= \lambda E\left[\frac{B(AJ_A, t)}{B} - 1\right] - \lambda^* E^*\left[\frac{B(AJ_A, t)}{B} - 1\right] = \text{jump risk premium of } B \end{aligned}$$

Q.E.D.

Appendix C. 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 quotation errors in SPX options, we generally follow Constantinides, Jackwerth and Savov (2013) ("CJS") to filter the data. As in CJS, 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. As in CJS, we apply the following specific filters:

1. *Level 1 Filters:* 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.

2. *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 or maturity, but we remove all options with zero open interest. Following CJS, we also remove options with less than seven days to maturity. We also apply "implied interest rate < 0," "unable to compute IV," "IV," and "put-call parity" filters.[31]

[31] 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 equity options, as put-call parity only holds with inequality for American options, we apply a different set of filters. We follow Frazzini and Pedersen (2012) to detect likely data errors. Specifically, we drop all observations for which the ask price is lower than the bid price and the bid price is equal to zero. In addition, we require options to have positive open interest, and non-missing delta, implied volatility, and spot price. We also drop options violating the put-call parity bounds for American options, and basic arbitrage bounds of a non-negative "time value' P-V where V is the option "intrinsic value' equal to $\max(K - S, 0)$ for puts. We then drop equity options with a time value $(P - V)/P$ (in percentage of option value) below 5%, as the low time value tends to lead to early exercise. Furthermore, to mitigate the effect of the outliers, we drop options with embedded leverage, $\frac{\partial P}{\partial S}\frac{S}{P}$, in the top or bottom 1% of the distribution. Finally, we drop the options on the firms whose $\mu_{t,\tau}$ and $\sigma_{t,\tau}$ are in the top or bottom 5% of the distribution.

We obtain stock prices and accounting information from the Center for Research in Security Prices ("CRSP"). We use SPX returns in the postwar period (1946 - 2013) to compute asset returns and *ex ante* default probabilities for our pseudo firms.

We construct the risk-free zero coupon bonds from 1-, 3-, and 6-month T-bill rates and 1-, 2-, and 3-year constant maturity Treasury yields obtained from the Federal Reserve Economic Data ("FRED") database. We convert constant maturity yields into zero-coupon yields and linearly interpolate to match option maturities. We also obtain commercial paper rates from FRED, which we use to compute credit spreads for short-term debt.

We construct the panel data of corporate bond prices from the Lehman Brothers Fixed Income Database, TRACE, the Mergent FISD/NAIC Database, and DataStream, prioritized in this order when there are overlaps among the four databases. Detailed descriptions of these databases and the effects of prioritization are discussed in Nozawa (2014). In addition, we remove bonds with floating coupon rates and embedded option features. We also apply several filters to remove observations that may be subject to erroneous recording. Following Duffee (1998), we remove bonds with buy-in prices greater than twice and less than 1/100 of their par amounts. We also remove observations for bonds that show large bounce-backs. Specifically, we compute the product of adjacent monthly returns and remove both observations if the product is less than -0.04. For example, if the price of a given bond jumps up by more than 20 percent in one month and then comes down by more than 20 percent in the following month, we assume that the price observation in the middle is recorded with errors and exclude that observation.

Appendix D. Default Frequencies.

Our goal is to construct pseudo bonds that match the realized default frequencies of the actual corporate bonds used as our main empirical benchmark. To that end, we employ a large dataset of corporate defaults spanning the 44-year period from 1970 to 2013 obtained from Moody's Default Risk Service. 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 estimates 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 horizons of below one year, and default frequencies are not provided by Moody's for such short time horizons.

Table A1 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. firms. Our results are directly comparable to Moody's historical default rates (reported in Moody's (2014)) for one- and two-year horizons. As Table A1 shows, our estimated default rates closely match the Moody's global default rates for those horizons.

The last two columns of Table A1 report default rates for U.S. firms in NBER-dated booms and recessions. Predictably, we find that default frequencies are higher in recessions than in booms across all credit ratings. At the 1-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%). Default frequencies for speculative-grade bonds also show large variations over the business cycle. For example, a B-rated bond has a 3.57% default rate at the 1-year horizon during booms but more than twice that in recessions (as compared to an unconditional average of 4.01%).

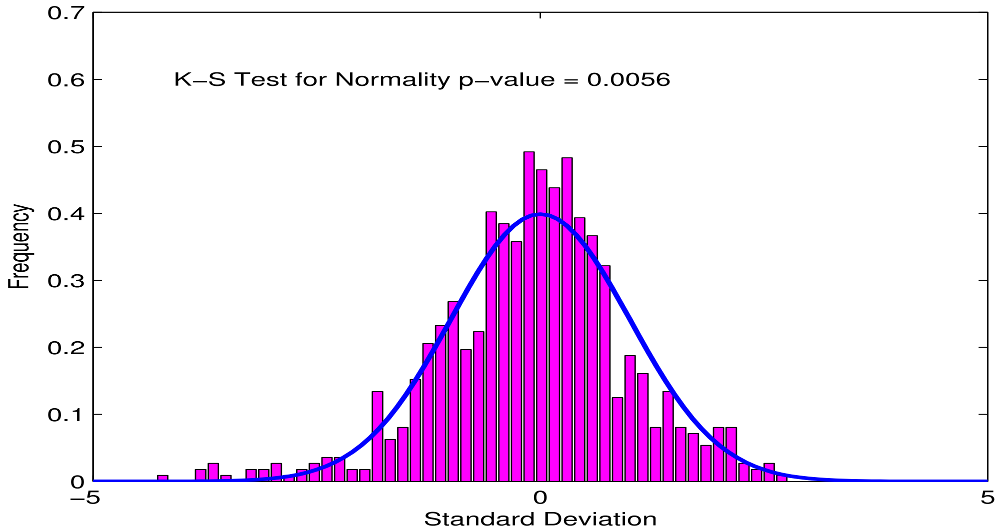
Table A1 also shows default frequencies at short horizons of 30, 91, and 183 days. At the 30-day horizon, all investment-grade bonds have essentially zero historical default frequencies (although, in recessions, the historical default rate ticks up 0.01% for bonds rated A- and Baa). Some more action for these bonds is observable at the 91- and 183-day horizons, especially during recessions. For example, Baa-rated bonds have defaulted with 0.04% and 0.12% frequencies at the 91- and 183-day horizons (respectively) during recessions, which are much higher than the corresponding unconditional default frequencies of 0.02% and 0.05%. High-yield bonds, by contrast, exhibit relatively substantial historical default activity even at short horizons. For instance, B-rated bonds have 0.22%, 0.75%, and 1.69% unconditional default frequencies over 30, 91, and 183 days, respectively, which increase to 0.43%, 1.48%, and 3.33%, respectively, during recessions.

Appendix E. Additional Figures and Tables.

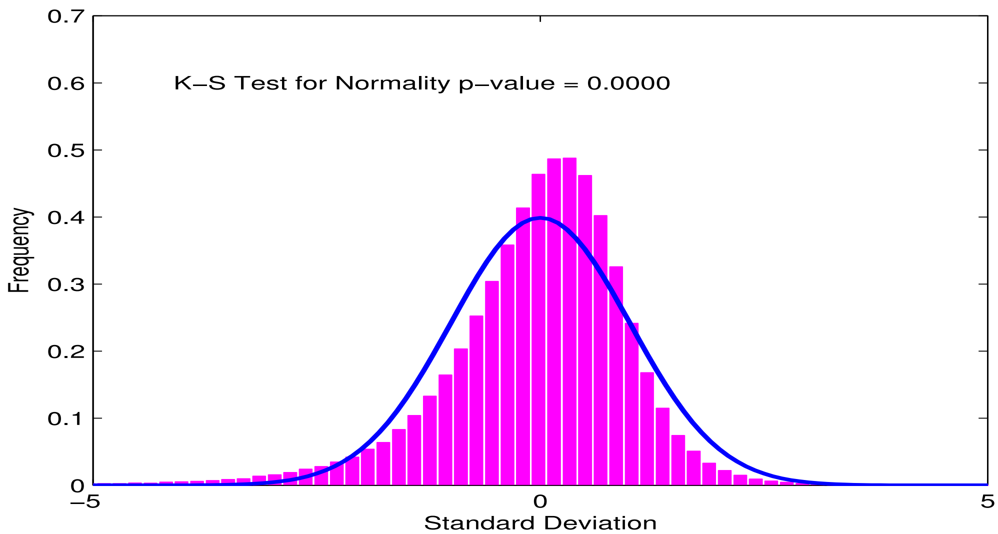
This appendix contains additional figures and tables referred to in the main text.

Figure A1: 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.

Table A1: 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 A2: 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 columns 3 and 4 report default frequencies during NBER booms and recessions, respectively. The two panels on righ-hand-side report the results of our credit rating methodology for SPX and single-stock pseudo bonds. Pseudo bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index (SPX) or individual stocks (Single-Stock). 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. In each subpanel, the first two columns report the *ex ante* average default probabilities for pseudo 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 stock return (excluding 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 (SPX)							Pseudo Bonds (Single-Stock)						
				Ex ante Def. Prob.		*Ex post* Default Frequency					*Ex ante* Def. Prob.		*Ex post* Default Frequency				
	Mean	Boom	Bust	Boom	Bust	Mean	C.I. (2.5%)	C.I. (97.5%)	$\overline{K/A}$	$\overline{\tau}$	Boom	Bust	Mean	C.I. (2.5%)	C.I. (97.5%)	$\overline{K/A}$	$\overline{\tau}$
						Target Maturity: 30 days											
IG	0.00	0.00	0.01	0.01	0.02	0.38	0.00	0.92	0.74	54							
Ba	0.05	0.04	0.11	0.10	0.19	0.38	0.00	0.92	0.80	45	0.07	0.19	0.10	0.03	0.17	0.69	50
B	0.22	0.19	0.43	0.33	0.97	0.57	0.00	1.23	0.85	39	0.58	1.23	0.35	0.16	0.53	0.77	50
Caa-	1.89	1.61	3.47	1.59	3.80	2.47	1.11	3.82	0.90	39	1.65	3.64	1.98	1.49	2.48	0.82	50
						Target Maturity: 91 days											
IG	0.01	0.01	0.03	0.01	0.08	0.57	0.00	1.22	0.65	118	0.05	0.15	0.02	0.01	0.04	0.55	105
Ba	0.19	0.16	0.38	0.22	0.71	0.57	0.00	1.22	0.73	115	0.27	0.66	0.30	0.10	0.49	0.63	102
B	0.75	0.65	1.48	1.18	3.05	1.71	0.00	3.51	0.81	84	1.50	3.42	0.96	0.43	1.50	0.71	96
Caa-	4.90	4.07	9.51	4.22	9.93	7.43	3.60	11.25	0.88	79	4.24	9.82	4.46	3.03	5.89	0.79	91
						Target Maturity: 183 days											
Aaa/Aa	0.00	0.00	0.03	0.01	0.02	0.77	0.00	1.96	0.57	194	0.01	0.04	0.01	0.00	0.02	0.31	285
A/Baa	0.03	0.02	0.09	0.15	0.39	0.96	0.00	2.51	0.67	182	0.14	0.35	0.08	0.02	0.13	0.49	232
Ba	0.47	0.40	0.91	0.48	1.46	2.11	0.00	4.83	0.72	184	0.61	1.45	0.66	0.18	1.14	0.57	211
B	1.69	1.47	3.33	2.32	6.26	2.30	0.00	5.24	0.79	180	2.71	6.53	1.82	0.76	2.88	0.68	191
Caa-	8.88	7.25	17.73	7.51	18.08	8.43	2.63	14.23	0.86	178	7.61	18.24	7.44	4.95	9.93	0.79	177
						Target Maturity: 365 days											
Aaa/Aa	0.01	0.00	0.05	0.01	0.06	1.16	0.00	3.08	0.46	356	0.03	0.11	0.04	0.00	0.07	0.31	484
A/Baa	0.10	0.08	0.24	0.30	0.78	2.13	0.00	5.02	0.59	340	0.38	0.75	0.21	0.00	0.42	0.44	437
Ba	1.19	1.08	1.91	1.35	2.71	3.29	0.00	7.61	0.70	350	1.52	3.14	1.33	0.24	2.42	0.54	396
B	4.01	3.57	7.31	4.97	11.03	6.98	0.42	13.53	0.79	347	5.27	12.08	3.69	1.46	5.92	0.68	339
Caa-	15.37	12.63	29.49	13.23	29.15	13.76	3.37	24.15	0.86	346	13.47	29.82	13.28	8.92	17.65	0.84	294

Table A3: Two-Year Pseudo and Corporate Bonds: Subsamples

Credit spreads and summary statistics of pseudo bonds (Panels A and B), and corporate bonds (Panels C). Pseudo bonds are constructed from a portfolio of risk free debt minus put options on the S&P500 index (Panel A) or individual stocks (Panel B). 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). 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. Corporate bonds are non-callable corporate bonds with time to maturity between 1.5 and 2.5 years.

Credit Rating	Credit Spread	Monthly Returns in Excess of T-bill (%) Mean	Std	Sharpe Ratio	Skew	Excess Kurtosis	Credit Spread	Monthly Returns in Excess of T-bill (%) Mean	Std	Sharpe Ratio	Skew	Excess Kurtosis
		January 1996 – December 2004						January 2005 – August 2013				
						Panel A: Pseudo Bonds (SPX)						
Aaa/Aa	38	0.13	0.51	0.24	3.28	13.86	62	0.15	0.71	0.22	-0.12	3.97
A/Baa	121	0.23	0.79	0.29	-0.66	8.85	141	0.28	0.94	0.3	0.53	2.29
Ba	211	0.30	1.11	0.27	-0.75	4.29	265	0.24	1.67	0.15	-2.28	14.32
B	301	0.32	1.43	0.22	-0.78	3.25	436	0.35	2.13	0.17	-1.35	7.25
Caa-	445	0.36	1.89	0.19	-0.70	1.92	593	0.35	2.7	0.13	-1.3	5.82
						Panel B: Pseudo Bonds (Single-Stock)						
Aaa/Aa	90	0.19	0.60	0.31	-1.17	1.57	112	-0.05	0.53	-0.09	-0.89	1.42
A/Baa	237	0.39	1.41	0.27	-0.39	3.28	212	0.14	1.02	0.14	-1.28	6.67
Ba	330	0.36	1.17	0.31	-0.74	2.33	367	0.21	1.54	0.13	-1.48	6.23
B	503	0.47	1.42	0.33	-1.07	2.11	630	0.32	2.33	0.14	-1.61	6.6
Caa-	838	0.83	2.03	0.41	-0.95	2.17	994	0.65	2.83	0.23	-0.92	2.53
						Panel C: Corporate Bonds						
Aaa/Aa	43	0.08	0.63	0.13	0.43	4.16	62	0.12	1.06	0.11	-0.64	18.12
A/Baa	124	-0.11	2.16	-0.05	-6.14	45.13	131	0.22	0.64	0.33	0.73	8.90
Ba	412	0.24	3.70	0.07	0.05	12.28	346	0.46	1.29	0.35	-2.18	18.64
B	606	0.54	4.62	0.12	0.09	9.47	495	0.59	1.31	0.45	0.74	6.21
Caa-	1631	-1.67	4.27	-0.39	0.11	-0.76	1258	1.28	4.55	0.28	0.35	6.40

Table A4: 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 to D), or corporate bonds (Panel E and F). The explanatory variable $R^e_{i,t}$ is the excess return on assets (columns 4 to 8) or equity (columns 9 to 13). 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	Mean	$t(Mean)$		Bonds on Assets					Bonds on Equities			
Rating	(%)		α	$t(\alpha)$	β	$t(\beta)$	R^2	α	$t(\alpha)$	β	$t(\beta)$	R^2
			Panel A: Pseudo Bonds (SPX): January 1996 - December 2004									
Aaa/Aa	0.13	(1.63)	0.09	(1.61)	0.06	(2.41)	0.20	0.09	(1.57)	0.03	(2.45)	0.17
A/Baa	0.23	(2.88)	0.07	(0.80)	0.19	(5.45)	0.62	0.07	(0.75)	0.08	(4.75)	0.56
Ba	0.30	(2.73)	0.16	(1.71)	0.26	(8.75)	0.74	0.18	(1.56)	0.09	(6.15)	0.65
B	0.32	(2.29)	0.14	(1.35)	0.33	(9.47)	0.78	0.13	(0.99)	0.09	(6.44)	0.67
Caa-	0.36	(2.00)	0.20	(1.92)	0.41	(12.72)	0.84	0.21	(1.20)	0.10	(6.02)	0.64
			Panel B: Pseudo Bonds (SPX): January 2005 - August 2013									
Aaa/Aa	0.15	(2.14)	0.14	(2.14)	0.07	(3.26)	0.18	0.15	(2.20)	0.04	(2.26)	0.11
A/Baa	0.28	(3.11)	0.16	(2.34)	0.17	(7.55)	0.48	0.17	(2.09)	0.07	(5.74)	0.35
Ba	0.24	(1.50)	0.16	(2.01)	0.28	(10.20)	0.66	0.19	(1.85)	0.09	(6.86)	0.46
B	0.35	(1.67)	0.20	(2.33)	0.40	(14.88)	0.77	0.27	(2.09)	0.10	(8.08)	0.49
Caa-	0.35	(1.30)	0.15	(1.75)	0.53	(19.88)	0.85	0.23	(1.49)	0.11	(9.15)	0.54
			Panel C: Pseudo Bonds (Single-Stock): January 1996 - December 2004									
Aaa/Aa	0.19	(3.22)	0.15	(2.53)	0.09	(4.08)	0.29	0.15	(1.09)	0.04	(1.65)	0.16
A/Baa	0.39	(2.85)	0.09	(0.93)	0.17	(8.96)	0.68	0.29	(2.29)	0.07	(4.43)	0.42
Ba	0.36	(3.22)	0.19	(2.09)	0.20	(13.48)	0.66	0.27	(3.63)	0.09	(9.76)	0.59
B	0.47	(3.41)	0.20	(1.87)	0.29	(20.25)	0.78	0.23	(2.79)	0.11	(12.46)	0.70
Caa-	0.83	(4.24)	0.27	(2.16)	0.43	(22.76)	0.85	0.27	(2.24)	0.14	(13.04)	0.74
			Panel D: Pseudo Bonds (Single-Stock): January 2005 - August 2013									
Aaa/Aa	-0.05	(-0.88)	-0.04	(-0.99)	0.07	(4.13)	0.25	-0.04	(-0.51)	0.03	(2.31)	0.11
A/Baa	0.14	(1.44)	0.13	(2.62)	0.19	(7.82)	0.58	0.10	(1.44)	0.10	(7.12)	0.55
Ba	0.21	(1.37)	0.08	(1.83)	0.31	(10.86)	0.76	0.03	(0.34)	0.15	(8.76)	0.68
B	0.32	(1.38)	0.07	(1.08)	0.44	(11.79)	0.85	-0.06	(-0.44)	0.19	(9.08)	0.71
Caa-	0.65	(2.36)	0.11	(1.51)	0.58	(17.89)	0.89	-0.11	(-0.57)	0.20	(10.53)	0.66
			Panel E: Corporate Bonds: January 1996 - December 2004									
Aaa/Aa	0.08	(1.25)						0.38	(11.57)	-0.03	(-5.64)	0.85
A/Baa	-0.11	(-0.48)						0.40	(2.54)	-0.02	(-0.31)	0.02
Ba	0.24	(0.55)						-0.83	(-1.07)	0.54	(11.36)	0.91
B	0.54	(0.72)						5.00	(2.38)	0.78	(2.78)	0.65
Caa-	-1.67	(-1.17)						-2.75	(-1.85)	-0.11	(-1.61)	0.12
			Panel F: Corporate Bonds: January 2005 - August 2013									
Aaa/Aa	0.12	(1.13)						-0.06	(-0.43)	0.03	(0.90)	0.08
A/Baa	0.22	(3.41)						0.10	(1.75)	0.08	(5.15)	0.46
Ba	0.46	(3.59)						0.33	(2.51)	0.13	(3.67)	0.53
B	0.59	(4.52)						0.44	(3.36)	0.07	(5.90)	0.42
Caa-	1.28	(2.35)						1.18	(2.35)	0.09	(2.65)	0.20

Table A5: Credit Spreads and Returns of Short-Horizon Pseudo and Corporate Bonds

Credit spreads and excess returns summary statistics are shown for short-term SPX pseudo bonds (columns 2 to 7), single-stock pseudo bonds (columns 8 to 13), and corporate bonds (columns 14 to 19). Pseudo bonds are constructed from a portfolio of risk free debt minus SPX put options or individual stocks' put options. Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability (i.e. the probability the put option is in the money at maturity) in booms and recessions. Corporate bonds are non-callable corporate bonds with time to maturity close to the one reported in the Panel's heading. The sample is monthly and runs from 1996 to 2013.

Credit Rating	Credit Spread	Monthly Returns in Excess of T-bill (%)					Credit Spread	Monthly Returns in Excess of T-bill (%)					Credit Spread	Monthly Returns in Excess of T-bill (%)				
		Mean	Std	Sharpe Ratio	Skew	Ex. Kurt.		Mean	Std	Sharpe Ratio	Skew	Ex. Kurt.		Mean	Std	Sharpe Ratio	Skew	Ex. Kurt.
	Pseudo Bonds (SPX)						Pseudo Bonds (Single-Stock)						Corporate Bonds					
Target Maturity: 30 Days																		
IG	77	0.05	0.13	0.38	1.24	6.48												
Ba	165	0.09	0.32	0.28	-1.95	25.53	285	-0.23	0.79	-0.29	-4.00	20.78						
B	286	0.11	0.69	0.16	-8.35	100.01	402	-0.20	0.80	-0.25	-2.86	12.90						
Caa-	503	0.22	0.91	0.24	-5.00	53.90	600	-0.12	1.05	-0.12	-5.70	52.35						
Target Maturity: 91 Days																		
IG	64	0.08	0.26	0.30	-3.56	31.68	168	-0.01	0.70	-0.01	4.01	27.97						
Ba	133	0.10	0.71	0.15	-7.82	95.83	183	-0.06	0.42	-0.13	-2.79	18.51						
B	262	0.19	0.66	0.28	-2.82	23.88	308	0.00	0.62	0.01	-2.85	25.32						
Caa-	495	0.26	1.19	0.22	-4.33	33.71	532	0.05	0.94	0.06	-2.35	17.47						
Target Maturity: 183 Days																		
Aaa/Aa	50	0.07	0.29	0.24	-2.16	25.79	84	-0.14	0.46	-0.29	-2.98	10.88	24	-0.03	0.90	-0.03	-3.78	30.72
A/Baa	106	0.13	0.45	0.28	-0.62	17.45	118	-0.04	0.39	-0.10	-1.81	8.41	98	0.14	0.36	0.40	2.19	10.73
Ba	169	0.12	0.83	0.15	-5.10	51.00	175	0.00	0.52	0.00	-1.80	12.48	235	0.24	0.81	0.30	-1.06	13.33
B	287	0.22	1.00	0.22	-2.43	17.05	336	0.04	0.94	0.04	-2.63	18.64	320	0.23	1.92	0.12	-2.22	10.38
Caa-	471	0.29	1.45	0.20	-2.33	14.92	662	0.11	1.45	0.07	-1.92	10.91	1206	0.81	2.74	0.30	1.94	9.28
Target Maturity: 365 Days																		
Aaa/Aa	42	0.07	0.42	0.17	1.20	16.06	92	0.00	0.58	0.00	-0.71	6.44	43	0.15	0.62	0.25	2.47	14.30
A/Baa	97	0.16	0.61	0.26	0.97	14.49	123	0.11	0.63	0.18	-1.70	14.17	134	0.16	0.76	0.21	-1.23	17.33
Ba	186	0.17	1.03	0.17	-2.78	22.70	201	0.09	0.86	0.11	-2.53	17.65	341	0.41	1.55	0.26	4.68	39.36
B	311	0.28	1.29	0.22	-1.15	7.22	435	0.14	1.40	0.10	-2.76	19.08	610	0.72	2.36	0.30	2.12	14.51
Caa-	469	0.32	1.75	0.18	-1.49	8.48	898	0.33	1.93	0.17	-1.46	7.30	1352	1.66	4.20	0.40	1.38	2.78

Table A6: Assets as Shares of Individual Firms in the S&P500: Equivalent European Options

This table contains several results for pseudo bonds constructed from individual stocks as presented in the paper, 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. Columns 2 to 4 report the Gaussian-kernel weighted average credit spread of pseudo bonds. 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

	Credit Spreads			Monthly Returns in Excess of T-bill (%)				
	Average	Boom	Recession	Mean	Std	SR	Skew	Ex. Kurt
Aaa/Aa	104	98	187	0.02	0.55	0.03	-0.90	1.23
A/Baa	219	216	240	0.25	1.18	0.21	-0.65	4.60
Ba	343	333	407	0.28	1.34	0.21	-1.35	6.21
B	553	520	770	0.38	1.89	0.20	-1.71	8.51
Caa-	891	825	1318	0.70	2.38	0.29	-1.02	3.37

Panel B: Regression of Pseudo Bonds Excess Returns on Assets' Excess Returns

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	0.02	(0.48)	0.01	(0.20)	0.07	(5.13)	0.26
A/Baa	0.25	(3.10)	0.11	(2.01)	0.17	(11.67)	0.64
Ba	0.28	(3.05)	0.12	(1.85)	0.24	(9.28)	0.68
B	0.38	(2.92)	0.11	(1.24)	0.36	(10.00)	0.79
Caa-	0.70	(4.29)	0.15	(1.70)	0.49	(15.17)	0.85

Panel C: Regression of Pseudo Bonds Excess Returns on Pseudo Equities' Excess Returns

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	0.02	(0.48)	0.02	(0.25)	0.03	(2.89)	0.13
A/Baa	0.25	(3.10)	0.18	(2.67)	0.07	(6.12)	0.44
Ba	0.28	(3.05)	0.16	(2.49)	0.11	(11.00)	0.58
B	0.38	(2.92)	0.08	(0.89)	0.15	(11.42)	0.66
Caa-	0.70	(4.29)	0.08	(0.65)	0.16	(14.50)	0.65