OPTION-BASED CREDIT SPREADS

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<u>ABSTRACT</u>

We propose a non-parametric empirical benchmark for credit risk analysis. We build fictitious "pseudo firms" that purchase real traded assets by issuing equity and zero-coupon bonds. By no-arbitrage, these bonds equal Treasuries minus put options on the firms' assets, which are all observable. We exploit our pseudo firms as a laboratory, and empirically show that their credit spreads are large and countercyclical, illiquidity and corporate frictions are unlikely determinants of bonds' credit spreads, infrequent rating changes and idiosyncratic asset uncertainty greatly increase spreads, and, in a banking application, discount rate shocks substantially increase banks' tail risks and default correlations.

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1. Introduction

The understanding of credit risk is critical to many areas of research, with questions ranging from the size of credit spreads to the determinants of their dynamics, and from the degree of tail risk in large bond portfolios to the source of systemic risk in banking. The literature is vast. Yet, questions about credit risk are hard to answer with purely empirical methods, because corporate bonds are complicated securities, the market values of the assets of the firms issuing the bonds are not observable, and the corporate bond market has its own market-microstructure idiosyncrasies. Fully empirical methodologies, moreover, do not easily facilitate the analysis of counterfactuals to learn from "what if" experiments. Instead, counterfactual experiments generally must be tackled by positing stylized structural models of default risk. The structural model-based approach also presents its own difficulties, as such models are highly parameterized, the results depend on model specifications such as the assumed distribution of shocks, and they are often genuinely difficult to estimate.

In this paper, we propose a third way, namely, a non-parametric, fully empirical framework that is still sufficiently flexible to serve as the basis for "what if" empirical experiments on credit risk. Specifically, like much of the literature before us, we exploit Merton's (1974) insight that a firm's debt is economically equivalent to risk-free debt minus a put option on the assets owned by the firm.[1] In contrast with previous literature, however, we turn this basic insight on its head, and exploit real traded put options to learn about credit risk. We build fictitious firms, which we call "pseudo firms," that have simple and observable balance sheets. Our pseudo firms have assets comprised of *real* traded securities, and have liabilities comprised of equity and zero-coupon bonds. From Merton's insight, the market values of such zero-coupon bonds equal default-free bonds minus put options on the traded securities held as assets by the pseudo firms. Using *observed* prices of traded put options and Treasuries, we can thus extract the empirical properties of the zero-coupon bonds issued by our pseudo firms. We call such zero-coupon bonds "pseudo bonds."

The simplicity of our pseudo firms, whose market values of both assets and liabilities are observable and whose default events occur mechanically when put options are in-the-money at maturity, makes them ideal benchmarks to study questions about credit risk. As is the case with traditional parametric models, moreover, we can vary the characteristics of our

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[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 pseudo 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.

pseudo firms (including their leverage, default probabilities, bankruptcy costs, asset riskiness, and so on) to run "what if" empirical experiments on credit risk. These experiments provide direct empirical evidence on the factors that affect firms' credit spreads and default risks.

We begin by analyzing pseudo bonds issued by pseudo firms that hold two types of assets – namely, (i) the S&P 500 ("SPX") index; and (ii) shares of individual stocks that comprise the S&P 500 index. This choice is dictated by data availability, and, in a later section we show our empirical results extend to pseudo firms holding other assets including commodities, foreign currencies, and fixed income securities. We refer to the pseudo bonds issued by firms (i) and (ii) as "SPX pseudo bonds" and "single-stock pseudo bonds," respectively.

We find several interesting empirical results. First, pseudo bonds' average credit spreads are large and similar in magnitude to the credit spreads of real corporate bonds, especially for bonds with low default probabilities. For example, the credit spreads of two-year SPX pseudo bonds corresponding to the default probabilities for Aaa/Aa and A/Baa bonds are 0.51% and 1.26%, respectively. The spreads of single-stock pseudo bonds for those two default probabilities are 0.98% and 2.18%. These spreads are very similar to the average credit spreads observed for actual Aaa/Aa and A/Baa corporate bonds – i.e., 0.62% and 1.15%, respectively. For high-yield ("HY") debt, SPX pseudo bonds range between 2.14% (for Ba-rated bonds) and 4.69% (for Caa-rated bonds), while single-stock pseudo bonds range between 3.46% and 9.20%. Once again, these spreads are close to actual corporate bond spreads, which are 3.16% for Ba-rated bonds and 13.82% for Caa- rated bonds, respectively.

Second, these large credit spreads hold not only for medium-term bonds (two years to maturity in our implementation) but also for very short-term pseudo bonds. For example, investment-grade ("IG") SPX pseudo bonds with 30 and 91 days to maturity have average credit spreads of 0.78% and 0.61%, respectively, which are very close to the average credit spreads of 0.62% and 0.60% of IG firms' commercial paper. Pseudo bond spreads thus are consistent with the puzzling hefty credit spreads of very short-term paper issued by corporations with a negligible probability of default over such a short horizon.

Third, illiquidity in corporate bonds does not seem to be the main source of the large observed credit spreads. We measure market liquidity using the Roll (1984) bid-ask bounce measure and find that liquidity is much higher for pseudo bonds than real corporate bonds. Because pseudo bonds display large credit spreads that match those of real corporate bonds, it seems unlikely that such high credit spreads are only due to illiquidity in the bond markets.

Fourth, our results also indicate that large credit spreads are unlikely due to investors' systematic over-prediction of default frequencies or of the size of losses given default. Indeed,

using our pseudo firm laboratory we can test for this over-prediction in the data. We find that our *ex ante* measures of default probabilities are in fact similar to *ex post* default frequencies, and that the loss given default ("LGD") of pseudo bonds is smaller than for real corporate bonds. Because pseudo bonds have large credit spreads, over-prediction of default probabilities or LGDs thus are unlikely to be the explanation of high credit spreads.

Fifth, we find that pseudo bond spreads increase during recessions. In particular, HY pseudo bond credit spreads increased during the 2008 financial crisis by the same amount as HY corporate bond spreads, which suggests that nothing particularly anomalous was going on in HY bond markets during the crisis. By contrast, IG pseudo bond spreads increased during the crisis by less than real IG corporate bond spreads, showing that perhaps some market frictions impaired the IG market during that period.

These results highlight the use of pseudo firms as a laboratory to answer questions about credit risk. We push this laboratory idea further by running data-based "what if" experiments that would be impossible to implement with real corporate data. As a first experiment, we quantify the potential bias that may be introduced in average credit spreads 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.[2] We find that as the rating assignment frequency decreases from every month to every eighteen months, average spreads increase substantially, *e.g.* by over 50% for highly rated pseudo bonds.

As a second experiment, we investigate the impact of idiosyncratic 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 firms' asset values. Our methodology using pseudo firms overcomes both hurdles. We find not only that, even controlling for the endogeneity of credit ratings, higher idiosyncratic uncertainty implies higher credit spreads (except for Aaa/Aa pseudo bonds), but especially that the impact is large and similar in magnitude to the differential in credit spreads *across* credit ratings.

We finally highlight the flexibility of using pseudo firms as a laboratory for credit risk analysis by going through a banking example. Specifically, we study the source of default risk of fictitious pseudo *banks* that extend loans to individual pseudo firms. Because then pseudo banks' assets are comprised solely of portfolios of pseudo bonds, we exploit the empirical returns on pseudo bonds to compute the empirical distribution of pseudo banks' assets and thus their default risk and minimum capital requirements. Our empirical results suggest

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[2]For instance, it is customary for financial reports to provide average credit spreads by credit ratings. See e.g. *http://www.bondsonline.com/Todays_Market/Corporate_Bond_Spreads.php*

that common fundamental shocks to the individual firms' assets (which are observable for pseudo firms) are greatly amplified by the leveraged nature of bank loans, leading to severely negatively skewed and leptokurtic return distributions of pseudo banks' assets. Such fundamental shocks, moreover, affect the cross-section of pseudo banks that make loans to the same universe of pseudo firms but whose portfolios are otherwise randomly assigned. Finally, because such fundamental shocks to pseudo firms are mostly due to discount rate shocks, our results highlight the discount rate channel as a key determinant of banks' risks.

We extend our basic empirical results on credit spreads in multiple directions. First, we consider several other types of assets that our pseudo firms can buy. In particular, we consider commodities (oil, natural gas, gold, corn, soybeans), foreign currencies (GBP, EUR, JPY, CHF, AUD, CAD), and coupon bonds (through the use of swaptions). Although the data coverage is not as good as with SPX and single-stock pseudo bonds, we find similar average credit spreads, especially for highly rated pseudo bonds. We also find that such credit spreads of pseudo firms with different types of underlying assets display a strong comovement over time, highlighting that similar factors affect the variation in spreads.

Second, we restrict the "single-stock" sample to those firms that have negligible leverage to avoid the possibility that our results somehow depend on the fact that equity is itself levered. The results are noisier but similar.

Finally, we add realistic bankruptcy costs to our pseudo firms. Specifically, we add a portfolio of traded put options to match observed corporate recovery rates. In this case the credit spreads of our pseudo bonds become larger and, in fact, exceed the credit spreads of real corporate bonds for highly rated bonds, and match those for low rated bonds. Overall, the results are reasonable.

Our empirical findings using pseudo bonds have numerous additional implications. First, they suggest that the large credit spreads are unlikely to be solely attributable to theories of corporate behavior, such as early and/or optimal default (*e.g.,* Black and Cox (1976), Leland and Toft (1996)), large bankruptcy costs (*e.g.,* Leland (1994)), 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 pseudo firms are very simple ones in which their asset values are observable, information is symmetric, managerial frictions do not exist (because there is nothing to be managed), the leverage and default boundaries are set mechanically, and default only occurs at maturity. Yet, independently of the type of underlying assets, our

pseudo bonds display properties that are surprisingly close – qualitatively and quantitatively – to those of real corporate bonds. Instead, our results provide an indirect argument that large credit spreads may be due to 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.

Indeed, our results indicate that the explanation for high credit spreads is related to the notorious empirical finding that out-of-the-money put options are very expensive in the options literature – *i.e.*, high credit spreads are plausibly attributable to an additional insurance premium required by investors to hold securities with tail risk. In essence, our empirical results show a good deal of integration across corporate bond and option markets, as the risk premiums investors require to hold securities that are especially affected by tail risk are similar.

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).Huang and Huang (2012) discuss the deficiencies of the lognormal Merton model and show that numerous structural models calibrated to match true default probabilities generate credit spreads that are still too small compared to the data. Most of these structural models have implications only for 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 very different from ours, as we do not use any parametric model, but instead go straight to the data and analyze the credit spreads of our pseudo firms through traded options.

A small number of papers link options to credit spreads, but their focus and methodologies are quite different from ours. 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 of firms are related to their credit default swap spreads. These papers focus on using options of individual firms to match bond spreads of *those* firms. Our approach is different, as we consider (pseudo) bonds of fictitious (pseudo) firms that in fact do not exist in reality. Our goal is to obtain general insights about the nature of credit risk and use pseudo firms as a

laboratory to run "what if" experiments. Although the empirical results of those papers are consistent with ours, the focus and methodologies are very different.

In fact, our approach is mostly 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. Collin-Dufresne, Goldstein, and Yang (2012) estimate a structural model of default to get at the same question, and find that CDO spreads were fairly priced when compared to the estimated model's predictions. Although similar in spirit (*i.e.*, we also use put options to learn about credit spreads), our approach is not limited to learning about the credit risk of CDOs and instead uses pseudo firms to analyze the general properties of credit spreads and to run "what if" experiments for credit risk analysis.[3]

The paper is organized as follows. Section 2. describes our approach for computing option-based credit spreads. Section 3. describes the data and summarizes the empirical results about credit spreads. Section 4. use pseudo firms as a laboratory to study potential sources of high credit spreads. Section 5. offers an application of our framewor to study credit risk in banking. Section 6. provides numerous extensions to our results. Section 7. concludes. An On-Line Appendix contains numerous extensions and additional material.

2.   Option-Based Credit Spreads

We begin with a description of our approach using the SPX index as the sole underlying asset owned by our hypothetical pseudo firms. Let $A_{i,t}$ be the market value of the SPX index that is purchased by pseudo firm i at time t and let $K_{i,t}$ denote the face value of zero-coupon debt the firm issues at t. Let $t + \tau$ be the debt's maturity. 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,

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[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.

[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.

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

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

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 SPX index, which has an observable price $\widehat{P}_t^{SPX}(t+\tau, K_{i,t})$. Thus, denoting by $\widehat{Z}_t(t+\tau)$ the observable value of a risk-free zero-coupon bond at t with maturity $t + \tau$, by no-arbitrage the value of defaultable debt is:

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

A "hat" indicates that the price is directly observable. We rely on Treasury and SPX put option data to compute the empirical properties of 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 compute the credit spread on the pseudo bond issued by pseudo 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 a simple illustration of the procedure, let $t =$ June 29, 2007. The SPX index on that day was $A_t = 1503.35$ and the put options with maturity $t + \tau =$ Dec 19, 2009 and strike prices $K_{1,t} = 800$ and $K_{2,t} = 1150$ were quoted on CBOE at $\widehat{P}_t^{SPX}(t + \tau, 800) = \$4.7$ and $\widehat{P}_t^{SPX}(t + \tau, 1150) = \$30.15$, respectively.[5] The value of a Treasury zero-coupon bond was $\widehat{Z}_t(t + \tau) = \$88.81$. From these data, we can build two SPX pseudo firms, one with low leverage, $L_{1,t} = K_{1,t}/A_t = 800/1503.35 = 53\%$, and one with high leverage $L_{2,t} = 1150/1503.35 = 76\%$. Using (2), we can compute the no-arbitrage benchmark values of the pseudo bonds "issued" by these two pseudo firms. These values are, in units of $100 principal, $\widehat{B}_t(t+\tau, 800) = \$88.22$ and $\widehat{B}_t(t+\tau, 1150) = \$86.19$, respectively, and their credit spreads are 0.27% and 1.24%, respectively.

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[5]For this simple illustration, we use all available mid quotes from CBOE. In the empirical section, we subject all the data to batteries of filters to ensure we only use reliable quotes. In addition, we only consider pseudo bonds that are comparable to corporate bonds. Thus, the high-leverage pseudo bond discussed next would be dropped from the sample by the end of 2008 as its default probability (in Panel D) increased above a threshold we impose to make it comparable with Caa- real corporate bonds. See Section 3.

Repeating this procedure over time, Panel A of Figure 1 plots the time series of these two pseudo bond prices for the period June 2007 to November 2009, along with the (rescaled) SPX index. Panel B plots their leverage ratios. The low-leverage pseudo bond price steadily increases over time – like any zero-coupon bond – except during the 2008 crisis, when it drops substantially. Still, this pseudo bond eventually pays 100% of principal at maturity. The pseudo bond issued by the high-leverage firm instead displays a larger price drop during the financial crisis, which never fully recovers. This pseudo firm eventually defaults and bond holders would only receive the "recovery amount" $A_{t+\tau}/K_{i,t} = 95\%$ of principal value.

Panel C plots the credit spreads of the two pseudo bonds. The high-leverage pseudo bond always has a higher credit spread than the low-leverage pseudo bond. Both credit spreads are low initially but increase during the financial crisis. The credit spread of the low-leverage pseudo bond then converges back to a negligible number by the end of the sample, whereas the high-leverage pseudo bond displays credit spreads of over 80% as it nears maturity. (Panel D plots the bonds' default probabilities, discussed in Section 2.1.)

We use a similar procedure to construct pseudo bonds of pseudo firms that purchase shares of individual stocks, such as Apple. The only caveat is that such put options 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.[6]

We emphasize that our focus is not to compare, say, the "Apple-based" pseudo bonds to the true corporate bonds issued by Apple Inc. These are different securities issued by different firms. For instance, the "Apple-based" pseudo firm may be highly leveraged and its bonds have high default probability (if $K_{i,t}$ is very large) while Apple Inc. itself has low leverage and its bonds have low default probability. Our objective is rather to learn about the credit risk of pseudo firms, which take the statistical properties of their underlying assets as exogenous. Our choice of using individual stocks is motivated by the wealth of data that they provide, as options on S&P 500 stocks are heavily traded and fairly liquid. Section 6. shows that our results are robust to the type of underlying assets.[7]

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[6] As a robustness check, we also performed all of our calculations using European option price equivalents based on implied volatilities of American options, and obtained similar results. See On-Line Appendix.

[7] One interpretation of our pseudo firm is as a leveraged closed-end fund that purchases shares of just one individual stock, and finances the purchase using equity and zero-coupon bonds. The option-based credit spreads would correspond to the credit spreads of the bond issued by such a closed-end fund.

2.1. *Ex Ante* Default Probabilities

In order to facilitate a consistent comparison between pseudo bonds and real corporate bonds, we first 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

$$p_t(\tau) = \Pr\left[A_{i,t+\tau} < K_{i,t} \,|\, \mathcal{F}_t\right] \tag{3}$$

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

When pseudo 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:

$$\ln\left(\frac{A_{t+\tau}}{A_t}\right) = \mu_{t,\tau} - \frac{1}{2}\sigma_{t,\tau}^2 + \sigma_{t,\tau}\varepsilon_{t+\tau} \tag{4}$$

where $\varepsilon_{t+\tau}$ are standardized unexpected asset returns. 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.[8] Given estimates of $\mu_{t,\tau}$ and $\sigma_{t,\tau}$, we collect the (overlapping) history of shocks

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

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 $p_t(\tau)$ in (3) as follows:

$$p_t(\tau) = \Pr\left[\varepsilon_{t+\tau} < X_{i,t} \,|\, \mathcal{F}_t\right] \quad \text{where} \quad X_{i,t} = \frac{\ln(L_{i,t}) - \left(\mu_{t,\tau} - \frac{1}{2}\sigma_{t,\tau}^2\right)}{\sigma_{t,\tau}} \tag{5}$$

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[8]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.

Thus, we can estimate such probabilities simply as:

$$\widehat{p}_t(\tau) = \frac{n(\varepsilon_{s+\tau} < X_{i,t})}{n(\varepsilon_{s+\tau})} \quad \text{for all} \quad s + \tau < t. \tag{6}$$

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 maturity $t + \tau$. The empirical distribution of shocks $\varepsilon_{t+\tau}$ thus determines these default probabilities. Panel A of Figure A1 in the On-Line Appendix presents the histogram of shocks $\{\varepsilon_{t+\tau}\}$ for maturity $\tau = 2$. The Kolmogorov-Smirnov test rejects normality at 1% confidence level.

To illustrate, Panel D of Figure 1 plots the default probabilities of the two SPX pseudo bonds in Panel A. The high-leverage pseudo firm has higher default probability than the low-leverage pseudo firm, which is not surprising because both pseudo firms have the same underlying assets, the SPX. (As we shall see, when firms differ from the type of underlying assets, firms with the same leverage may have different default probabilities depending on the underlying asset volatility). Both default probabilities increased during the financial crisis, with the high-leverage pseudo bond jumping to almost 100% and hovering around that value up to maturity. The default probability of the low-leverage bond returned to zero by maturity, as it became clear that no default would occur.

We extend the above procedure to the case of single-stock pseudo bonds. When pseudo firm i's assets $A_{i,t}$ consist of shares of an individual stock included in the SPX, we must take into account survivorship bias – i.e., if at time t a given stock is part of the SPX, it must have done well in the past and thus its shocks are biased upwards. To avoid survivorship bias, for every t we consider the full cross-section of all firms underlying the SPX index before t (including those that 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 the On-Line Appendix shows the histogram of the resulting normalized shocks. These shocks display fat tails, and the Kolmogorov-Smirnov test rejects normality at the 1% confidence level.

3. Preliminary Empirical Results

3.1. Data

Before we move to our empirical implementation, we briefly describe the data. (See On-Line Appendix A for more detailed description of data and filters used.)

We use the OptionMetrics Ivy database for daily prices on SPX index options and options on individual stocks from January 4, 1996, through July 31, 2014. We also use the SPX options data from Market Data Express ("MDR") to cover the 1990 to 1995 sample. 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 generally apply 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/or embedded options (*e.g.,* callable bonds). We also employ five-year credit default swap ("CDX") indices using data from Markit.

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

3.2. Average Pseudo Bond Credit Spreads

We begin by focusing on the 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 2 plots average credit spreads of two-year pseudo bonds against their estimated default probabilities, both for the SPX pseudo bonds (diamonds) and for single-stock pseudo bonds (circles).[9] For comparison, the figure also plots average credit spreads for real corporate

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[9] At every given time t only certain maturities $\hat{\tau}_{i,t}$ are available. We take the Gaussian kernel-weighted average of all bonds with $p_t(\hat{\tau})$ in the given bin, 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, and τ is the targeted maturity. We use (2) with $\hat{\tau}_{i,t}$ instead of τ for all computations.

bonds (triangles) relative to their own default probabilities, where the latter are based on Moody's historical 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 low default probabilities. Indeed, for default probabilities between 0 and 1%, the average credit spreads are around 0.76% for SPX pseudo bonds and 1.7% for single-stock pseudo bonds. These credit spreads are approximately the same as the average credit spreads observed on real corporate bonds (1.1%) for comparable default probabilities. As the probability of default increases, the credit spreads of both SPX and single-stock pseudo bonds increase, reaching 2.9% and 5.8%, respectively, for default probabilities in the [10%,11%] bin, and 5.4% and 9.3%, respectively, for default probabilities in the [25%,26%] bin. Corporate bond spreads increase by comparable amounts as default probabilities increase – $i.e.$, 5.71% and 11% for default probabilities around 10.5% and 25%, respectively. (The data on 2-year corporate bonds are sparse at high default probabilities, and we thus compute averages on a coarser intervals centered at 10.5% and 25%.) Finally, we see that SPX-based credit spreads are uniformly lower than single-stock credit spreads. The main reason is that, as shown in Section 6., single-stock pseudo bonds have fatter tails, and thus entail a higher LGD than SPX pseudo bonds (but still lower than real corporate bonds).

For comparison purposes, the dotted dashed line in Panel A is the credit spreads implied by the original Merton (1974) model, which assumes that asset values are lognormally distributed. Credit spreads of both pseudo bonds and real bonds are far larger than those implied by the lognormal Merton model.[10]

Panels C and E of Figure 2 present plots similar to those in Panel A, but we divide the sample into booms and recessions. Credit spreads of both pseudo bonds and real bonds are high in both subsamples, and they are especially high during recessions. Real bonds' spreads are though a bit higher than pseudo bonds' spreads in recessions.

The right-hand-side panels of Figure 2 plot credit spreads against book leverage.[11] Panel B shows that both real bonds' and pseudo bonds' average credit spreads increase substantially with leverage. Leverage, however, is not a sufficient statistic for credit spreads, which also depend on the volatility and tails of the shock distribution. Default probabilities, on the left-hand-side panels, correct for these additional influences.

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[10]We simulate the Merton (1974) model to compute average credit spreads in order to take into account discretization bias and stochastic volatility. See the On-Line Appendix E for details.

[11]We use book leverage rather than market leverage because the latter cannot be computed for real firms, as their assets are not observable. Book leverage for real firms is given by "Book Value of Debt/(Book Value of Debt plus Market Equity)," and for pseudo firms is given by "Face Value of Debt / (Face Value of Debt plus Market Equity)," where "Market Equity" is the value of the corresponding call option.

4.   A Laboratory for Credit Risk Analysis

The average credit spreads of pseudo bonds shown in Figure 2 are large and comparable to credit spreads of real corporate bonds. We now exploit our pseudo firm laboratory to investigate the potential sources of these large spreads.

4.1.   Testing for Over-Prediction of Default Probabilities

One possible explanation of high credit spreads is that investors over-estimate the probability of default of corporate bonds. We can use our pseudo firm laboratory to test this hypothesis. In fact, because we assign default probabilities to pseudo bonds using a well-defined rule (see Section 2.1.), we can test whether *ex post* default frequencies are similar to *ex ante* probabilities. Figure 3 carries out this test using data from 1970 to 2014.[12]

Panel A 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. Panel B shows the same results for the SPX pseudo bond. In this case, point estimates of *ex post* default frequencies are different from *ex ante* probabilities but still within confidence intervals. The confidence bands for SPX pseudo bonds are wide, however, because SPX pseudo bonds are built from a *single* pseudo firm that has only SPX shares as assets – *i.e.*, we do not have a cross-section of firms over which to average defaults. Thus, the mean *ex post* default rate is noisy, and the confidence bands are large.[13] Still, overall, the evidence shows that our *ex ante* default probabilities are not too high and hence that over-prediction of default probabilities is not an explanation for large credit spreads.

Our results are instead consistent with the large literature documenting that out-of-the-money equity put option prices are especially high. The novelty of our approach is to document that such "overpricing" of put options is quantitatively consistent with observed spreads on actual corporate bonds, an indication that option markets and corporate bond

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[12]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 2014 is chosen to match the Moody's sample, used in Section 4.2.

[13]Intuitively, out of our 45-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.

markets show a good deal of integration and that the same forces shape risk premia in both markets. In particular, it appears that bond holders require hefty premia to hold securities with large tail risk, just as they do for options.

4.2. Pseudo Credit Ratings

To better understand pseudo bond credit spreads and their relation to real corporate bond spreads, we now group pseudo bonds into portfolios by assigning pseudo credit ratings to pseudo bonds based on their default probabilities $\widehat{p}_{i,t}(\tau)$ as computed in Section 2.1.[14] 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, we estimate *ex post* default frequencies at various horizons from 30 days up to two years. We use our own estimates rather than Moody's default frequencies for three main reasons: first, we are interested in the variation of default frequencies over the business cycle; second, we analyze default frequencies at horizons of below one year; and third, we need to group IG bonds into coarser categories (*e.g.* Aaa/Aa and A/Baa) because of the lack of sufficiently granular option strike prices to distinguish across default frequencies.[15] On-Line Appendix B further discusses the construction of these data. For reference, Table A2 in On-Line Appendix F 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.

Given the estimated default frequencies of real corporate bonds, for each pseudo bond i we compare its default probability $\hat{p}_{i,t}(\tau)$ to the real corporate bond default probabilities, and thus assign a credit rating. As in Figure 3 we also test whether *ex post* default frequencies are close to the *ex ante* default probabilities, and they are. Table A3 in On-Line Appendix contains the results and On-Line Appendix C1 further discuss the methodology. The next subsection exploits these portfolios of pseudo bonds grouped by credit ratings to further discuss the properties of credit spreads.

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[14]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 exercise.

[15]Even with this coarser definition of credit ratings, SPX and single-stock pseudo bonds in the Aaa/Aa category have 160 and 153 months of missing observations, out of 295 and 223 in our samples, respectively. They have have 62 and 11 months of missing observations, respectively, in the A/Baa category.

4.3. Pseudo Bond Credit Spreads by Maturity and Credit Rating

Columns two to six of Table 1 report the average credit spreads of pseudo bonds (Panels A and B) and corporate bonds (Panel C) for maturities ranging between 30 days to two years across credit ratings. We consider two broad credit rating categories, Investment Grade ("IG") and High Yield ("HY"), as well as the five sub-categories Aaa/Aa, A/Baa, Ba, B, Caa-. The broader categories are useful to ensure sufficient data coverage. For short-horizon bonds, for instance, we have sufficient data to cover the IG category as a whole but insufficient granularity in strike prices to differentiate across IG sub-categories. Indeed, for single-stock pseudo bonds, we do not have reliable data to cover the 30-day maturity at all. Similarly, we rely on commercial paper for 30- and 91-day maturities, for which corporate bond quotes are unreliable. We thus miss data for HY corporate bonds for these short maturities.

With these caveats, the results of Table 1 show that irrespective of their maturity, IG and HY credit spreads of pseudo bonds are very similar to the IG and HY credit spreads of corporate bonds, respectively, which is consistent with the finding in Figure 2. Comparing Panel C with Panels A and B across rows, the matching between pseudo bonds and corporate bonds is especially close for highly rated bonds, although SPX pseudo bonds have lower credit spreads than both single-stock pseudo bonds and corporate bonds for HY categories (*see* Section 6. for a discussion). In all cases, however, the pseudo bond credit spreads are far higher than those implied by the lognormal Merton model, which are zero for IG bonds and between 0.13% to 0.8% for HY bonds (results not reported).

These empirical results on pseudo firms thus shed further light on the substantial risk premia investors require to hold securities with large tail risk. For instance, the results in Table 1 show that option prices are consistent with the puzzling empirical regularity that 1- and 3-month commercial paper issued by highly rated (Aaa/Aa) companies – with negligible probability of default – exhibit a large 0.6% spread over Treasuries on average. Indeed, three-month SPX and single-stock pseudo bonds have 0.61% and 1.33% credit spreads, respectively. (We discuss the source of the difference in Section 6.)

4.4. The Business Cycle and the 2008 Financial Crisis

The last four columns of Table 1 take a closer look at two-year bonds (similar results hold for other maturities). First, we see that high credit spreads of pseudo bonds are not just resulting from high credit spreads during recessions or the 2008 crisis, but are also high in boom times. In fact, comparing Panel A and B with Panel C, the business cycle variation of

credit spreads is comparable to the corresponding variations in real corporate bond spreads.

Figure 4 presents graphical representations of the time series of monthly credit spreads of two-year IG and HY pseudo bonds and corporate bonds. The focus on IG and HY bonds enables us to compare the credit spreads to the Markit IG and HY CDX indices, which are generally believed to be a better reflection of corporate credit risk because they are more liquid than the actual corporate bonds on which they are based. They are thus a good benchmark to compare our option-based credit spreads.

The credit spreads of both SPX and single-stock pseudo bonds, real corporate bonds, and CDX indices increased substantially during the 2008 financial crisis, especially for HY bonds, and then reverted to more normal levels by 2010. Interestingly, the increase in HY pseudo bond credit spreads in 2008 was identical to the rise in corporate bond and CDX spreads, thus suggesting that nothing anomalous was happening in the high-yield credit market in that important historical period. HY pseudo and corporate bond spreads also increased in 1992 and 1998 around the two previous recessions.

The correlations across the four indices (two pseudo bonds, real corporate bonds, and CDX) are reported in the left corner of each panel. With the exception of IG single-stock pseudo bonds and corporate bonds (whose pairwise correlation is just 3%, mostly because pseudo bond spreads were so high in the 1990s compared to corporate bond spreads), the correlations across all these credit risk measures are high, ranging from 29% between IG SPX pseudo bonds and IG corporate bonds (Panel A) to 92% between HY SPX pseudo bonds and the HY CDX (Panel B).

4.5. Market Liquidity and Credit Spreads

Illiquidity in the corporate bond market is often considered to be a critical determinant of large credit spreads. We assess this notion using our pseudo bond laboratory. Specifically, following Bao, Pan, and Wang (2011), we use the Roll (1984) "bid-ask bounce" as a measure of market liquidity. The Roll measure reflects the degree to which bid and ask prices bounce up and down, with the logic being that large reversals indicate relatively less market 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 market illiquidity measure for pseudo bond i in month t as

$$Illiquidity_t = \sqrt{-Cov_t(\Delta p_{i,t,d}^{Bid \to Ask}, \Delta p_{i,t,d+1}^{Ask \to Bid})} \tag{7}$$

where $\Delta p_{i,t,d}^{Bid \to Ask} \equiv \log Ask_{i,t,d} - \log Bid_{i,t,d-1}$ and $\Delta p_{i,t,d}^{Ask \to Bid} \equiv \log Bid_{i,t,d} - \log Ask_{i,t,d-1}$.[16] 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 (see footnote 9) of the pseudo bonds for which we can compute the Roll measure. In addition, we 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. Instead, we compute the Roll measure using daily transaction prices. Specifically, the Roll measure for corporate bond i in month t is

$$Illiquidity_t = 2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Transaction}, \Delta p_{i,t,d+1}^{Transaction})} \tag{8}$$

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. The portfolio-level Roll measure is the value-weighted average of all corporate bonds for which the Roll measure can be calculated.

The last two columns of Table 1 show the results. Comparing Panels A and B, we see that the liquidity of SPX pseudo bonds is far higher than the liquidity of single-stock pseudo bonds. Both the bid-ask spreads and the Roll measure for SPX pseudo bonds are about one-fifth the size of those same market liquidity measures for single-stock pseudo bonds. This is not altogether surprising given that SPX options are far more liquid than most individual equity options.[17]

Comparing Panels A and B to Panel C, it appears that pseudo bonds – especially those based on the SPX – have far greater market liquidity than real corporate bonds. Single-stock pseudo bonds have market liquidity measures that are somewhat closer to those of real corporate bonds, except for lower-rated bonds for which corporate bonds still show far lower market liquidity. Overall, these results suggest that market liquidity alone is unlikely to be the main source of large credit spreads.

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[16]This formula slightly differs from Roll (1984) formula, which is used instead in equation (8) below. Because for pseudo bonds we have available bid and ask prices, 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).

[17]Panel A of Table 1 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.

4.6. Credit Spreads and the Frequency of Credit Rating Revisions

In the above analysis, an important question pertains to the potential bias in average credit spreads when credit rating agencies do not update their credit ratings sufficiently often (David (2008), Huang and Huang (2012), Feldhutter and Schaefer (2013)). 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, it is important to gauge how the frequency of credit rating assessments may impact *ex post* average credit spreads.[18] Our pseudo firm laboratory enables us to estimate the extent of any such bias by simply modifying the frequency with which we assign pseudo credit ratings to pseudo firms.[19]

Panel A of Table 2 reports the results. As we sort single-stock pseudo bonds in credit rating portfolios every 3, 6, 12, 15, and 18 months, average credit spreads generally increase, except for the lowest credit rating. The increase is substantial. For example, A/Baa pseudo bonds' credit spreads increase from 0.98% at monthly assignment frequency to 1.64% at 12-month frequency, to 2.01% at 18-month frequency.

As first pointed out by David (2008), the intuition behind the increase in average credit spreads as the frequency of credit rating assignments declines lies in the convexity of the credit spread with respect to the firm's leverage ratio. As we fix the credit rating for longer periods, the stochastic variation in the leverage ratio implies an increase in credit spreads that is higher on the upside (when leverage increases) than on the downside (when leverage decreases). An upper bias in average credit spreads thus is to be expected. Our empirical results show that such convexity effects are in fact significant for highly rated pseudo bonds, as average credit spreads may increase by as much as 50% when the credit rating frequency declines. For lower rated pseudo bonds, the convexity effect does not appear to be strong and possibly more than overcome by noise in the data, as there is not much of a pattern in credit spreads as credit rating assignment frequency declines.

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[18]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 rule for frequency of evaluations.

[19]An interesting extension is to "endogenize" the timing of credit rating changes, such as assuming they are more likely after large movements in underlying credit spreads. This endogenous channel may further increase the bias discussed here.

4.7. Uncertainty about Asset Values and Credit Spreads

We now exploit our laboratory for credit risk analysis to investigate the vexing issue of how idiosyncratic 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. Pseudo bonds thus should have prices that are decreasing in underlying idiosyncratic asset uncertainty. The empirical question, however, is the extent to which higher underlying uncertainty increases 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 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 in which everything stays constant except uncertainty about underlying asset values are rare, and (*ii*) idiosyncratic asset value uncertainty is difficult to measure. Our 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 idiosyncratic uncertainty of our pseudo firms' asset values by directly analyzing idiosyncratic 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 idiosyncratic asset volatility categories. Idiosyncratic asset volatility is computed from the volatility of residuals from a simple market model. Panel B of Table 2 reports the results.

Panel B1 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 idiosyncratic 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 B2). The magnitudes are large, moreover, especially for lower-rated bonds. For instance, a Ba-rated pseudo bond has 2.79% spread in the low-volatility bin but a 4.75% 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 1). In contrast to other credit ratings, Aaa/Aa credit spreads are decreasing in volatility. Although this result is interesting, data are sparse in this category and the results thus are noisy.

Panel B2 demonstrates the intuitive fact that, conditional on individual credit ratings, high underlying asset volatility corresponds to lower leverage. Panel B3 provides a sense of the difference in average asset volatility within credit ratings. For example, 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 21% to 38% for Caa- bonds.

5. A Banking Application

The previous sections document that pseudo bonds and real corporate bonds are quite similar along many dimensions and demonstrate how the pseudo firm laboratory can be utilized to study questions related to credit spreads. In this section we go a step further and show an example in which we can exploit the pseudo firm laboratory to study even more specific types of credit-related questions, such as the source and the size of tail risk in bank lending and its impact on bank default risks.

Consider a hypothetical bank that makes zero-coupon commercial loans to our single-stock pseudo firms. Equivalently, the "pseudo bank" purchases pseudo bonds from the pseudo firms to which it extends credit. To analyze the impact of maturity transformation and default risk, let the pseudo bank issue debt with only one month to maturity, such as 30-day commercial paper or certificates of deposit. Figure 5 shows a schematic representation of the pseudo bank's balance sheet. On the left-hand-side of the figure are the set of pseudo firms' assets, namely, the stocks of the firms comprising the SPX index. In the middle are the single-stock pseudo firms, described earlier. And on the far right is a hypothetical pseudo bank, whose assets are the pseudo firms' bonds. Below, we will compare shocks to fundamental assets, on the left-hand-side of the figure, to shocks to the pseudo bank's assets, on the right-hand-side of the figure. All of these shocks are empirical and observable to us.

The pseudo bank defaults if the market value of its assets is 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 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 $R_{t-1,t}^{Port} > -(1 - \frac{K_{t-1}^{Bank}}{A_{t-1}^{Bank}}) = -(1 - L_{t-1}^{Bank})$, where L_{t-1}^{Bank} is the bank's leverage ratio at $t-1$.

We consider three types of pseudo bond portfolios that comprise the assets of a pseudo bank. The first is an "All " portfolio consisting 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. The pseudo bank only extends one loan to each pseudo firm.

We construct pseudo bank loan portfolios to have approximately constant characteristics across our 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.[20] We also choose a minimum portfolio size $N = 20$ to ensure some diversification benefits for the pseudo bank. For every month t, for each firm and rating category, we randomly choose one maturity bin per pseudo 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.

We repeat this procedure for every month in the overall 1996 – 2014 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 month t. The portfolio return itself is not simulated and is the actual market return for the chosen pseudo bonds. Because we consider 1,000 random portfolios, our results can be interpreted as representing 1,000 different random pseudo banks.

We are interested in investigating both the tails of the distributions of the banks' assets, as well as the amplification effect of any shocks to the pseudo firms' fundamentals (*i.e.*, the assets of the pseudo firms, which are observable to us), on the values of pseudo bank assets. Both quantities can be gleaned by looking at Figure 6, which plots the distribution of standardized returns of the pseudo banks' portfolios against the standardized returns of

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

the assets of the pseudo firms. Specifically, Panel A considers loans to "All" firms, while Panel B and C consider loans only to IG and HY firms, respectively.

Focusing on Panel A, the scatter plot clearly shows the amplification of fundamental shocks to the assets of the pseudo firms on the assets of the pseudo banks. A three standard deviation shock to fundamentals (the $x-$axis) may easily translate into a five standard deviation shock to pseudo banks' assets (the $y-$axis), and a five standard deviation fundamental shock into an eight standard deviation shock to bank assets. Recall, moreover, that our loan portfolios are randomly assigned to the pseudo banks, which implies that these random portfolios would all lose value at the same time and thus may be considered a symptom of systemic risk. Indeed, 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 combinations of returns across different random portfolios (pseudo banks) on that date. In other words, even if pseudo banks' loan portfolios are well-diversified across credit ratings and borrowers, the leverage of the pseudo bond portfolios and the comovements in the values of assets of pseudo firms are sufficient to generate a potential "Black Swan" scenario that could have a devastating effect on the bank itself (or, in fact, the banking sector as a whole).

The reason for this amplification effect is that, although the standard deviation of the loan portfolios is normally very low (*i.e.*, bonds/pseudo bonds have normally low volatility), common negative shocks to fundamentals generate correlation *across* pseudo bonds. As is well known, higher bonds' default correlation strongly increases the tails of the banks' asset distributions. Finally, note that such common shocks to fundamentals are not likely driven by shocks to the cash flows across pseudo firms. Rather, they are more likely joint discount rate shocks that affect the valuation of the assets of all of the pseudo firms, thereby generating a large tail event to pseudo banks that is attributable to discount rate shocks.[21]

As a final exercise, we can use the return distribution of our pseudo bank's assets to calculate the amount of equity capital required to make the probability of the bank's default "small." For example, the 100%, 99.5%, and 99% percentiles of the (non-standardized) 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

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[21]See e.g. Vuoltenaaho (2002) on the role of discount rate shocks on individual stocks.

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.

6. Extensions

In this section we extend our main results in multiple directions. First, we consider other types of assets that our pseudo firms may purchase. Second, we extend our results to introduce bankruptcy costs. Third, we consider asset pricing tests on bonds' excess returns.

6.1. Other Types of Underlying Assets

In this section we consider additional types of assets that our pseudo firm may purchase by issuing zero-coupon bonds and equity.

Commodities. Let our pseudo firm purchase a commodity, such as crude oil, financed by issuing zero coupon bonds and equity. The same argument as in Section 2. implies that the benchmark value of a zero coupon bonds of our pseudo firm is given by expression (2) but with a put option on oil, $\widehat{P}_t^{oil}(t+\tau, K_{i,t})$, instead of the SPX option, $\widehat{P}_t^{SPX}(t+\tau, K_{i,t})$. While options on oil are not available, we use options on crude oil futures from CME. By selecting options with the same expiration date as the underlying futures, such options effectively pay the desired payoff $\max(K_{i,t} - A_{t+\tau}, 0)$ when exercised at maturity. Although options on futures are American style, as with single stocks we employ far out-of-the-money options whose American exercise premium is likely negligible.

In addition to oil, we consider corn, soybeans, natural gas, and gold, for which CME options have sufficient coverage in the time series and across strike prices. Although the start dates of the commodity samples range from February 1985 for corn to October 1992 for natural gas, strike price coverage was insufficient to compute pseudo credit spreads before 1995 for HY bonds and before 2000 for IG bonds. Even then, a large number of missing observations remain in the data.

Foreign currencies. Assume that our pseudo firm purchases foreign currency, such as Euros, by financing it with zero-coupon bonds and equity. The same argument as in Section 2. implies that the values of zero coupon bonds are given by (2) but with put options on Euros, $\widehat{P}_t^{Euro}(t + \tau, K_{i,t})$, instead of SPX options, $\widehat{P}_t^{SPX}(t + \tau, K_{i,t})$. We obtain OTC currency options data from JPMorgan on nine currencies (CAD, EUR, NOK, GBP, SEK,

CHF, AUD, JPY, NZD), as well as options on currency futures from CME. JP Morgan currency data are presented in specific buckets of implied volatilities, which suggest that the data are interpolated to some degree. The available strikes, moreover, only allow us to compute pseudo bonds for very low credit ratings, and then only starting in 1999 for Caa-, 2001 for B, and 2007 for Ba (the latter only for a brief period). CME data do not have sufficient coverage for two-year options to be used in the main tables, but results for 1-year CME-based currency pseudo bonds are available in the On-Line Appendix. The sample for CME currency options starts in 1985, but limited strike coverage only allows us to compute low-rated pseudo bond spreads for most of the sample.

Fixed Income Securities. We also consider a pseudo firm that purchases a fixed-rate coupon bond $\mathcal{B}_t(c, M)$ with unitary principal, coupon rate c, maturity date M, and a LIBOR-equivalent credit quality. The pseudo firm finances its purchase of $\mathcal{B}_t(c, M)$ by issuing zero-coupon bonds, also with unitary principal, and a maturity date of $t + \tau$. The asset value of the pseudo firm at $t + \tau$ is $A_{t+\tau} = \mathcal{B}_{t+\tau}(c, M)$. Thus, the payoff of the zero coupon bond issued by the pseudo firm at maturity $t + \tau$ is

$$\text{Bond payoff at } t + \tau = 1 - \max(1 - A_{t+\tau}, 0) = 1 - \max(1 - \mathcal{B}_{t+\tau}(c, M), 0)$$

The payoff $\max(1 - \mathcal{B}_{t+\tau}(c, M), 0)$ is the same as the payoff on a payer swaption (*i.e.*, an option to enter into a swap and pay the fixed rate c) with a unitary notional amount, strike swap rate c, maturity $t + \tau$ and tenor $M - (t + \tau)$.[22] Thus, the value of the pseudo firm's zero-coupon bond before maturity is

$$\widehat{B}_t(t + \tau, 1) = \widehat{Z}_t(t + \tau) - \widehat{P}_t^{swap}(t + \tau, c, M)$$

where $\widehat{P}_t^{swap}(t + \tau, c, M)$ is the observable traded value of a payer swaption. By choosing different strike swap rates c we obtain different leverage levels – *i.e.*, lower strike swap rates correspond to lower values of the underlying bond $\mathcal{B}_t(c, M)$. In addition, we compute

$$\text{Default Probability} = p_t(\tau) = Pr\left(\mathcal{B}_{t+\tau}(c, M) < 1 | \mathcal{F}_t\right)$$

We obtained swaption data from ICAP beginning in July 2002. Data have sufficient coverage for us to compute pseudo bond credit spreads for all credit ratings over the entire sample.

Un-levered corporate equity. The analysis of single-stock pseudo bonds raises a potential question about the impact on pseudo credit spreads of the fact that pseudo firm assets are equities of real companies, and thus themselves inherently levered. Such levered corporate equity may increase the negative skewness of the assets of the pseudo firms compared

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[22]We assume the credit quality of the swaption counterparty and underlying swap counterparty are also LIBOR-equivalent.

to the case of unlevered corporate equity. This point is relevant only insofar as it may bias the default probabilities and LGDs of our pseudo firms, as the latter take the distribution of assets as exogenous. We already showed in Figure 3 that our *ex ante* methodology to assess pseudo firm default probabilities works well. As we show below, moreover, the LGDs of pseudo firms are actually *smaller* than the ones of real companies because we assume zero bankruptcy costs (which instead affect the negative skewness of real corporate bonds). Although our methodology takes into account the point of leveraged corporate equity just discussed, it is useful nonetheless to provide some empirical results for the subset of the SPX companies that have negligible leverage.[23]

Moving to our empirical results, Panel A of Table 3 shows that for high credit ratings, the credit spreads of pseudo firms with assets consisting of commodities, currencies, and fixed-income securities are similar to SPX and single-stock credit spreads, ranging 0.32% and 0.51%. The average credit spread of single-stock pseudo firms restricted to unleveraged corporate equity (last column) is higher than both at 2.3%. For lower credit ratings, the credit spreads of commodity and fixed-income pseudo firms are smaller than those of real corporate bonds. We discuss why below.

The credit spreads across asset classes also show a good deal of comovement in the time series. We construct two simple factors – one for IG and one for HY pseudo bonds – as the average of standardized pseudo credit spreads across the five asset classes (*i.e.*, SPX, single stocks, commodities, currencies, and fixed income).[24] Regressions of individual IG spreads on the factor yield R^2s that range from 52% (fixed income) to 66% (SPX). The comovement is even higher for HY spreads, with R^2s ranging from 65% (commodities) to 83% (SPX). Given the different nature of the underlying assets of the pseudo firms, this high level of comovement is an additional indication of common risk factors affecting credit spreads. Figure 7 plots the factor along with standardized credit spreads for pseudo-bonds with one- and two-years to maturity, and for IG and HY credit ratings. The comovemnt across credit spreads with different types of underlying assets is evident from the figure, especially around the 2008 crisis.

To assess the differences in credit spreads across types of assets in more detail, Panel B of Table 3 shows the LGDs of real corporate bonds and pseudo bonds. Real corporate bonds

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[23]We define "negligible leverage" as a ratio of long-term debt to total asset of less than 5%. There is, of course, another selection bias. Namely, the subset of companies that do not have debt tend to have high volatility and thus potentially even larger tails than companies with high leverage – *i.e.*, there is a reason why such firms do not have any debt.

[24]Because of missing observations and different samples, it is difficult to run standard principal component analysis. The average standardized credit spread is a simple alternative. See the On-Line Appendix.

have around 60% losses on average in case of default, which are higher than any of the pseudo bonds we consider. For any bond with default probability $\widehat{p}_{i,t}(\tau)$ at t, the LGD at $t + \tau$ is $(K_{i,t} - A_{t+\tau})/K_{i,t}$ conditional on a default (*i.e.*, $A_{t+\tau} < K_{i,t}$.) For each credit rating and for each type of pseudo firm we can thus compute the average of these losses given default.[25] We find that LGDs are between 10% and 15% for SPX pseudo firms, between 25% and 50% for single-stock pseudo firms, between 11% and 17% for commodities pseudo firms, around 5% for currency pseudo firms, and around 2.4% for fixed-income pseudo firms. These results are consistent with the fact that commodities, currencies, and fixed-income securities have much thinner tails than single stocks and the SPX index, which explains the difference in credit spreads shown in Panel A. We make LGDs uniform across pseudo bonds by adding bankruptcy costs in the next section.

6.2. Bankruptcy Costs and Loss Given Default

As a second extension, we consider the more realistic case in which pseudo firms face bankruptcy costs following a default. As shown in Panel B of Table 3 the average LGDs of corporate bonds are higher than the LGDs of pseudo bonds. We now consider a portfolio of put options to obtain LGDs of pseudo bonds that more closely resemble those in the data.

Specifically, let κ_i be pseudo firm i's bankruptcy costs. Then, the payoff at $t + \tau$ of the pseudo bond is

$$\text{Bond Payoff at } t + \tau = \begin{cases} K_{i,t} & \text{if } A_{t+\tau} > K_{i,t} \\ (1 - \kappa_i)A_{t+\tau} & \text{if } A_{t+\tau} < K_{i,t} \end{cases}$$

In other words, the payoff to bond holders following a default is $(1 - \kappa_i)A_{t+\tau}$, and the LGD (as a fraction of principal) is $LGD(\kappa_i) = \kappa_i \, A_{t+\tau}/K_{i,t}$. We can write the bond payoff as

$$\text{Bond Payoff at } t + \tau = K_{i,t} - (1 - \kappa_i)\max\left(K_{i,t} - A_{t+\tau}, 0\right) - \kappa_i \, K_{i,t} \, 1_{A_{t+\tau} < K_{i,t}}$$

For example, using the SPX index as the pseudo firm's assets, the pseudo bond value is then

$$\widehat{B}_t\left(t + \tau, K_{i,t}\right) = K_{i,t}\widehat{Z}_t(t + \tau) - (1 - \kappa_i)\widehat{P}_t^{SPX}\left(t + \tau, K_{i,t}\right) - \kappa_i V_t^{Digital}(K_{i,t}) \qquad (9)$$

where $V^{Digital}(K_{i,t})$ is the value of a digital put option that pays $K_{i,t}$ if $A_{t+\tau} < K_{i,t}$ and nothing otherwise. Because digital options are not traded, we approximate their values with yet another portfolio of traded put options. Specifically, a digital option has value

$$V_t^{Digital}(K_{i,t}) = K_{i,t}\frac{\partial P(K)}{\partial K}\Big|_{K=K_{i,t}} \approx \frac{K_{i,t}}{K_{i,t} - K'_{i,t}}\left(P(K_{i,t}) - P(K'_{i,t})\right)$$

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[25]We do not need options to do these calculations, and therefore we use the full 1970 - 2014 sample for SPX and individual options. For other options, we use the sample of underlying asset prices corresponding to the sample period of option data, as the long time-series of underlying assets are not always available.

where the first equality stems from standard results, and $K'_{i,t}$ is the closest strike price below the target strike price $K_{i,t}$.[26] Finally, for every t, we use historical data to compute κ_i on an *ex ante* basis to match LGDs reported by Moody's. We take into account business cycle variation in LGDs by computing different estimates κ_i depending on whether month t is during a boom or recession. The full methodology is laid out in the On-Line Appendix C.

Panels C and D of Table 3 show the results. First, Panel D shows that all of the *ex post* realized LGDs of pseudo firms are now similar to the corporate LGDs shown in the second column. Our *ex ante* methodology to compute bankruptcy costs thus works well. Second, Panel C shows that credit spreads of pseudo firms are larger than without bankruptcy costs (which is intuitive) and are somewhat larger than the credit spreads of corporate bonds. For example, focusing on A/Baa credit rating – which has better coverage than Aaa/Aa – we find that credit spreads of pseudo firms are 3.14% for the SPX, 5.91% for single stocks, 2.07% for commodities, 4.21% for coupon bonds, and a whopping 8.5% for unleveraged corporate equity. All of these credit spreads are larger than the actual corporate credit spread of 1.15% for this rating category. A caveat to these results, however, is that adding LGDs requires us to drop pseudo bonds with the lowest leverage ratios (*i.e.* option strike prices), which results in a larger number of missing observations for highly rated bonds. Nevertheless, the results show that accounting for reasonable LGDs generates high credit spreads for pseudo bonds.

6.3. Pseudo Bond Portfolio Returns

We present the results of additional tests in the On-Line Appendix C and only summarize the results here for brevity. First, average pseudo bond excess returns and volatility increase as credit ratings deteriorate, which is consistent with corporate bonds. Second, the Sharpe ratios of pseudo bonds are similar to those of corporate bonds, ranging from 15% to 33%. A regression of pseudo bond returns on their equity excess returns (call options), moreover, produces a significant alpha, exactly as is the case for real corporate bonds. An alpha also mostly appears when we regress pseudo bond excess returns on pseudo firm assets (which are observable for pseudo bonds but not for real bonds). Finally, a standard set of risk factors (the market portfolio, Fama and French HML and SMB, the term premium, the default premium, volatility, and tail factors) do not explain away the positive alphas in pseudo bond returns, just as they do not explain the alphas of real corporate bond returns. In sum, there are many similarities between pseudo bond returns and real corporate bond returns.

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[26]The value of a digital option with unit notional is $V_t^{digital}(K) = Z(t, t+\tau) \int_0^K f^*(A_{t+\tau}) dA_{t+\tau}$ where $f^*(A_{t+\tau})$ is the (forward) risk neutral probability density. Because put options are given by $P(K) = Z(t, t+\tau) \int_0^K (K - A_{t+\tau}) f^*(A_{t+\tau}) dA_{t+\tau}$, we find $\frac{\partial P(K)}{\partial K} = Z(t, t+\tau) \int_0^K f^*(A_{t+\tau}) dA_{t+\tau}$.

7. Conclusions

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 tail and default risk in banking. Our 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 S&P 500 index portfolio, individual firms' stocks, commodities, foreign currencies, fixed-income securities, and the like – we study the empirical properties of the pseudo bonds issued by such firms. In addition, we can utilize such hypothetical pseudo firms to run data-based experiments on credit risk that would be impossible to undertake using actual corporate debt.

Our empirical results show that pseudo bonds (whose values are directly observable and involve no parametric assumptions or estimation) share numerous similarities with real corporate bonds, such as large and countercyclical credit spreads. The data thus indicate a good deal of integration between corporate bond and option markets, and the existence of similar risk premiums that investors require to bear the risk of tail events. Using our pseudo firms as a laboratory, we also find that over-prediction of default probabilities, market illiquidity, asymmetric information, and corporate frictions – which do not apply to our pseudo firms – are unlikely to explain the large observed credit spreads. In addition, we empirically document that infrequent credit rating assignments and idiosyncratic asset uncertainty do positively impact average spreads.

Finally, we illustrate the use of our pseudo firm laboratory to investigate the nature of tail risk in bank loan portfolios. Specifically, we look at the empirical distribution of several random loan portfolios made by random pseudo banks to pseudo firms. 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.

Our methodology based on hypothetical pseudo firms can be widely extended to investigate numerous additional questions on credit risk. We leave such extensions to future research.

Figure 1: Two SPX Pseudo Bonds
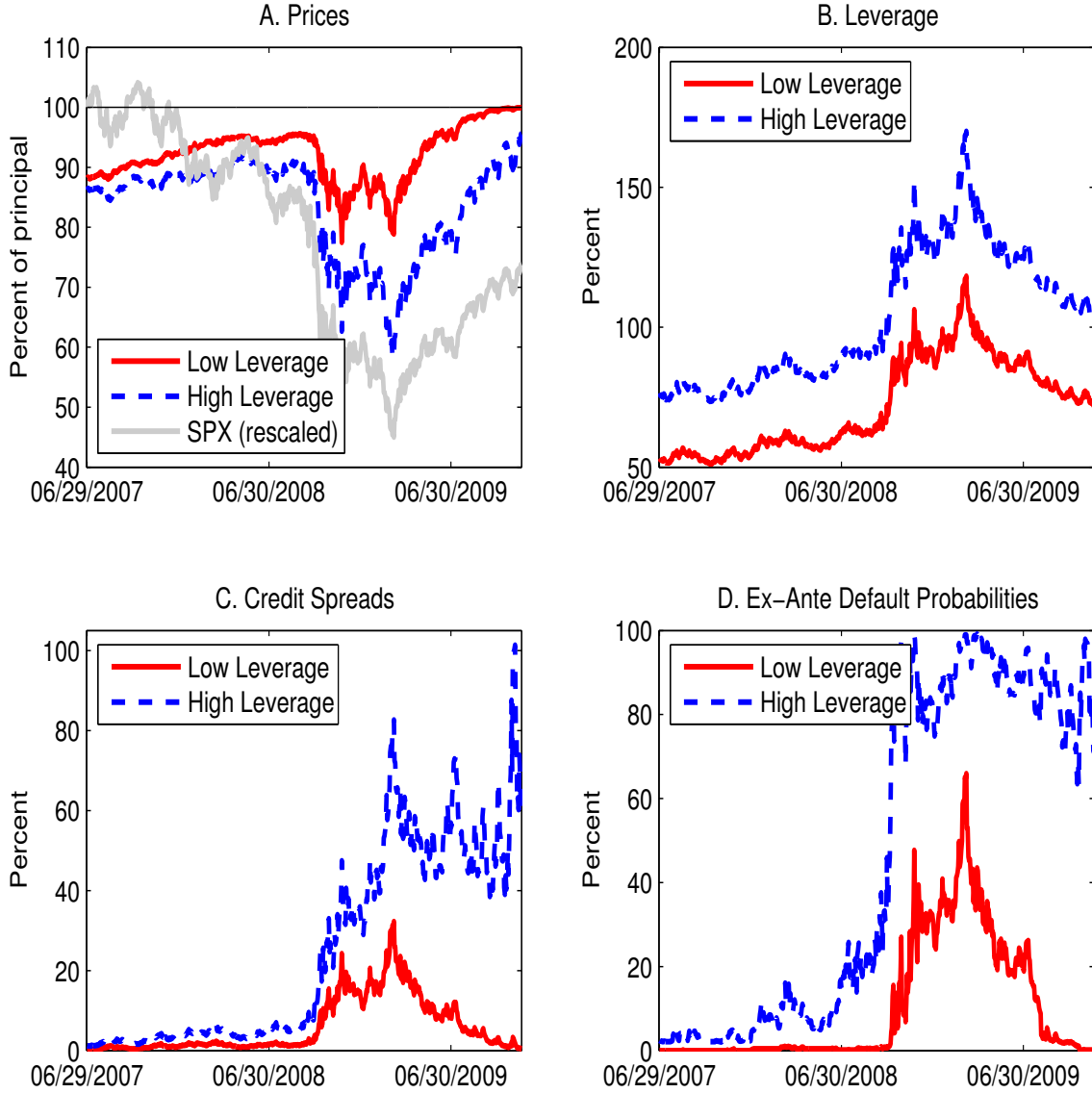
Notes: Panel A reports the no-arbitrage prices of two SPX pseudo bonds from June 2007 to November 2009 as percent of principal. The pseudo bonds are issued by two fictitious pseudo firms, one with low leverage (solid red line) and one with high leverage (dashed line). The figure also reports the (normalized) value of assets of the two firms, namely, the SPX index (solid grey line). Panel B reports the market leverage of the two pseudo firms $L_{i,s} = A_s/K_{i,t}$, in percentage. Panel C reports the implied credit spread of the two pseudo bonds in Panel A, while Panel D report their *ex ante* default probabilities, which are computed from the historical, backward-looking empirical distribution of SPX returns.

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Figure 2: Credit Spreads of Two-Year Pseudo Bonds
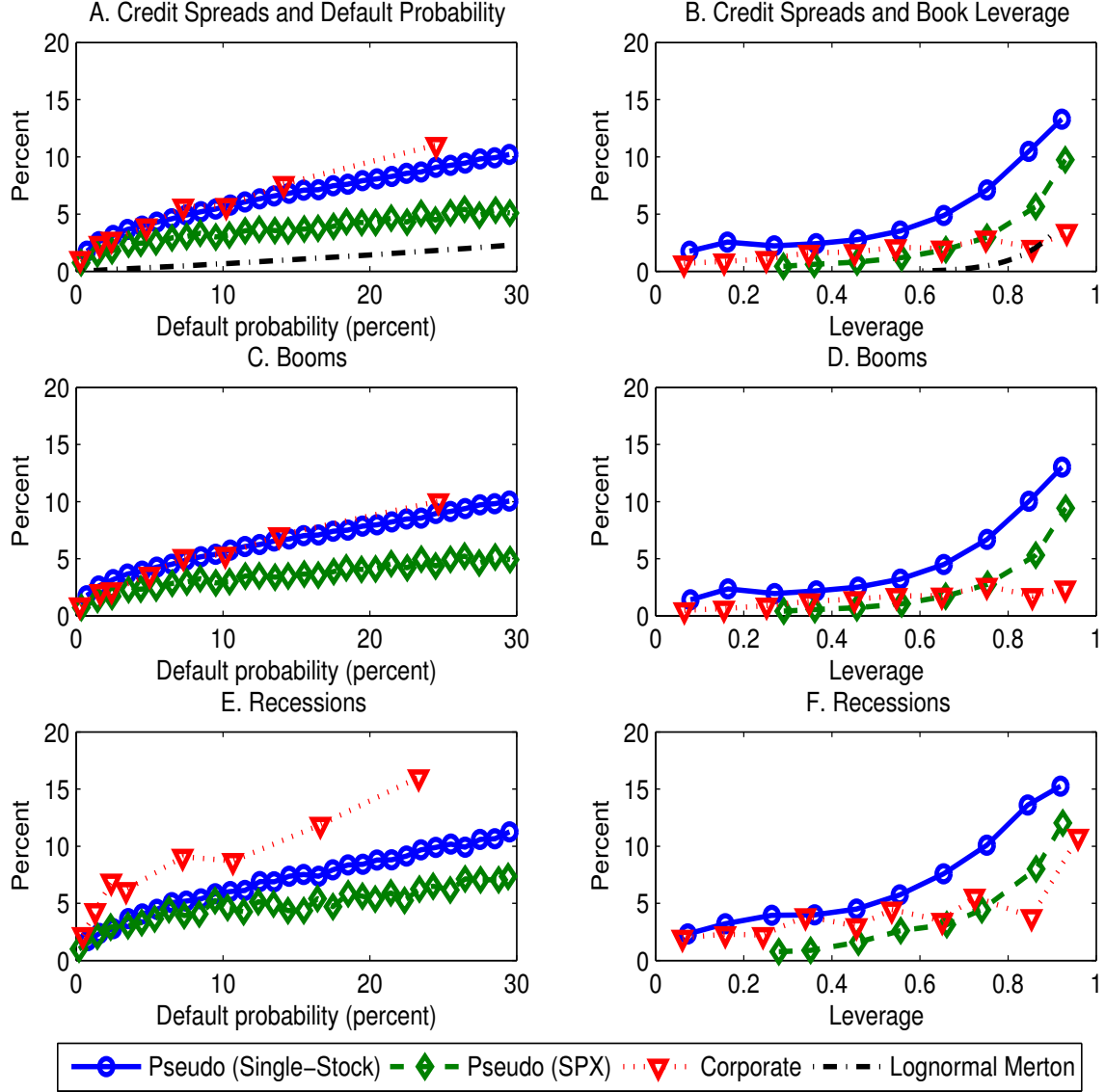
Notes: Credit spreads of single-stock pseudo bonds (circles), SPX pseudo bonds (diamond), real corporate bonds (triangles), and implied by the lognormal Merton model (dash dotted line). Left panels report the credit spreads plotted against the probability of default. Right panels report credit spreads plotted against book leverage. For pseudo bonds, the default probability is computed from the empirical distribution of asset returns. 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. For pseudo bonds and the Merton's model, the book leverage ratio 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, 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 1990 – 2014 for SPX pseudo bonds and real corporate bonds, and 1996 – 2014 for single-stock pseudo bonds.

Figure 3: *Ex Ante* Default Probabilities versus *Ex Post* Default Frequencies
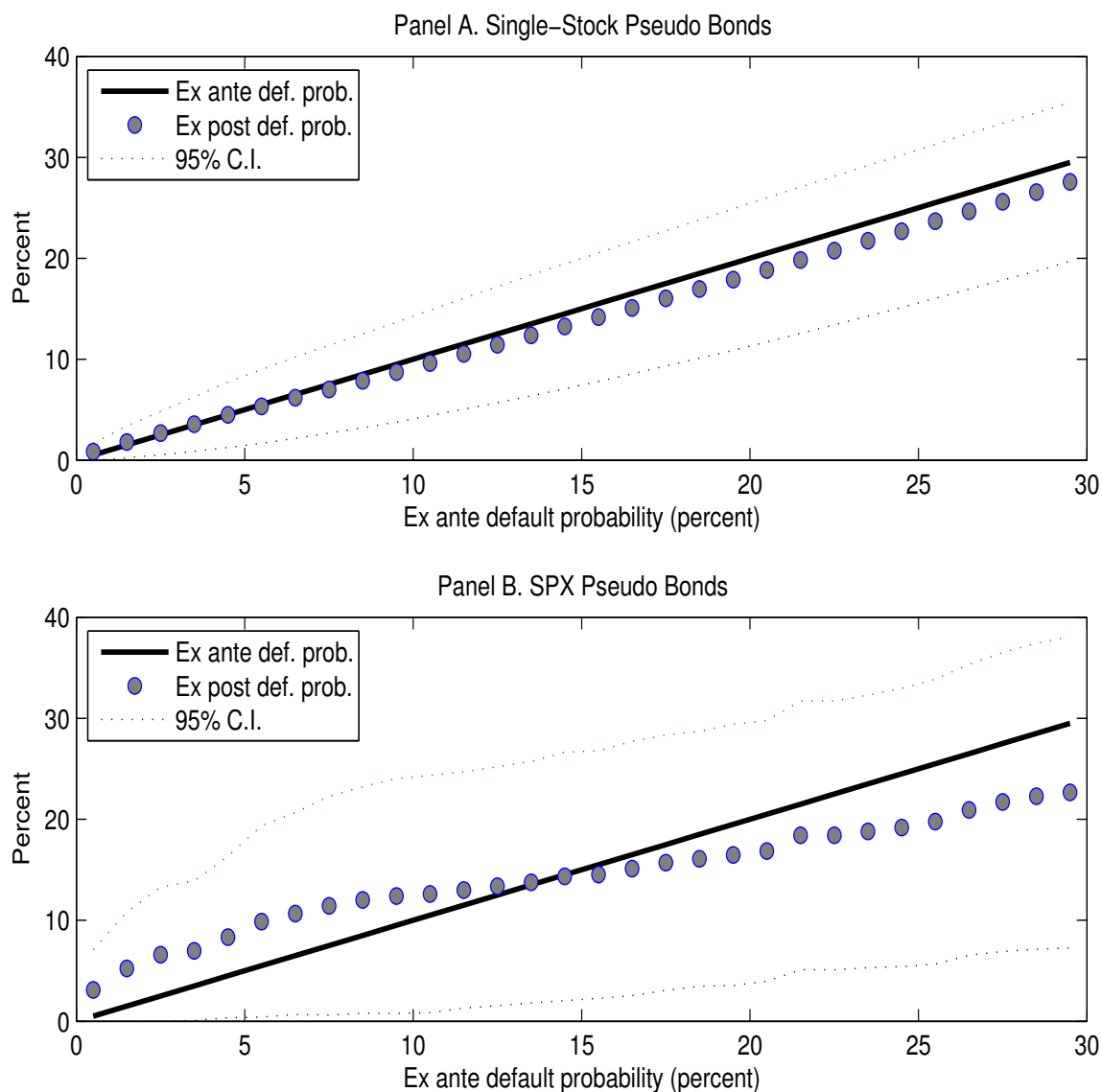
Notes: Panel A plots the estimated *ex post* default frequencies of pseudo bonds based on single-stock (circles) together with their 95% confidence intervals (dotted lines) against the 45 degree line, which represent the *ex ante* default probability for each of the pseudo bonds. The sample is 1970 to 2014. Panel B plots the same quantities for SPX pseudo bonds.

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

Panel A. Investment Grade Pseudo and Corporate Bonds Spreads

Panel B. High Yield Pseudo and Corporate Bonds Spreads
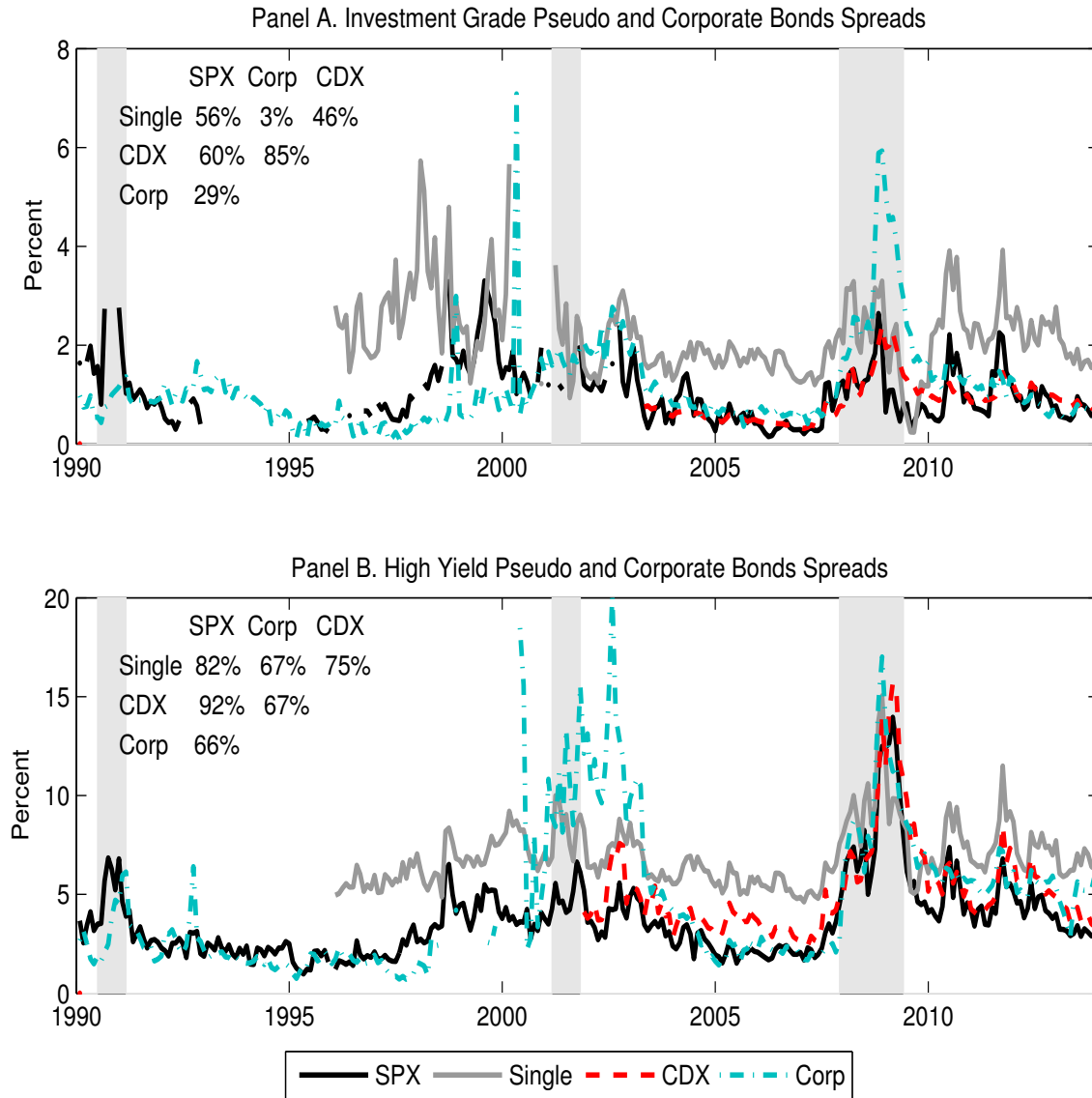
Notes: Credit spreads of two-year pseudo and corporate bonds. Pseudo bonds are constructed from risk free debt minus put options on individual stocks (solid grey line), or put options on SPX index (solid black line). Investment Grade (IG) and High Yield (HY) pseudo credit ratings of pseudo bonds are assigned based on their *ex ante* default probabilities computed from the empirical distribution of asset returns. Corporate bond data (dashed-dot line) are from the Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE and DataStream. IG and HY credit ratings of corporate bonds are from Moody's. IG and HY CDX indices (dashed line) are from Markit. The correlations in the top left corners of each panel are the empirical correlations of credit spreads on common samples. Shaded vertical bars denote NBER-dated recessions. The data frequency is monthly from January 1990 to August 2014 for corporate and SPX pseudo bonds, but the sample starts on Jan 1996 for single-stock pseudo bonds, on November 2001 for HY CDX index, and on April 2003 for IG CDX index.

Figure 5: The Assets of a Pseudo Bank

Apple-based Pseudo Firms

Assets	Liabilities
Apple Stock	Pseudo Apple Debt = = $K_1 Z(T_1)$ – Apple Put

	Equity = Apple Call

Fundamental Assets

Apple Stock

P&G Stock

JPM Stock

P&G-based Pseudo Firms

Assets	Liabilities
P&G Stock	Pseudo P&G Debt = = $K_2 Z(T_2)$ – P&G Put

	Equity = P&G Call

JPM-based Pseudo Firms

Assets	Liabilities
JPM Stock	Pseudo JPM Debt = = $K_n Z(T_n)$ – JPM Put

	Equity = JPM Call

Pseudo Bank

Assets	Liabilities
Pseudo Apple Debt	Debt = $K Z(t)$ – Put
Pseudo P&G Debt	
Pseudo JPM Debt	Equity = Call

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: Pseudo Banks' Asset Returns versus Fundamental Asset Returns
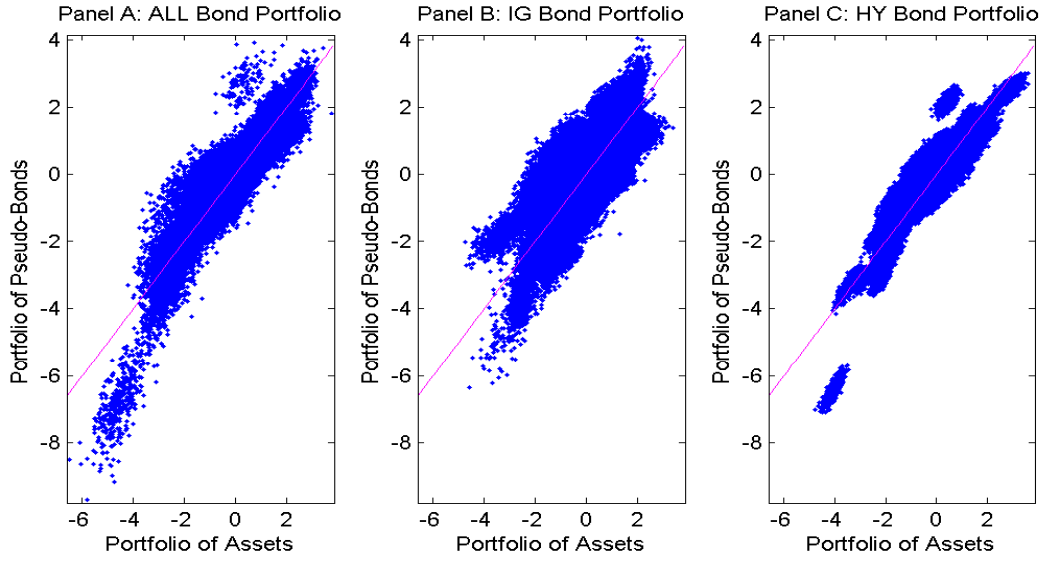
Notes: Panels A, B, and C show the scatter-plot of pseudo bond portfolio returns versus underlying asset portfolio returns. The distributions have been normalized to have zero-mean and unit standard deviations. The random portfolios are constructed as follows: For every month t, we consider all potential 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 "All" portfolio (Panel A), 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. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. In either case, if the minimum number of firms condition is not met, we record a missing observation for the portfolio return in the month. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

Figure 7: Comovement of Pseudo Bond Credit Spreads
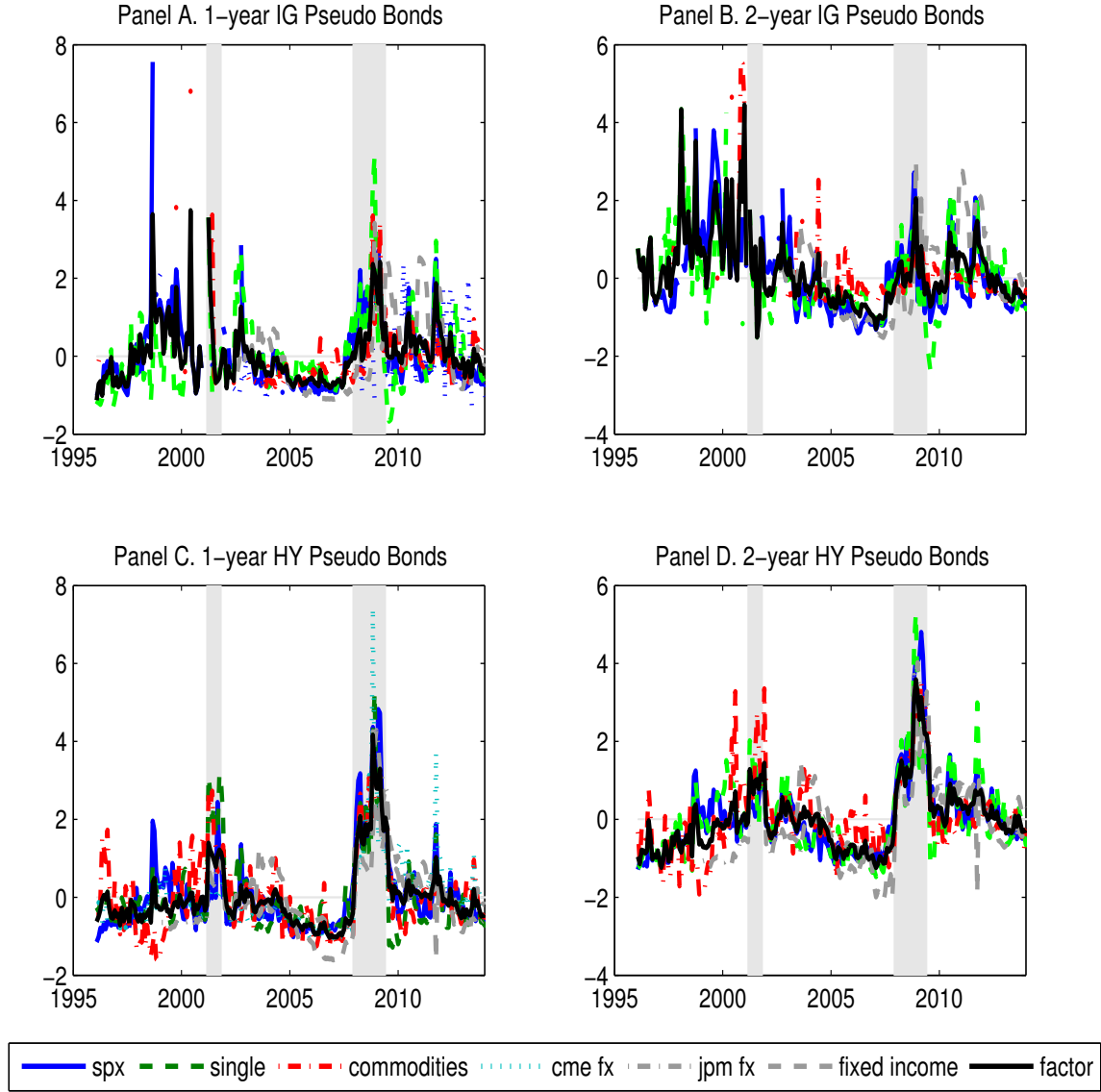
Notes: The four panels in this figure plot the standardized average credit spreads of pseudo firms with different types of assets, across maturity (1-year and 2-year) and credit rating (IG and HY). The type of assets underlying the pseudo firms are the (i) the SPX index; (ii) single-stocks; (iii) commodities; (iv) foreign exchange (CME dataset); (v) foreign exchange (JPM dataset); (vi) fixed-income, through swaptions. Each panel also report a factor (black line) which corresponds to the cross-sectional average of the standardized credit spreads in each panel. The sample is January 1996 to August 2014, except for JP Morgan FX which begins in January 1999, and fixed income, which begins in July 2002.

Table 1: Pseudo and Corporate Bonds

Credit spreads and illiquidity measures for pseudo bonds (Panels A and B), and corporate bonds (Panel C). Pseudo bonds are constructed as risk free debt minus put options on individual stocks (Panel A) or on the SPX index (Panel B). Pseudo credit ratings are assigned based on the pseudo bonds' *ex ante* default probabilities, computed from the empirical distribution of asset returns. "B/A" is the bid-ask spread for each pseudo bond portfolio, computed as the kernel-weighted average of bid-ask spreads $(B_{i,t}^{Ask} - B_{i,t}^{Bid})/B_{i,t}^{Mid}$. "Roll" is the Roll (1984) illiquidity measure for pseudo bond portfolios, computed as the kernel-weighted average of individual bonds' measures $\sqrt{-Cov_t(\Delta p_{i,t,d}^{Bid \to Ask}, \Delta p_{i,t,d+1}^{Ask \to Bid})}$ from daily prices. Corporate bonds are non-callable bonds, except for 30 and 91 days for which we use commercial paper. The Roll illiquidity measure for corporate bond portfolios is the value-weighted average of individual bonds' measures, computed as $2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Transaction}, \Delta p_{i,t,d+1}^{Transaction})}$ from daily prices.

| Credit Rating | Credit Spreads (bps) | | | | | 2-year Bonds | | | |
| | Days to Maturity | | | | | Credit Spreads (bps) | | Iliquidity Measures | |
	30	91	181	365	730	Boom	Recession	B/A (%)	Roll (%)
Panel A. Single-Stock Pseudo Bonds (Jan 1996 – Aug 2014)									
IG		133	106	112	217	216	223	1.04	0.52
HY	520	432	510	640	688	652	938	1.44	0.59
Aaa/Aa			68	71	98	98	103	0.80	0.26
A/Baa			106	112	218	217	223	1.04	0.52
Ba	255	164	164	193	346	338	400	1.13	0.52
B	387	297	327	424	569	540	769	1.30	0.56
Caa-	582	525	650	867	920	862	1324	1.47	0.62
Panel B. SPX Pseudo Bonds (Jan 1990 – Aug 2014)									
IG	78	61	63	64	99	94	138	0.31	0.08
HY	268	282	298	300	362	313	701	0.33	0.14
Aaa/Aa			46	39	51	47	74	0.29	0.09
A/Baa			90	83	126	118	191	0.33	0.08
Ba	280	120	150	166	214	192	355	0.33	0.10
B	206	222	255	270	315	281	547	0.33	0.11
Caa-	424	418	420	424	469	409	884	0.32	0.15
Panel C. Corporate Bonds (Jan 1990 – Aug 2014)									
IG	62	60	115	107	110	92	235		1.15
HY			471	473	458	395	866		1.97
Aaa/Aa	30	28	37	55	62	56	106		0.88
A/Baa	66	64	124	114	115	95	249		1.24
Ba			290	310	316	255	706		1.85
B			631	597	556	502	913		2.10
Caa-			1190	1196	1382	1221	2632		2.91

Table 2: The Size of Credit Spreads. Credit Rating Frequencies and Asset Uncertainty

Panel A shows average credit spreads of single-stock pseudo bonds for six sorting frequencies, from one month to eighteen months. 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. The sample is the pseudo bonds of pseudo firms whose assets are the stock of individual firms that are in the SPX index. The sample is January 1996 to August 2014. Credit spreads are expressed in basis points. Panel B shows the impact of asset idiosyncratic volatility on pseudo bond' credit spreads. For each time t, we first sort pseudo bonds according to their pseudo credit rating, and then according to the idiosyncratic volatility of their pseudo firm's assets (individual stocks). Idiosyncratic volatility is computed from the residuals of a market model regression. Panel B1 reports the average credit spreads for each credit rating / volatility bin, while Panels B2 and B3 report the average leverage K/A and the average asset volatility for each credit rating / volatility combination, respectively.

Panel A: Average Credit Spreads and the Frequency of Credit Rating Assignments

Frequency	1 month	3 months	6 months	12 months	15 months	18 months
Aaa/Aa	98	106	148	164	193	201
A/Baa	218	229	257	337	335	343
Ba	346	360	392	390	473	595
B	569	571	577	567	683	687
Caa-	920	898	865	831	976	908

Panel B: Average Credit Spreads and the Uncertainty of Assets

	B1. Average Credit Spread			B2. Average K/S			B3. Average Volatility		
Credit	Idiosyncratic Volatility			Idiosyncratic Volatility			Idiosyncratic Volatility		
Rating	Low	Medium	High	Low	Medium	High	Low	Medium	High
Aaa/Aa	125	91	105	0.54	0.48	0.42	0.16	0.19	0.23
A/Baa	166	250	277	0.55	0.56	0.51	0.19	0.24	0.31
Ba	279	354	475	0.66	0.63	0.60	0.20	0.26	0.36
B	489	555	697	0.81	0.77	0.71	0.20	0.27	0.38
Caa-	851	900	1031	0.98	0.94	0.87	0.21	0.27	0.38

Table 3: Extensions: Types of Assets and Bankruptcy Costs

Credit spreads and losses-given-defaults are shown for corporate bonds and for pseudo bonds. Pseudo bonds are constructed from a portfolio of risk free debt minus put options on the SPX index (column "SPX"), on individual stocks (column "Single Stocks"), on commodity futures (column "Commodities"), on foreign currency (column "Currencies"), swaptions (column "Fixed Income"), or single-stocks for underlying firms with negligible leverage (column "Low Leverage"). 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 Panel B the loss-given-default (LGD) are computed from the empirical distribution of asset returns. Panel C and D report credit spreads and ex-post LGDs for pseudo bonds that contain bankruptcy costs calibrated to match corporate LGDs. In this case, pseudo bonds are constructed from a portfolio of risk-free debt, put options and digital put options, the latter approximated from traded put options. Corporate bonds are non-callable corporate bonds with time to maturity between 1.5 and 2.5 years. LGD for corporate bonds are from Moody's. Sample periods vary: SPX and single stocks: 1/1996 to 8/2014; commodities: mid 1980s to 2/2015; Foreign currencies: 1/1999 to 12/2014; Swaptions: 7/2002 to 12/2014.

Credit Rating	Corporate	SPX	Single Stocks	Commodities	Currencies	Fixed Income	Low Leverage
Panel A: Credit Spreads across Types of Assets (bps)							
Aaa/Aa	62	51	98	32	51	34	230
A/Baa	115	126	218	70	52	74	374
Ba	316	214	346	147	51	87	528
B	556	315	569	263	87	161	805
Caa-	1382	469	920	435	175	282	1141
Panel B: Ex-Post Loss-Given-Default (%)							
Aaa/Aa	61.0	10.2	49.6	10.9	-	-	40.1
A/Baa	57.0	10.2	41.6	12.1	-	-	34.0
Ba	59.0	14.9	30.1	15.5	3.6	1.3	30.1
B	56.0	15.1	27.1	17.0	5.5	2.4	26.6
Caa-	63.0	18.0	25.0	15.4	8.0	4.0	28.1
Panel C: Credit Spreads adjusted for Loss-Given-Default (bps)							
Aaa/Aa	62	132	-	121	-	241	700
A/Baa	115	314	591	207	-	421	859
Ba	316	540	916	396	544	585	1182
B	556	905	1394	942	641	1066	1784
Caa-	1382	1398	2095	1513	953	1782	2409
Panel D: Ex-Post Loss-Given-Default with adjustment (%)							
Aaa/Aa	61.0	-	58.5	-	-	-	45.9
A/Baa	57.0	60.0	56.6	59.5	-	-	48.2
Ba	59.0	60.3	56.3	59.0	58.8	58.8	54.4
B	56.0	57.7	52.9	55.8	56.1	55.4	50.8
Caa-	63.0	65.8	59.7	62.3	63.2	62.5	59.9

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