Option-Based Credit Spreads

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Abstract

We present a novel empirical benchmark for analyzing credit risk using "pseudo firms" that purchase traded assets financed with equity and zero-coupon bonds. By no-arbitrage, pseudo bonds are equivalent to Treasuries minus put options on pseudo-firm assets. Empirically, like corporate spreads, pseudo-bond spreads are large, countercyclical, and predict lower economic growth. Using this framework, we find that bond market illiquidity, investors' over-estimation of default risks, and corporate frictions do not seem to explain excessive observed credit spreads, but, instead, a risk premium for tail and idiosyncratic asset risks is the primary determinant of corporate spreads.

1. Introduction

The understanding of credit risk, its time variation, and its relation to the aggregate economy is critical to policy makers, market participants, and researchers. Yet, questions about credit risk are hard to answer with purely empirical methods because corporate bonds are complicated and often illiquid securities, the market values of the assets of firms issuing bonds are not observable, leverage is endogenous, and the corporate bond market is replete with market-microstructure idiosyncrasies. Fully empirical methodologies, moreover, do not easily facilitate analyses of counterfactuals to learn from "what-if" experiments. Instead, counterfactual experiments generally must be tackled by positing stylized structural models of default risk, which give rise to other challenges arising from dependencies on highly parameterized models, model specifications (*e.g.*, assumed distributions of shocks), and genuine difficulties in estimation.

In this paper we propose a novel, option-based methodology for analyzing credit risk. We build fictitious firms, which we call "pseudo firms," that have simple and empirically observable balance sheets. Our pseudo firms have assets comprised of *real* traded securities, and liabilities comprised of equity and zero-coupon bonds. In the absence of arbitrage, the market value of a pseudo firm's zero-coupon bond is equal to the value of a comparable default-free bond minus the market value of a put option on the traded securities held as assets by the pseudo firm.[1] Using *observed* prices of traded put options and Treasuries, we extract the empirical properties of zero-coupon bonds "issued" by pseudo firms, which we call "pseudo bonds."

To be concrete, consider a pseudo firm that purchases the S&P500 (SPX) index portfolio financed by issuing equity and zero-coupon debt with face value K and maturity T.[2] The asset value of this pseudo firm is $A_t = SPX_t$, which is observable. At maturity, the bond holders of this pseudo firm receive the minimum between K (no default) or the assets of the pseudo firm A_T (default). The payoff to bond holders thus is $\min(K, A_T) = K - \max(K - A_T, 0)$, which is the payoff of the risk-free debt K minus the payoff on a put option on the SPX. The no-arbitrage value of the pseudo bond at $t < T$ is:

$$\widehat{B}_t(K, T) = K\widehat{Z}_t(T) - \widehat{P}_t^{SPX}(K, T), \tag{1}$$

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[1]The basic insight that corporate debt can be viewed as risk-free debt plus a short put option is attributable to Merton (1974). We distinguish between this Merton *insight* – which requires no assumptions about the distribution of the values of underlying assets owned by the pseudo firm – and the Merton *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.

[2]SPX^{SM} is a service mark registered by the Chicago Board Options Exchange. Our use of the abbreviation SPX refers throughout the text to the S&P500 index generally.

where $\widehat{Z}_t(T)$ is the risk-free discount factor at time t corresponding to maturity T, and $\widehat{P}_t^{SPX}(K,T)$ is the value of an SPX put option at t with strike price K and maturity T. Quantities denoted with "hats" indicate that their prices are observable from Treasuries and traded option prices, which comprise the observed values of the liabilities of the pseudo firm, $\widehat{B}_t(K,T)$. Although the pseudo firm is fictitious, we can nonetheless observe the values of its assets and debt from traded securities and thus we have a fully observable balance sheet.[3]

To illustrate, Panel A of Figure 1 plots the time series of two pseudo bond prices $\widehat{B}_t(K_i,T)$ constructed from equation (1) using Treasuries and two different SPX put options traded on the Chicago Board Options Exchange (CBOE). Both put options have maturity dates of $T = 12/18/2009$, and are distinguished only by their different strike prices, $K_1 = 800$ and $K_2 = 1150$. The two strike prices imply two different leverage ratios K_i/A_t – $i.e.$, low and high leverage for $K_1 = 800$ and $K_2 = 1150$, respectively, where the value of assets A_t is the value of the SPX index. The time series of leverage is plotted in Panel B.

Panel A of Figure 1 shows that the low-leverage pseudo bond price steadily increases over time (like any zero-coupon bond) except during the 2008 crisis, when the price drops substantially as the SPX ($i.e.$, the asset value of the first pseudo firm) declines by over 50%. Nevertheless, this pseudo bond recovers in 2009 and eventually pays 100% of principal at maturity. The pseudo bond issued by the high-leverage pseudo firm, however, displays a larger price drop during the financial crisis, and the bond never fully recovers. Indeed, the second pseudo firm eventually defaults, as the the value of the SPX on December 18, 2009 was $A_T = 1102.47$ and hence $A_T/K_2 = 95\%$ – $i.e.$ bond holders of the high-leverage pseudo firm would have lost 5% of principal value.

Panel C plots the time series of credit spreads implied by the two pseudo bond prices $\widehat{B}_t(K_i,T)$ and Treasuries. Their dynamics highlight the variations in credit spreads during the financial crisis, a topic to which we return later. Indeed, for the first year or so, the two credit spreads were increasing, albeit by relatively small amounts. September 2008 (when Lehman failed and AIG was bailed out), however, was a clear turning point when spreads of both pseudo firms – especially the high-leverage one – skyrocketed. The difference in reactions of the credit spreads of the two pseudo firms (which are otherwise identical except for leverage) highlights the increase of a firm's financial fragility and sensitivity to shocks in asset value changes resulting from leverage.

Our methodology also allows us to exploit standard econometric tools to compute pseudo bonds' *ex ante* default probabilities – $i.e.$, the probabilities $p_t(K) = Pr[A_T < K | \mathcal{F}_t]$, where

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[3]For completeness, note that equity holders of the pseudo firm are instead entitled to the residual payoff $\max(A_T - K, 0)$ at maturity T and to all cash dividends paid by SPX portfolio until then.

$\mathcal{F}_t$ reflects the information available at t. Panel D of Figure 1 plots these default probabilities for the two pseudo firms discussed above. Both probabilities increase substantially during the 2008 financial crisis, especially for the high-leverage pseudo bond. Although the leverage ratio K_i/A_t is a major determinant of the default probability and credit spreads, a comparison of Panels B, C, and D in Figure 1 also indicates the significantly non-linear relation between leverage, credit spreads, and default probabilities.

As this example illustrates, we can treat pseudo firms like any other real firm to learn about credit risk. In this paper, we systematically analyze the empirical properties of pseudo bond credit spreads ("pseudo spreads") constructed as illustrated above. We begin by analyzing pseudo firms with two types of assets: (i) the SPX (as in the previous illustration); and (ii) shares of individual stocks that comprise the SPX. We refer to the pseudo bonds issued by firms (i) and (ii) as SPX and single-stock pseudo bonds, respectively. In a later section, we show that our results extend to pseudo firms holding other assets, such as commodities, foreign currencies, and fixed income securities.

Average credit spreads on pseudo bonds are large and similar in magnitude to credit spreads on actual comparable corporate bonds, especially for bonds with high credit ratings. For example, credit spreads of two-year SPX pseudo bonds corresponding to the default probabilities for Aaa/Aa and A/Baa bonds are 0.42% and 1.19%, respectively.[4] The spreads of single-stock pseudo bonds for those two default probabilities are 0.68% and 1.71%. These spreads are very similar to the average credit spreads observed for actual Aaa/Aa and A/Baa corporate bonds – *i.e.,* 0.71% and 1.21%, respectively. For high-yield (HY) debt, SPX pseudo bond spreads range between 2.09% (for Ba-rated bonds) and 4.96% (for Caa-rated bonds), whereas single-stock pseudo bond spreads range between 3.08% and 8.62%. These spreads are close to actual corporate bond spreads, which are 2.93% for Ba-rated bonds and 9.56% for Caa- rated bonds, respectively.

In addition, pseudo credit spreads are high not only for medium-term bonds (*i.e.,* 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 0.52% and 0.45%, respectively, which are very close to observed average credit spreads of 0.61% and 0.60% on actual IG-rated firms' commercial paper. Pseudo spreads thus are consistent with the puzzling hefty credit spreads of short-term paper issued by corporations with a seemingly negligible probability of default over such

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[4]We use the credit ratings nomenclature of Moody's Investors Service (Moody's) throughout this paper. Nevertheless, the credit ratings that we later assign to pseudo bonds are not intended to match the ratings that actually would have been assigned by Moody's or any other rating agency to such bonds (if they existed) based on their own ratings criteria.

short time horizons. These results suggest a good deal of integration between corporate bond and options markets.

Given that the magnitudes of spreads between pseudo bonds and corporate bonds are similar, we examine popular explanations for the high and time-varying credit spreads of corporate bonds.[5] Although illiquidity of corporate bonds is often cited as an explanation for high credit spreads (*e.g.* Bao, Pan and Wang (2013)), we find that pseudo bonds are much more liquid than corporate bonds, which suggests that illiquidity is not the whole story. Similarly, our empirical tests on pseudo bonds' default probabilities suggest that high credit spreads are unlikely due to investors' systematic over-prediction of default frequencies or the magnitudes of losses given default (*e.g.* Feldhütter and Schaefer (2016)).

Our empirical results also suggest that 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), David (2008)), corporate investment behavior (*e.g.,* Kuehn and Schmid (2014)), and the like. As the SPX example above shows, our pseudo firms are simple entities in which asset values are observable, information is symmetric, managerial frictions do not exist, leverage and default boundaries are exogenous, and default only occurs at maturity. Yet, independently from the type of underlying assets, our pseudo bonds display properties that are surprisingly close – qualitatively and quantitatively – to those of real corporate bonds.

Instead, we find evidence that idiosyncratic asset uncertainty has a substantial independent impact on credit spreads. Because we can observe both the assets and liabilities of pseudo firms, we can measure idiosyncratic uncertainty as the residual volatility from a market model on equity, and find that pseudo credit spreads are strongly positively related to residual volatility, even after controlling for *ex ante* default probabilities and losses conditional on default. Our results indicate the presence of a hefty risk premium associated with idiosyncratic tail risk.

Finally, we exploit our option-based methodology to provide further evidence and interpretations of the forces that shape the credit spreads around the business cycle, especially during the 2008 - 2009 financial crisis. In particular, we follow Gilchrist and Zakrajsek

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[5]The literature refers to the high credit spreads of corporate bonds as the "credit spread puzzle" – *i.e.*, the observation of actual credit spreads that are well in excess of the spreads implied by mainstream risky debt valuation models, such as the Merton (1974) model.

(2012) in their analysis of corporate credit spreads (the "GZ spread") and show that pseudo credit spreads also strongly covary with the business cycle and that higher spreads strongly predict lower future economic growth. The simplicity of the payoff structure of our pseudo bonds further allows us to decompose the pseudo spread into expected loss and residual risk-premium components. We find that the risk-premium component also predicts lower future economic growth, especially for long time horizons. Our empirical results are broadly consistent with the findings of Gilchrist and Zakrajsek (2012) for corporate credit spreads, and suggest that the business cycle variation of credit spreads is affected by time-variation in the insurance premium that investors require to hold securities with large tail risk over the business cycle. Consistent with this interpretation, we find that the difference between single-stock pseudo spreads and the SPX pseudo spreads – an index of a risk premium for idiosyncratic tail risk – also predicts lower future growth.

We finally extend our empirical results to study the impact of bankruptcy costs and to include other types of assets that our pseudo firms can buy, including commodities, foreign currencies, and coupon bonds (by using 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 credit spreads of such pseudo firms with different types of underlying assets display strong covariation over time, especially during the 2008 financial crisis, highlighting that similar factors affect variations in spreads.

Our paper is 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. Chen et al. (2009), Bahmra et al. (2010), and Chen (2012) show that models featuring habit formation and/or macro-economic risk are partly able to reconcile the evidence. Most of this literature focuses on long-term debt but cannot explain short-term credit spreads. Zhou (2001) and Duffie and Lando (2001) obtain high short-term credit spreads in models featuring jumps in asset values and asset value uncertainty, respectively. Gomes and Schmid (2016) propose a general equilibrium model to link credit spread fluctuations to the business cycle. The approaches of all of these papers, however, are very different from ours, as we do not use any parametric model and instead go straight to the data and analyze the credit spreads of our pseudo firms through traded options.

A small number of papers document the link between out-of-the-money put options and credit spreads (e.g., Cremers, Driessen and Maenhout (2008) and Car and Wu (2011)). These

papers concentrate on using options of individual firms to match bond spreads of those firms. Our approach is different, as we use options to create fictitious securities that resemble bonds only in terms of their payoff functions. Although we use individual stocks for some part of our analyses (but we also use indices and other non-equity assets), we do not match pseudo bonds with issuers' actual bonds. Our goal is rather to study pseudo bonds as economic equivalent benchmarks that are driven by the same macroeconomic shocks to assets and uncertainty which affect corporate bond prices.

Our approach is most closely 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 credit spreads 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 address 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 properties of corporate credit spreads.[6]

The paper is organized as follows. Section 2. describes our data and our main empirical results. Section 3. exploits pseudo firms as a testing ground to study potential sources of high credit spreads. Section 4. discusses the relation between pseudo credit spreads, economic growth, and credit supply shocks. Section 5. provides extensions to our results. Section 6. concludes. A Technical Appendix contains various extensions.

2. Option-Based Credit Spreads

2.1. Data

We rely on data from the Center for Research in Security Prices (CRSP) for individual stock prices and values of the SPX index.

Our daily prices on SPX index options and options on individual stocks from January 4, 1996, through July 31, 2015, are from the OptionMetrics Ivy database. For SPX options in

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[6]Although 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 et al. (2005)), such synthetic bonds, however, do not facilitate the same kind of analysis that we undertake here.

the period from 1990 through 1995, we use data from Market Data Express (MDR). To filter our data, we generally follow the approach of Constantinides, Jackwerth, and Savov (2013) for SPX options in order to minimize the effects of quotation errors and the methodology of Frazzini and Pedersen (2012) for individual equity options. To be conservative, we use bid prices for options to calculate our pseudo bond prices.

We construct our corporate bond panel data using the Lehman Brothers Fixed Income Database, TRACE, the Mergent FISD/NAIC Database, and DataStream. In the event of overlaps across the four databases, we prioritize sources in the order just shown. For filtering, we broadly adopt the same approach as Gilchrist and Zakrajsek (2012) (GZ), and hence consider all U.S. corporate bonds with the exception of bonds with embedded options (*e.g.*, puttable bonds), subordinated debt, and bonds with floating-rate coupons. As in GZ, however, we include callable bonds but adjust credit spreads for the predicted call premium. We obtained the GZ spread data until June 2015 from the authors' web site.

For credit derivatives, we use five-year CDX indices from JP Morgan and single-name credit default swap (CDS) spreads from Markit. We use price/spread data on both the North American IG and HY CDX indices, denoted CDX.IG and CDX.HY, respectively.

We obtain our risk-free and commercial-paper rates from the Federal Reserve Economic Data (FRED) database, where the latter are used to measure short-term credit spreads.

2.2. Default Probabilities and Pseudo Ratings

To facilitate a consistent comparison of pseudo spreads with actual spreads on corporate bonds, we assign pseudo bonds to different pseudo rating categories according to their default probabilities. For every t and pseudo bond i with maturity τ and face value K_i, we use past data to compute default probabilities $\widehat{p}_{i,t}(\tau) = Pr[A_\tau < K_i | \mathcal{F}_t]$. Technical Appendix C describes the full procedure, which can be summarized for SPX pseudo bonds as follows:

(*i*) We assume that log asset growth is $\ln(A_{t+\tau}/A_t) = \mu_{t,\tau} + \sigma_{t,\tau}\varepsilon_\tau$ where the distribution of ε_t is unspecified;

(*ii*) We use data before t to estimate volatility $\sigma_{t,\tau}$ by fitting a GARCH(1,1) model and expected future growth $\mu_{t,\tau}$ through a predictive regression;

(*iii*) Based on data prior to t, we compute the historical frequency distribution of shocks: $\varepsilon_{s,\tau} = (\ln(A_{s+\tau}/A_s) - \mu_{s,\tau})/\sigma_{s,\tau}$ (see Figure A1 in the Technical Appendix);

(iv) We utilize the historical shock distributions to estimate probabilities of default $\widehat{p}_{i,t}(\tau) = Pr[A_{t+\tau} < K_i | \mathcal{F}_t] = Pr[\varepsilon_\tau < X_i | \mathcal{F}_t]$ (where $X_i = (\ln(K_i/A_t) - \mu_{t,\tau})/\sigma_{t,\tau})$) by computing the frequencies with which $\varepsilon_{s,\tau} < X_i$ occur in the historical sample data. For the example in the introduction, the results of our methodology are shown in Panel D of Figure 1. We follow a similar methodology when assets are comprised of non-SPX securities with only minor modifications based on data availability and, for individual stocks, some issues with survivorship bias for which we must account.

(v) As a final step, for every t we assign each bond i with maturity τ to a pseudo rating category by comparing its estimated default probability $\widehat{p}_{i,t}(\tau)$ with historical average default frequencies across credit rating bins estimated from Moody's historical bond default dataset to reflect booms and recessions for various horizons τ.[7]

(vi) In addition to default probabilities, we exploit parameters $\mu_{t,\tau}$, $\sigma_{t,\tau}$ and the shock distribution as computed in step (iii) to recover the asset value distribution conditional on time-t information, and estimate the loss-given-default of each pseudo bond on an *ex ante* basis by computing the average of $1 - A_{t+\tau}/K_i$ conditional on $A_{t+\tau} < K_i$.

2.3. 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 from 30 days to two years across credit ratings. We consider five pseudo rating categories: Aaa/Aa, A/Baa, Ba, B, and Caa-. We also define two broad pseudo rating categories: IG (which includes categories Aaa/Aa and A/Baa); and HY (which includes Ba, B, and Caa-). The broader IG and HY categories are useful in situations where insufficient data is available in the more granular categories.[8] Moreover, corporate bond quotes are unreliable at short maturities and we thus rely on 30- and 91-day commercial paper quotes, which are only available for IG issuers.

The results in Table 1 show that, irrespective of maturity, IG and HY pseudo credit spreads are very similar to IG and HY credit spreads of corporate bonds, respectively. 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 somewhat lower credit spreads than both HY single-stock pseudo bonds and HY corporate

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[7]We rely solely on the methodology described herein – and not rating agency criteria – for this exercise.

[8]For example, short-horizon pseudo bonds have sufficient data to cover the IG category as a whole but insufficient granularity in strike prices to differentiate across IG sub-categories. For single-stock pseudo bonds, we do not have reliable data to cover the 30-day maturity at all.

bonds (*see* Section 3.3. for a discussion). In all cases, however, pseudo 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).

The left panels of Figure 2 compare option-based pseudo credit spreads, corporate bond spreads, and credit spreads implied by the lognormal Merton model (in Panel A) for two-year bonds. Single-stock pseudo spreads and average corporate spreads are very close across all rating categories. SPX pseudo credit spreads, however, are somewhat smaller than the other two, and this disparity becomes more pronounced for lower credit ratings. In Section 3.3. we show this difference is due to the additional idiosyncratic risks on a portfolio of bonds vis-a-vis a bond based on a diversified pool of assets.

These empirical results on pseudo firms shed further light on the substantial risk premia that investors require to hold securities with large tail risks. Indeed, from Table 1 option prices are consistent with the puzzling empirical regularity that 1- and 3-month commercial paper issued by highly rated IG companies – with negligible probabilities of default – exhibit a large 0.6% spread over Treasuries on average. Indeed, three-month single-stock and SPX pseudo bonds have 0.75% and 0.45% credit spreads, respectively, which are in line with commercial paper spreads and suggestive of a tail risk premium.

2.4. Pseudo Bond Credit Spreads over Time

The last four columns of Table 1 provide a closer look at two-year bonds. (Similar results hold for other maturities.) First, we see that high pseudo spreads are not merely an artifact of recessions or the 2008 crisis, but are also high in boom times. In fact, comparing Panels A and B with Panel C, the business cycle variation of pseudo credit spreads is comparable to corresponding variations in actual corporate bond spreads. Indeed, Panels C and E of Figure 2 show that the matching between pseudo spreads and corporate spreads is close during both booms and recessions, with the notable difference again that SPX pseudo spreads are uniformly lower than spreads on single-stock pseudo bonds and actual corporate bonds.

Figure 3 presents the time series of monthly credit spreads for two-year IG and HY pseudo bonds and actual corporate bonds. We focus on the broad IG and HY categories in order to compare credit spreads on pseudo bonds, actual corporate bonds, and the Markit CDX IG and HY indices. Credit spreads on both SPX and single-stock pseudo bonds, actual corporate bonds, and the CDX indices rose substantially during the 2008 financial crisis, especially for HY bonds, and then reverted to more normal levels by 2010. Interestingly,

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the increase in HY pseudo spreads in 2008 was virtually identical to the rise in corporate bond and CDX spreads, thus suggesting that nothing anomalous was happening in the HY credit market during that period. By contrast, IG corporate bond spreads increased far more than both CDX and pseudo bond spreads during the financial crisis, which suggests some potential impairments of IG-rated bonds at that time.

The correlations across the corporate, CDX, and pseudo spreads are reported in the left corners of the four panels. With the exception of IG single-stock pseudo bonds and corporate bonds (whose pairwise correlation is just 11% – mostly because pseudo bond spreads were so high in the 1990s compared to corporate bond spreads), the correlations across all of these credit spread measures are high, ranging from 38% between IG-rated SPX pseudo bonds and IG corporate bonds (Panel A) to 93% between HY-rated SPX pseudo bonds and the CDX.HY index (Panel C).

2.5.   Leveraged Equity as Assets of Pseudo Firms

One important advantage of analyzing the credit spreads of our pseudo firms in lieu of real firms is that we can observe the explicit asset values underlying the pseudo firms and therefore directly study the relation between credit spreads and the statistical properties of underlying asset values. Our methodology, moreover, allows us to side-step the vexing endogeneity issues of corporate financial and capital structure decisions, such as a firm's choice of leverage. For instance, the right-hand panels of Figure 2 strongly suggest that endogenous leverage has a large impact on the size of credit spreads. These three panels plot average credit spreads against firms' book leverage ratios and indicate that, as leverage increases towards 90%, pseudo credit spreads increase substantially, as Merton's insight predicts. Corporate bond spreads, however, increase by much less. Because the left-hand panels of the figure show that pseudo spreads match corporate spreads well when we control for default probabilities (*i.e.,* credit ratings), the large difference in credit spreads on the right-hand panels is likely the result of the endogeneity of leverage in real firms. In other words, as we would expect, only firms with low amounts of high-risk assets increase their leverage substantially.

On the issue of leverage, however, one legitimate question is whether using equity of real firms as assets for pseudo firms may somehow cloud our inferences about the sources of observed high credit spreads. Indeed, real firms' equity is itself leveraged, which in turn thickens the tails of equity return distributions as compared to distributions of the firms' underlying assets. Even if we properly match the default probabilities of pseudo firms in Table 1, the loss-given-default of pseudo firms may, in principle, be higher as a result of our

use of equity rather than the underlying firms' assets.

We find that this is not the case empirically. First, Panel A of Table 2 reports the credit spreads of pseudo firms whose assets are *not* stocks of levered firms. Specifically, Column 5 shows that the pseudo spreads of the subset of pseudo firms defined on stocks of unlevered firms are in fact *higher* than those defined on stocks of levered firms, reported again in Columns 3 and 4 for convenience. Such large pseudo credit spreads are consistent with our findings about endogenous leverage as discussed above – *i.e.*, those firms with no leverage choose not to issue debt exactly because if they did, their credit spreads would be very large as a result of the riskiness of their assets.

In similar fashion, Columns 6 to 8 of the same panel show that pseudo spreads are high even when we use other non-equity based assets, such as commodities, foreign currencies, and fixed income securities, especially for highly rated pseudo firms and when we adjust for loss-given-default (in Panels C and D). We discuss these results further in Section 5.1.

Second, Panel B of Table 2 shows that the loss-given-default of pseudo firms are in fact *lower* than those of real firms across credit rating categories, which suggests that the tails of equity return distributions are, if anything, too small when compared to the real potential losses on corporate bonds. The main channel through which our use of equity (instead of the underlying firms' assets) would induce larger tails thus does not actually hold in the data.

Finally, we show in the Technical Appendix that matching the corporate bonds of a real firm to pseudo bonds obtained from options on the equity of the *same* firm with the same credit rating results in pseudo spreads that are comparable to actual corporate bond spreads. Both spreads, however, are higher than CDS spreads on the same reference entity. The empirical evidence thus confirms the non-zero nature of the CDS-bond basis (*see, e.g.*, Culp, van der Merwe, and Stärkle (2016) for a survey) but also shows a comparable CDS-*pseudo* bond basis.[9] Although our focus is *not* on comparing the spread of a bond issued by a given firm with the pseudo spread computed from the equity of *that* firm (*e.g.*, comparing spreads on Apple-based pseudo bonds with bonds issued by Apple Inc.), these results provide some comfort that our methodology is robust.

In the Technical Appendix, we also ascertained (as a theoretical matter) through simulations based on Merton's lognormal model that the impact on credit spreads from equity

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[9]We thank an anonymous referee for suggesting the comparison of pseudo spreads with CDS spreads and bond spreads on a firm-by-firm basis. We remark, however, that it is difficult to secure a large sample of matched corporate bonds, pseudo bonds, and CDSs on a firm-by-firm basis. Because most firms in the SPX index are highly rated, we need deep out-of-the-money options to obtain pseudo bonds that match the high credit rating of the issuer, and such data is generally not available.

rather than underlying assets is very small, especially for highly rated firms. Instead, we find that Merton's lognormal debt valuation model implies a far larger negative skewness and kurtosis of log returns than what we observe in real firms' equity returns, which is consistent with our finding that the loss-given-defaut of pseudo bonds is smaller than loss-given-default on corporate bonds.

In sum, using equity as the assets on pseudo firms' balance sheets does not seem to induce any particular bias on pseudo credit spreads, despite the impact of leverage on most actual firms' equity values. On the contrary, by including equity on our pseudo firms' balance sheets, we can examine realistically the various sources of credit spread levels and dynamics by using actual market-determined data and our observations of both assets and liabilities of pseudo firms, to which we now turn.

3. Empirical Determinants of Credit Spreads

As shown in Table 1 and in Figure 3, pseudo credit spreads are large and share cyclical properties that are similar to those of real corporate bonds. We now exploit the simplicity of our pseudo firms to provide further insights on the determinants of credit spreads.

3.1. Corporate Bond Market Illiquidity

Illiquidity in the corporate bond market is often considered to be a critical determinant of large credit spreads. We can assess this notion using our option-based pseudo bonds. Specifically, following Bao, Pan, and Wang (2011), we use the Roll (1984) 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, the market illiquidity measure for pseudo bond i in month t is

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

where $\Delta p_{i,t,d}^{Bid \rightarrow Ask} \equiv \log Ask_{i,t,d} - \log Bid_{i,t,d-1}$ and $\Delta p_{i,t,d}^{Ask \rightarrow Bid} \equiv \log Bid_{i,t,d} - \log Ask_{i,t,d-1}$. We compute this Roll-like measure for all pseudo bonds that have more than 10 return observations in a month.[10] We calculate the portfolio-level Roll measure as the kernel-

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[10]This formula slightly differs from Roll (1984) (unlike equation (3), in which we use Roll's exact formu-

weighted average (*see* the Technical Appendix) 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. Roll's (1984) original illiquidity measure uses daily transaction prices and is computed as

$$Illiquidity_t = 2\sqrt{-Cov_t(\Delta p_{i,t,d}^{Transaction}, \Delta p_{i,t,d+1}^{Transaction})} \tag{3}$$

where $p_{i,t,d}^{Transaction}$ is the log transaction price of corporate bond i on day d. We then compute the Roll measure for all corporate bonds that have more than 10 return observations in a month, and 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 our results. 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, which is not surprising. 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.[11]

3.2. Over-Prediction of Default Probabilities

Apart from the relative illiquidity of the corporate bond market, another possible explanation of excessive observed credit spreads is that investors over-estimate the probabilities of default of corporate bonds (*see, e.g.,* Feldhütter and Schaefer (2016)). We can use our pseudo firms as a laboratory to test this hypothesis. In fact, because we assign default probabilities to pseudo bonds using a well-defined rule (*see* Section 2.2.), we can test whether *ex post* default frequencies are similar to *ex ante* probabilities. Figure 4 presents the results of this test using

lation.) Because we have available bid and ask prices for pseudo bonds, 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).

[11]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.

data from 1970 to 2014.[12]

Panel A of Figure 4 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 encompass 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 the *ex ante* probabilities but are still within the confidence bands. The confidence intervals 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] Nevertheless, the overall evidence shows that our *ex ante* default probabilities are not excessive and that over-prediction of default probabilities does not explain large credit spreads.

3.3. Idiosyncratic Tail Risks

As discussed above, we do not see compelling empirical evidence that high credit spreads are the result of illiquidity in the corporate bond market or over-prediction of default probabilities. Theories of corporate behavior, such as those summarized in the introduction, moreover, do not apply to our pseudo firms, and thus also are not likely explanations for the large credit spreads.

The high credit spreads of pseudo bonds are consistent, however, with the large literature documenting that out-of-the-money equity put option prices are especially high. Our approach documents that such "overpricing" of put options is quantitatively consistent with observed credit spreads on actual corporate bonds, which provides a strong indication that options and bonds markets are well integrated 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 risks, just as they do for options.[14]

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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 4 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.

[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.

[14]Out-of-the-money equity put options became especially expensive after the October 1987 market crash.

The results in Table 1 show that the average credit spread of single-stock pseudo-bonds is higher than the credit spreads on SPX pseudo bonds. This may appear puzzling at first because the SPX carries mostly systematic risk. The result is in fact rather intuitive and highlights the types of risk that impact corporate bond credit spreads. To illustrate, fixing a strike price K common to all bonds, Jensen's inequality implies:

$$
\begin{aligned}
\text{Payoff of SPX-Pseudo Bond} \quad &= \quad K - \max(K - \sum w_i A_{i,T}, 0) \\
&> \quad \sum w_i \left(K - \max(K - A_{i,T}, 0) \right) \\
&= \quad \text{Average of Payoffs of Single-Stock Pseudo Bonds}
\end{aligned}
$$

Thus, for a given K, the value of the portfolio of pseudo bonds is always lower than the value of a bond on the SPX index portfolio. Clearly, because in this example K is the same for both the SPX and single-stock pseudo bonds, the default probability of the SPX bond may be lower than the average default probabilities of single-stock pseudo bonds. As such, an adjustment for this valuation misalignment should be made. The results in Table 1 highlight that such an adjustment, however, is insufficient to curtail the idiosyncratic risk component that affects average spreads on a portfolio of corporate bonds.[15]

To dig deeper into the importance of idiosyncratic risk on credit spreads, we exploit our single-stock pseudo bonds and directly investigate the impact of idiosyncratic asset volatility on credit spreads. In general, a firm's credit spread depends on its probability of default, the loss-given-default, and the risk premium.[16] Idiosyncratic uncertainty may affect the former two quantities, but should not affect the third. We now show that, empirically, it does.

Whether and how idiosyncratic asset volatility impacts credit spreads is hard to address using actual corporate bond data, because asset values are non-observable and, hence, measuring idiosyncratic asset value volatility is problematic. In contrast, pseudo firms have observable balance sheets, and thus we can measure the idiosyncratic volatility of their asset

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It is thus possible that the SPX results may not hold on a pre-1987 sample. If so, a potential interpretation of our results is that the 1987 market crash made investors in options acutely aware of tail risk in the same manner that previous debt crises – such as the 1931 depression – made bond investors aware of the same type of tail risk. We thank an anonymous referee for suggesting this interpretation.

[15]Interestingly, the average spread of components of CDX index is higher than CDX spread itself, but the difference is not as high as the on observed for pseudo bonds.

[16]For instance, Chen et al. (2009) show that within a lognormal Merton model, modified to have a given loss-given-default (LGD) in case of default (as opposed to $K - A_{i,t+\tau}$), it is possible to write the credit spread as

$$
cs_t(\tau) = -\frac{1}{\tau} \log \left\{ 1 - LGD \times N \left[N^{-1}(p_t(\tau)) - \theta \sqrt{\tau} \right] \right\}
$$

where $N(.)$ is the cumulative normal distribution, $p_t(\tau)$ is the default probability, and θ is the market price of risk. Controlling for $p_t(\tau)$ and LGD, idiosyncratic uncertainty should not affect the credit spread as θ should not depend on it.

values from the standard deviation of the residuals from the basic market model.[17] For each time t, we then sort these single-stock pseudo bonds according to their pseudo credit ratings and then, for each credit rating category, we sort pseudo bonds into low, medium, and high idiosyncratic asset volatility categories. Table 3 reports the results.

Panel A indicates that for all rating categories except Aaa/Aa, credit spreads for pseudo bonds with high-volatility assets are higher than spreads on pseudo bonds with low-volatility assets. The magnitudes are large, moreover, especially for lower-rated bonds. For instance, a Ba-rated pseudo bond has 2.33% spread in the low-volatility bin but a 3.95% 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, the data are sparse and results are noisy within this category. Panel B demonstrates that, conditional on individual credit ratings, higher asset volatility corresponds to lower leverage.

Panel C shows that pseudo bonds of firms with higher idiosyncratic asset volatilities have higher losses-given-default, where the latter is computed as described in Section 2.2. Given the results in Panel B, higher idiosyncratic volatility is correlated with a fatter left-tail of the asset value return distribution, which in turn increases the loss-given-default for a given default probability.

To test whether the loss-given-default or idiosyncratic volatility is responsible for higher credit spreads, we run the following pooled regression:

$$\text{Pseudo Spread}_{i,t} = \underset{(2.97)}{0.109} + \underset{(10.92)}{0.532} \; \widehat{p}_{i,t} + \underset{(0.13)}{0.007} \; \widehat{LGD}_{it} + \underset{(3.89)}{0.045} \; log\left(\text{IdioVol}_{it}\right) + \varepsilon_{i,t}$$

where Pseudo Spread$_{i,t}$ is the pseudo credit spread of pseudo firm i at time t, $\widehat{p}_{i,t}$ is its *ex ante* default probability, $\widehat{LGD}_{it}$ is its *ex ante* loss-given-default, and IdioVol$_{it}$ is its idiosyncratic volatility. Values below the parameter estimates are t-statistics. This result shows that even controlling for the *ex ante* default probability – which is the best predictor of the credit spread – and the *ex ante* loss-given-default, the residual idiosyncratic volatility is significantly positively related to credit spreads. This finding suggests that idiosyncratic volatility may increase credit spreads through a risk premium component, in addition to the impact on default probability $\widehat{p}_{i,t}$ and tail risk $\widehat{LGD}_{it}$.

Our panel regression results are consistent with the idea that the average spread of a portfolio of single-stock pseudo bonds is higher than the spread on SPX pseudo bonds because

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[17]In addition to the market model, we also used the Fama French three-factor model to compute idiosyncratic volatility and found essentially the same results.

idiosyncratic risk impacts spreads over and beyond how they impact default probabilities and loss-given-default. Indeed, we find that the average credit spreads on HY single-stock pseudo bonds are strongly affected by the ratio of idiosyncratic volatility to total volatility, $R_t = $ Average IdioVol$_t$/Average TotalVol$_t$, as shown in the following time-series regression:

$$\text{Single-Stock Pseudo Spread}_t^{HY} = 0.71 + 0.65 \times \text{SPX Pseudo Spread}_t^{HY} + 0.04 \ R_t + \varepsilon_t$$
$$(0.54) \quad (9.70) \qquad\qquad\qquad (2.40)$$

In other words, the average spread of the HY single-stock pseudo bonds is strongly dependent on the average spread of the HY SPX pseudo bonds, but also on the ratio of idiosyncratic volatility vis-a-vis total volatility. A higher fraction of idiosyncratic risk relative to total risk thus is associated with higher average credit spreads. The R^2 of the regression is 67.4%.

To gauge the importance of idiosyncratic risk, we run a regression of the difference in the average single-stock HY spreads and the average HY SPX spread on the ratio of idiosyncratic volatility to total volatility R_t and find a significant slope coefficient (t-stat = 2.62) and $R^2 = 27\%$. Idiosyncratic risk thus explains about 27% of the variation of the excess credit spreads on HY single-stock pseudo bonds when compared to HY SPX bonds. Interestingly, the idiosyncratic volatility ratio R_t declined substantially during the 2008 – 2009 financial crisis, when both SPX and single-stock pseudo spreads skyrocketed. The difference between the two, however, dropped, highlighting that the dramatic increases in credit spreads during the crisis were not likely driven by idiosyncratic risk and more likely due to a rise in aggregate risk and risk premia. Finally, we do not find a comparable relation for IG pseudo bonds, which is consistent with the results about Aaa/Aa-rated bonds in Table 3. Overall, our results suggest that idiosyncratic asset risk is an important determinant of average corporate credit spreads and the cost of corporate debt capital.

We end this section with a tantalizing interpretation of our empirical results – namely, the impact of "diversification" on the cost of debt for a conglomerate as compared to a portfolio of single-segment firms. Taking the SPX as the "conglomerate" and the single stocks as single-segment firms, *ceteris paribus,* option prices suggest that we should see a diversification *premium* in the cost of debt. This simple interpretation of our results side-steps all the empirical issues concerning the endogeneity of leverage (*i.e.*, safer, more diversified conglomerates may lever more) and shows that a diversification premium arises as idiosyncratic uncertainty commands a risk premium on its own (*see e.g.*, Villalonga (2004)).

4. Pseudo Spreads and Economic Growth

We now exploit our pseudo bonds to discuss and shed further light on recent findings in the empirical macro-finance literature about the relation between credit spreads and future economic growth. In an important recent paper, Gilchrist and Zakrajsek (2012) (GZ) show that a measure of the credit spread – the "GZ spread" – strongly predicts future economic growth. In addition, a measure of bond mispricing – the excess bond premium – also independently predicts future economic growth. We now show that our pseudo credit spreads predict future economic growth as well as the GZ spreads.

4.1. Pseudo Credit Spread Indices

To compare our results to GZ spreads, we use our previous results to build two simple pseudo spread indices, one for single-name spreads and the other for SPX spreads. We calculate the pseudo spread index as the equally weighted average of IG and HY pseudo spreads in Table 1 for pseudo bond maturities of 183, 365 and 730 days. The equal weighting of IG and HY indices enables us to compute the value of an index with equal representation of IG and HY pseudo firms, which is important because our options data are far more widely available for options close-to-the-money and hence for HY pseudo firms.

Panel A of Figure 5 plots the time series of the GZ spread as compared to the SPX and single-stock pseudo spread indices. As shown, the three series are very highly correlated, with the SPX pseudo bond series mostly lying on top of the GZ spread series. The single-stock pseudo spread is a bit higher in some parts of the sample, which is not surprising given the discussion in Section 3.3.

Following GZ, we run the following predictive regression

$$\Delta_h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \gamma_1 \text{ Pseudo Spread}_t + \gamma_2 \text{ GZ Spread}_t + Controls_t + \varepsilon_{t+h} \quad (4)$$

where Δ_h is the "h-period" lag operator, and the number of lags p is determined by the Akaike Information Criterion. We only insert the component of the GZ Spread$_t$ that is orthogonal to the Pseudo Spread$_t$ whenever the latter is included in the regression. Our control variables are the term spread, the real Federal Funds rate, and the option-implied "fear index" as measured by the CBOE's VIX index, which has been shown to be an important predictor of future economic growth. This latter control is especially important in our specification because pseudo spreads are based on option prices and we want to ensure they do not just pick up the level of uncertainty as reflected by the market generally but rather tail risk.

Table 4 shows that, like the GZ spread, both the single-name (Panel A) and the SPX pseudo spreads (Panel B) predict future growth. The pseudo spread indices are significant across all specifications with no controls (besides lags) for payroll growth, unemployment changes, and industrial production growth. The results are weaker for GDP growth when using single stocks, and insignificant using SPX pseudo bonds. Adding controls does not generally affect our inferences, and, in fact, the adjusted R^2 increases only marginally. (The full specification with controls is in Table A9 in the Technical Appendix.)

To compare our results to the corporate based GZ spread, Table 4 also reports the results of the predictive regression (4) with GZ spreads as a predicting variable, as well as its orthogonal component to the pseudo spread index when the latter is also included. The results show that in most cases, pseudo spreads and GZ spreads have about the same explanatory power (R^2) of future economic activity. At the 12-month horizon, however, the single-stock pseudo spread index has a substantially higher R^2 for unemployment and industrial production growth (with no controls) and for industrial production growth and GDP growth (with controls).

At the three month horizon, moreover, the orthogonalized component of the GZ spread does not enter significantly in most specifications, showing that GZ spread does not seem to add information to the pseudo spreads. (The converse is also true.) At the 12-month horizon, however, the orthogonalized component of GZ spread enters significantly, and the R^2 increases substantially compared to the case in which either only the pseudo spread or the GZ spread is used in the regression. This increase in R^2 at the 12-month horizon when both indices are included indicates that the option-based and the corporate-based spreads do not exactly capture the same frequency of variation of future economic activity, and they reinforce each other in the predictive regression. Indeed, Panel A of Figure 5 suggests that pseudo spreads move at a slightly higher frequency than the GZ spread, which shows that GZ spreads are likely related to lower-frequency shifts in the macro economy.[18]

Tables A10 and A11 in the Technical Appendix show the results in the two subsamples before and after June 2005. Although the SPX pseudo spreads occasionally loses significance in the first subsample when all controls are used in the regression, both the GZ spread and the single-name pseudo spreads are mostly significant across the two subsamples. The special environment of the 2007 - 2009 financial crisis does not seem to be driving the results, but there is a difference between SPX spreads and single-name spreads, as we further comment in Section 4.3.

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[18]Indeed, the AR(1) and AR(12) coefficients of GZ spreads are 0.97 and 0.45, respectively, against the 0.82 and 0.12 of single-stock pseudo spreads, and 0.88 and 0.36 of SPX spreads, respectively.

4.2. Expected Loss and Risk Premium

The simplicity of the payoff structure of our pseudo bonds enables us to decompose the pseudo credit spread into an "expected loss" and a residual "risk premium" and thus gauge the source of the predictability of (pseudo) credit spreads onto future economic activity. More specifically, for each pseudo bond i at time t with maturity $T = t + \tau$ we can use information up to t to estimate the expected loss:

$$\text{Expected Loss}_{it}(K, T) = \widehat{p}_{it}(\tau) \times \widehat{LGD}_{it}(\tau) \times K$$

where $\widehat{p}_{it}(\tau)$ is the estimated *ex ante* probability of default, and $\widehat{LGD}_{it}(\tau)$ is the estimated *ex ante* percent loss-given-default (see Section 2.2.). Because the expected payoff of the pseudo bond is $K - \text{Expected Loss}_{it}(K, T)$, we can compute the actuarially fair, non-risk-adjusted value of each pseudo bond as

$$\widehat{B}_{it}^{P}(K, T) = \widehat{Z}_t(T) \times (K - \text{Expected Loss}_{it}(K, T))$$

where the superscript P indicates that this value is *not* risk adjusted. The credit spread defined on $\widehat{B}_{it}^{P}(K, T)$ thus only reflects the compensation for expected future losses, and we refer to this spread just as the "Expected Loss Spread" for short. We can finally compute the component of the pseudo credit spread that is a risk premium as a residual:

$$\text{Pseudo Bond Risk Premium}_{it} = \text{Pseudo Spread}_{it} - \text{Expected Loss Spread}_{it} \qquad (5)$$

As for the pseudo spread indices, we construct an equally weighted pseudo risk premium index as the average of the six indices that we can compute across the two credit qualities (IG and HY) and the three maturities (183, 365, and 730 days).

The pseudo risk premium computed above is the analog quantity in our setting of the excess bond premium introduced by GZ, which in their paper is a measure of "mispricing" that is embedded into credit spreads.[19] Given the simplicity of our pseudo bonds, our approach allows us to compute a pseudo risk premium in a simple, *ex ante* fashion. Clearly, by its very definition and similarly to the GZ excess bond premium, an unusually high (pseudo) credit spread is interpreted as a high risk premium. Panel B of Figure 5 plots the three series.

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[19]For each bond i at t, the GZ excess bond premium is given by GZ $\text{EBP}_{it} = $ GZ $\text{spread}_{it} - $ predicted GZ spread_{it}, where the "predicted GZ spread" is obtained from a panel predictive regression on a set of predictors run over the whole sample. The EBP index is obtained as the average across firms. In untabulated results, we find that the GZ EBP also has independent predictive ability in our sample, as in the original GZ. As in Table 4, the R^2 are comparable to those of the pseudo spreads.

Table 5 shows the results of the same predictive regressions as in Table 4, except that we now decompose the pseudo spread index into "Pseudo Risk Premium" and "Expected Loss Spread." First, the results show that the Expected Loss Spread is strongly significant across specifications. Because the expected loss spread only depends on *ex-ante* default probability and loss-given default but not directly on spreads, this result shows that higher risk indeed negatively predict future growth. Second, the results also show that, except for SPX pseudo bonds at the three-month horizon (Panel B, left columns), the Pseudo Risk Premium exhibits a strong independent predictive ability of future economic growth. In other words, an unusually high pseudo risk premium predicts a slowdown of future growth. The last row of each panel also shows that the increase in (adjusted) R^2 of adding the risk premium is rather substantial economically. For instance, at the 12-month horizon for single-stock spreads, the addition of the risk premium over expected losses increases the R^2 by 18%, 20%, 31% and 18% for Payroll Growth, Unemployment Change, Industrial Production Growth and GDP Growth, respectively.

4.3. Single-Stock and SPX Pseudo Spreads

The comparison of Panel A and Panel B of Table 4 also suggests that noticeable differences in predictive power exist between the two pseudo spread indices themselves (recall though the samples for the two indices are slightly different). Indeed, this is to be expected from the discussion in Section 3.3., as the single-stock pseudo spread should be more affected by idiosyncratic tail risk than the SPX index. To investigate the role of idiosyncratic tail risk, we run the following predictive regressions, whose results are reported in Table 6:

$$\Delta_h Y_{t+h} \quad = \quad \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \gamma_1 \text{ SPX Spread}_t \tag{6}$$

$$+ \gamma_2 \text{ Pseudo Spread Difference}_t + Controls_t + \varepsilon_{t+h} \tag{7}$$

where the "Pseudo Spread Difference" is either literally the difference between single-stock and SPX pseudo spreads (*i.e.* Single-Stock Spread$_t$ − SPX Spread$_t$) (Panel A), or the difference in the spreads' risk premium components computed in (5) (Panel B).

The results are illuminating. First, Panel A shows the pseudo spread difference (Single Stock Spread$_t$ − SPX Spread$_t$) is strongly significant across specifications. The addition of this spread difference, moreover, substantially increases the R^2 of the SPX predictive regressions, as shown in the last line of the panel. For instance, at the 12-month horizon including the pseudo spread difference increases the R^2 by 13% for Payroll Growth, 14% for Unemployment Change, 19% for Industrial Production, and 7% for GDP growth. Given the

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interpretation offered in Section 3.3. for the difference in average single stock pseudo spreads and SPX spread, it appears that priced idiosyncratic tail risk is a strong predictor of future economic activity.

Panel B presents the results from a comparable regression, but with the difference in pseudo-risk premia computed as in (5). The risk premium difference also enters strongly significant in the regression, although the improvement in R^2 is not as high as with the spread. For instance, at the 12-month horizon, the risk premium difference increases the R^2 by 8%, 9%, 14%, and 4% for Payroll Growth, Unemployment Change, Industrial Production Growth, and GDP growth, respectively.

To shed further light on the source of this predictability, Table A14 in the Technical Appendix documents that in the first subsample (Jan 1996 - Jun 2005), the pseudo spread difference is a significant predictor of future growth, but it loses significance in the second subsample (Jul 2005 - Jun 2015). The SPX spread is instead strongly significant especially in the second subsample. Given that the second subsample is dominated by the 2007 - 2009 financial crisis, this result is consistent with our findings in Section 3.3. that during the financial crisis idiosyncratic risk declined substantially, and thus that the variation in pseudo spreads was mostly due to systematic factors.

4.4. Intermediary Credit Constraints and Pseudo Bond Spreads

The previous sections show that option-based credit spreads and their risk-premium components strongly predict future economic activity. A natural interpretation of this empirical regularity is that in downturns risk premia increase, which in turn gives rise to higher pseudo credit spreads through the insurance premia that market participants are willing to pay to purchase put options. As the converse occurs in expansions, pseudo spreads predict future growth. The similarity between pseudo bonds and real corporate bonds – both are securities with large tail risk which pay less in downturns – may suggest that a similar risk-premium channel explains the predictability of real corporate bonds on future growth (see Table 4).

In the wake of the financial crisis, the recent literature ascribe the "excessively" high or low credit spreads to credit supply shocks to financial intermediaries. For instance, GZ interpret the predictability of the excess bond premium of future economic growth as evidence that a contraction in credit causally and adversely affects economic growth. The risk premium channel and the credit supply channel need not be in contradiction, however. Indeed, because option trading is often undertaken by intermediaries and dealers, it is possible

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that intermediaries' credit constraints may impact the quoted prices of the put options on which our pseudo spreads are based. For instance, Chen, Joslin, and Ni (2016) suggest that increases in put option prices during the financial crisis may be due to financial intermediaries purchasing "catastrophe insurance" to hedge the risk of potentially binding credit constraints in downturns.

This interpretation of the increase in put option prices resulting from intermediaries' hedge purchases is of course still consistent with the interpretation of time-varying premia for tail risk during the business cycle. Indeed, the willingness of intermediaries to purchase "catastrophe insurance" due to potentially binding credit constraints is akin to the desire of risk-averse agents to purchase downside insurance because of hightened risk aversion. Either way, higher credit spreads reflect an increase in the demand for compensation to bear relatively higher perceived downside risk (*i.e.* tail risk.) The additional insight is that this tail insurance risk premium may arise from credit supply contractions and not simply from changes in investor risk aversion that is independent of credit supply considerations.

To further support the risk premium argument, we see in Figure 5 that option-based credit spreads declined substantially *before* the 2008 financial crisis. Such credit spread compressions are interpreted in some of the literature as credit market being "frothy" and are a precursor to a deep recession (*see, e.g.,* Krishnamurthy and Muir (2016)). Our results indicate that pseudo bond spreads were also low before the credit crisis and it is unclear why excessive credit supply would affect the value of traded put options. Declines in market participants' risk aversion or expectations of future losses seem to also be plausible explanations to the compressed credit spreads, option-based or not.

5. Extensions

In this section we extend our main results to consider other types of assets that our pseudo firms may purchase, and to introduce bankruptcy costs.

5.1. Other Types of Underlying Assets

In this section we consider additional types of assets that pseudo firms may purchase by issuing zero-coupon bonds and equity. We previewed some of the results in Section 2.5., and we dig deeper here.

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 the Introduction implies that the benchmark value of a zero-coupon bond issued by our pseudo firm is given by expression (1), but now with a put option on oil, $\widehat{P}_t^{oil}(K, T)$, instead of an SPX option, $\widehat{P}_t^{SPX}(K, T)$. Options on physical oil do not generally have available data, and so we use options on light, sweet (a.k.a. West Texas Intermediate) crude oil futures contracts listed by CME instead. By selecting options with the same expiration dates as the underlying futures, such options are essentially worth $\max(K - A_T, 0)$ at maturity, where A_T is the price of physical crude. Although options on futures are American-style, we rely only on deep out-of-the-money options whose early exercise premia are negligible.

In addition to oil, we consider corn, soybeans, natural gas, and gold as additional pseudo firm assets, for which CME futures 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, the strike price coverage was insufficient for us to compute pseudo spreads prior 1995 for HY bonds and before 2000 for IG bonds. Even then, a large number of missing observation remains in the data.

Foreign Currencies. Assume that our pseudo firm purchases foreign currency (*e.g.* Euros) in the spot market by financing the purchase with zero-coupon bonds and equity. The values of zero-coupon bonds are given by (1), but with put options on Euros, $\widehat{P}_t^{Euro}(K, T)$, instead of SPX options, $\widehat{P}_t^{SPX}(K, T)$. We obtain 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. The JPMorgan currency options data are only available in specific buckets of implied volatilities, which suggests that the data are interpolated to some degree. The available strike prices, moreover, only enable us to compute pseudo bond prices for very low credit ratings, and even then only starting in 1999 for Caa-, 2001 for B, and 2007 for Ba (the latter only for a brief period). The CME currency futures options data do not provide sufficient coverage for two-year options to be useful in our main tables, but results for 1-year CME-based currency pseudo bonds are available in the Technical Appendix. The sample for CME currency options starts in 1985, but limited strike coverage only allows us to compute low-rated bond spreads for most of the sample.

Fixed Income Securities. We also consider a pseudo firm that purchases a fixed-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. The asset value of the pseudo firm at T is $A_T = \mathcal{B}_T(c, M)$. Thus, the payoff of the zero coupon bond issued by the

pseudo firm at maturity T is

$$\text{Pseudo bond payoff at } T = 1 - \max(1 - A_T, 0) = 1 - \max(1 - \mathcal{B}_T(c, M), 0)$$

The payoff $\max(1 - \mathcal{B}_T(c, M), 0)$ is the same as the payoff on a payer swaption (*i.e.*, an option to enter into a swap as the fixed-rate payer) with a unitary notional amount, fixed swap rate c, maturity T and tenor $M - T$.[20] Thus, the value of the pseudo bond before maturity is

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

where $\widehat{P}_t^{swap}(T, c, M)$ 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 $\mathcal{B}_t(c, M)$. Swaption data are from ICAP beginning in July 2002.

5.1.1. Results

Panel A of Table 2 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 from 0.32% and 0.51%. 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 time series of credit spreads across asset classes also show a good deal of comovement. We construct two simple factors for IG and 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).[21] Regressions of individual IG spreads on the pseudo-spread 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 (*e.g.*, investor risk aversion to tail risk independent of asset classes and systemic considerations) affecting credit spreads.[22]

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

[21]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 Technical Appendix.

[22]Recent research has documented a common factor in idiosyncratic volatility (*e.g.* Herskovic et al. (2016)). The common comovement of pseudo spreads thus is consistent with our empirical findings in Section 3.3. of a priced idiosyncratic risk embedded in pseudo spreads.

Figure 6 plots standardized credit spreads for pseudo bonds with two years to maturity for IG and HY credit ratings. The comovement across credit spreads with different types of underlying assets is evident from the figure, especially around the 2008 crisis. This evidence provides further support that spreads are affected by a common time-varying risk premium affecting spreads of bonds with different types of collateral.

To assess the differences in credit spreads across types of assets in more detail, Panel B of Table 2 shows the loss-given-default of real corporate bonds and pseudo bonds. Real corporate bonds have around 60% losses on average in case of default. We compute the loss-given-default of each pseudo bond with *ex ante* default probability $\widehat{p}_{i,t}(T)$ as the average percentage loss $(K_i - A_{i,T})/K_i$ conditional on a default (*i.e.*, $A_{i,T} < K_i$.)[23] We find that loss-given-default are between 25% and 50% for single-stock pseudo firms, between 10% and 15% for SPX 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.

5.2. Bankruptcy Costs and Loss Given Default

As shown in Panel B of Table 2, the average loss-given-default of corporate bonds are higher than the loss-given-default of pseudo bonds. As a second extension, we now introduce bankruptcy costs and find a portfolio of put options to yield loss-given-default of pseudo bonds closer to those of real bonds.

Specifically, let κ_i be pseudo firm i's bankruptcy costs. Then, the payoff at T of the pseudo bond with face value K can be written as

$$\text{Bond payoff at } T = K - (1 - \kappa_i) \max{(K - A_{i,T}, 0)} - \kappa_i \ K \ 1_{A_{i,T} < K}$$

where $1_{A_{i,T} < K}$ is the indicator function for default, $A_{i,T} < K$. That is, the payoff to bond holders is K if there is no default, but it is $(1 - \kappa_i)A_{i,T}$ in case of default. Thus, the loss-given-default LGD (as a fraction of principal) is $LGD(\kappa_i) = \kappa_i \ A_{i,T}/K$.

A portfolio of options can approximate the payoff with bankruptcy costs. For example, for a pseudo firm purchasing the SPX index, the Technical Appendix shows that we can

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[23]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.

approximate the pseudo bond value by

$$\widehat{B}_t(T, K) = K\widehat{Z}_t(T) - (1 - \kappa_i)\widehat{P}_t^{SPX}(K, T) - \kappa_i \ K \ \frac{\widehat{P}_t^{SPX}(K, T) - \widehat{P}_t^{SPX}(K', T)}{K - K'} \qquad (8)$$

where K' is the closest strike price below the target strike price K.

For every t, we use historical data to compute κ_i on an *ex ante* basis to match loss-given-default reported by Moody's. We take into account business cycle variations in loss-given-default by computing different κ_i estimates depending on whether month t is during a boom or recession. The full methodology is laid out in Technical Appendix C.

Panels C and D of Table 2 show the results. First, Panel D shows that all of the *ex post* realized loss-given-default of pseudo firms are now similar to the corporate loss-given-default shown in the second column. Our *ex ante* methodology to compute bankruptcy costs thus works well. Second, Panel C shows that pseudo spreads are larger with than without bankruptcy costs (which is intuitive) and are somewhat larger than the credit spreads of real corporate bonds.

6.   Conclusions

In this paper we have introduced hypothetical "pseudo firms" whose assets and liabilities are fully observable and thus provide an ideal testing ground to analyze issues related to credit risk, ranging from the size of credit spreads on defaultable bonds to the impact of credit supply shocks on credit spreads. 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 SPX portfolio, individual firms' stocks, commodities, foreign currencies, and fixed income securities, – we study the empirical properties of pseudo bonds issued by such firms and the pseudo spreads on such bonds.

Our empirical results show that, like corporate bond spreads, pseudo spreads are large, countercyclical, and that higher pseudo spread values predict lower future economic growth. The data thus indicate a high degree of integration between corporate bond and options markets, and the existence of similar risk premia that investors require to bear the risk of tail events. We also find that over-prediction of default probabilities and market illiquidity are unlikely to be the main explanations for observed large credit spreads. Instead, we find

that idiosyncratic asset volatility positively impacts average spreads over and beyond their theoretical impact on default probabilities and loss-given-default.

Our option-based approach offers a novel model-free methodology to study credit risk in (almost) controlled environments with a large number of potential applications.[24] The environment is controlled because we can choose the characteristics of pseudo firms, including their capital structure, leverage, the type and riskiness of underlying assets, and so on. We can therefore empirically study the credit risk of such pseudo firms without worrying about endogenous capital structure, corporate frictions, and the like. Such corporate frictions can still be investigated even with pseudo firms, however, as they can be introduced exactly as they are introduced in any Merton-type model. For instance, in addition to bankruptcy costs as in Section 5.2., it is possible to add taxes and study optimal capital structure. But the investigation of such important additional applications necessitates another paper.

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[24]Some of these applications of pseudo firms are contained on the web site "Credit Risk Laboratory" available at `http://faculty.chicagobooth.edu/pietro.veronesi/research/Credit_Risk_Lab/`

Figure 1: Two SPX Pseudo Bonds
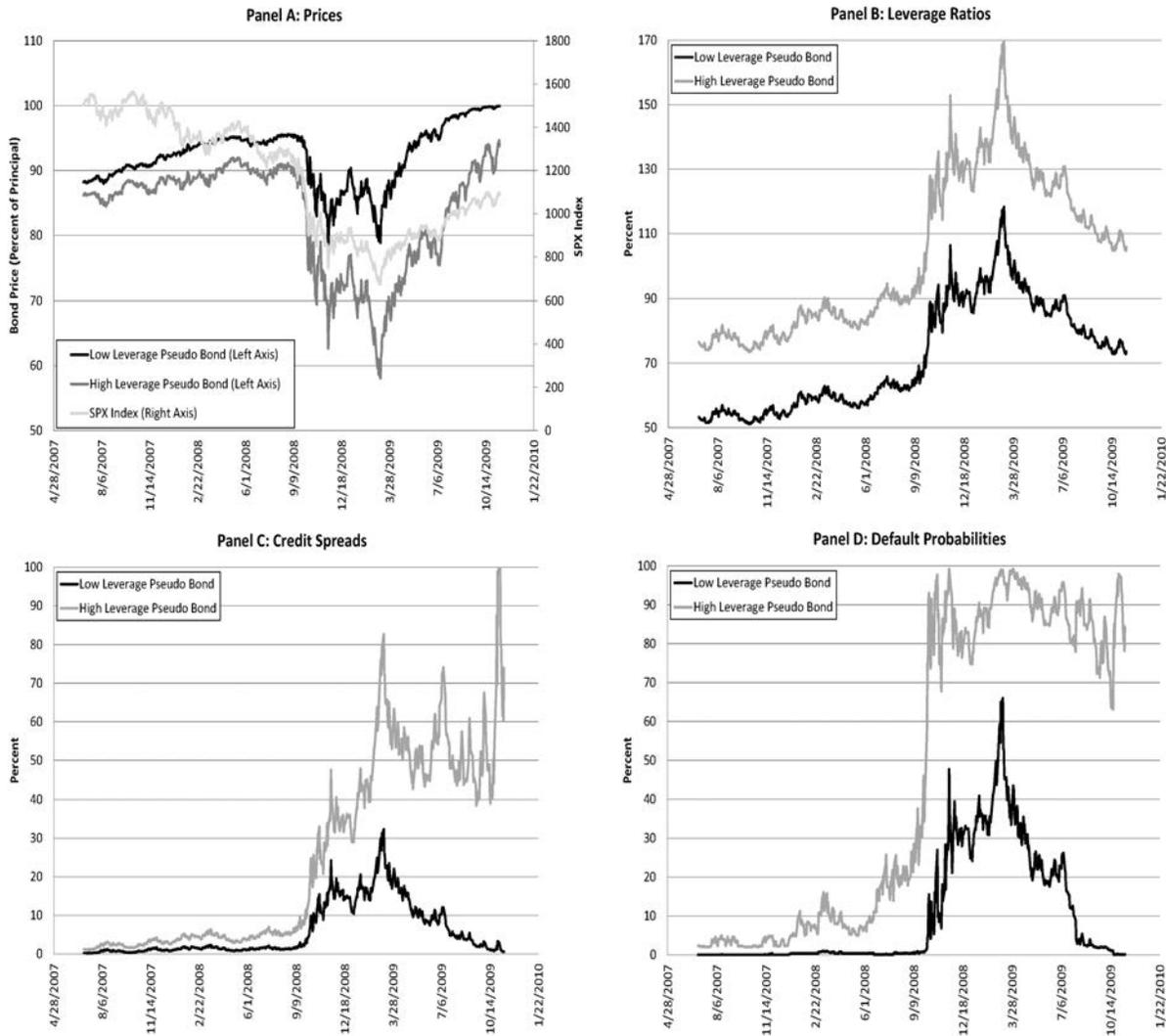
Notes: Panel A reports the no-arbitrage prices of two SPX pseudo bonds from June 2007 to November 2009 as percent of principal. The pseudo bonds are issued by two pseudo firms, one with low leverage (black line) and one with high leverage (dark grey line). The figure also reports the values of assets of both firms, namely, the SPX index (light grey line). Panel B reports the market leverage of the two pseudo firms $L_{i,s} = \widehat{B}_{i,t}/A_t$, in percentage terms. Panel C reports the implied credit spread of the two pseudo bonds in Panel A, while Panel D reports their *ex ante* default probabilities, computed from the historical empirical distribution of SPX returns.

Figure 2: Credit Spreads of Two-Year Pseudo Bonds
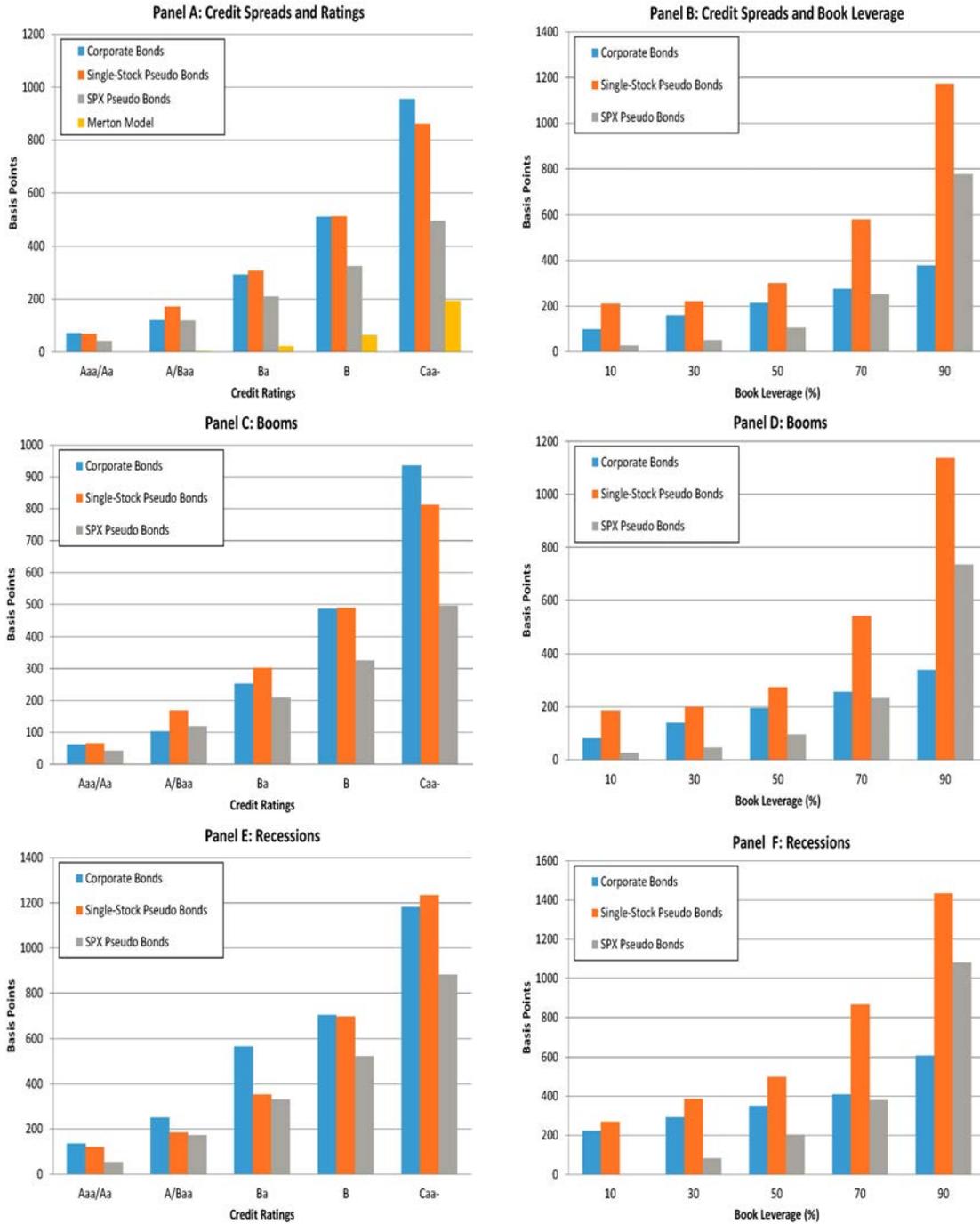
Notes: Credit spreads are shown for corporate bonds, single-stock pseudo bonds, SPX pseudo bonds, and implied by the lognormal Merton model (in Panel A). For corporate bonds, the credit ratings are from Moody's. For pseudo bonds, the credit ratings are imputed by comparing their *ex ante* default probabilities to Moody's default frequencies in booms and in recessions. For each pseudo bond, we compute its default probability from the empirical distribution of asset returns. For the Merton model, the default probability is obtained from its implied lognormal distribution. For corporate spreads, book leverage is defined as (book value of debt) / (book value of debt plus market equity). For pseudo bonds, book value of debt is defined as (face value of debt)/(face value of debt plus pseudo market equity), where market equity equals the value of a call option. The sample is 1990 – 2015 for SPX pseudo bonds and real corporate bonds, and 1996 – 2015 for single-stock pseudo bonds.

Figure 3: Credit Spreads of Two-Year Pseudo and Corporate Bonds Over Time
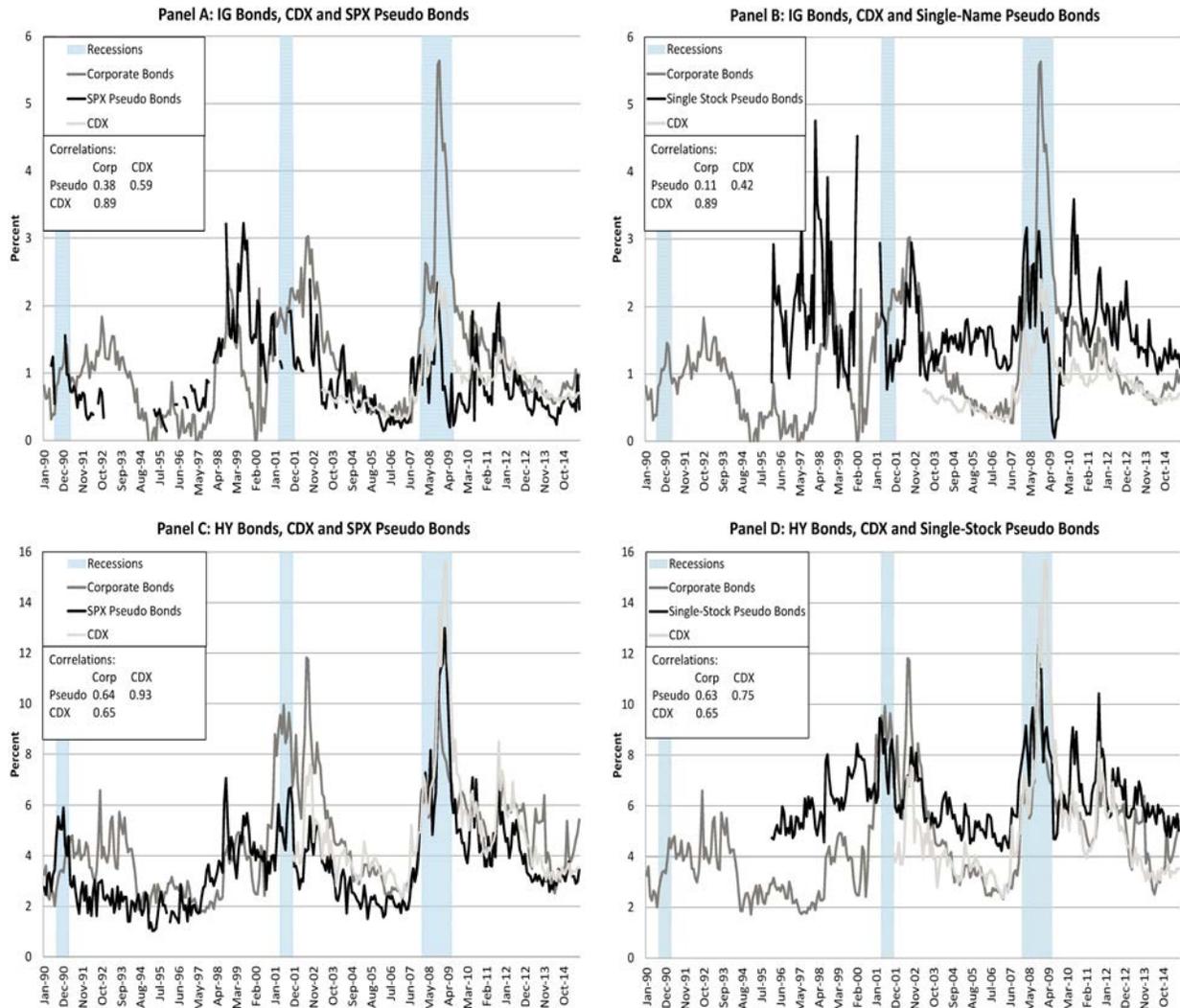
Notes: Credit spreads are shown for two-year pseudo and corporate bonds. Pseudo bonds are constructed from risk-free debt minus put options on individual stocks, or put options on SPX index. Investment Grade (IG) and High Yield (HY) pseudo credit ratings of pseudo bonds are assigned based on their *ex ante* default probabilities computed from the empirical distribution of asset returns. Corporate bond data 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 are from Markit. Shaded vertical bars denote NBER-dated recessions. The data frequency is monthly from January 1990 to July 2015 for corporate and SPX pseudo bonds, but the sample starts in January 1996 for single-stock pseudo bonds, in November 2001 for CDX.HY index, and in April 2003 for CDX.IG index.

Figure 4: *Ex Ante* Default Probabilities versus *Ex Post* Default Frequencies

Panel A. Single–Stock Pseudo Bonds

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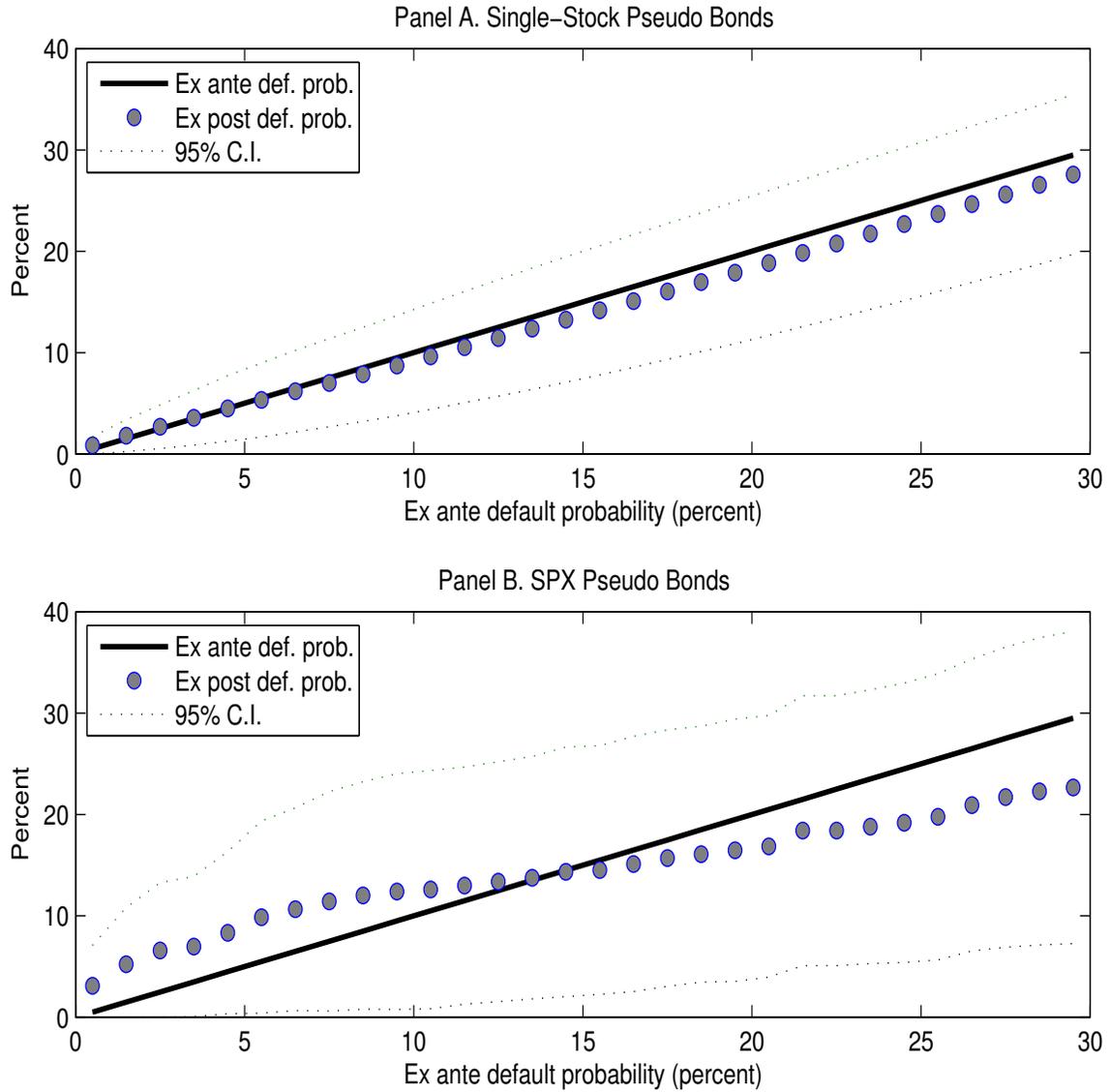
Notes: Panel A plots the estimated *ex post* default frequencies of pseudo bonds based on single-stock (circles) together with their 95% confidence intervals (dotted lines) against the 45 degree line, which represent the *ex ante* default probability for each of the pseudo bonds. The sample is 1970 to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

Figure 5: GZ versus Pseudo Spreads
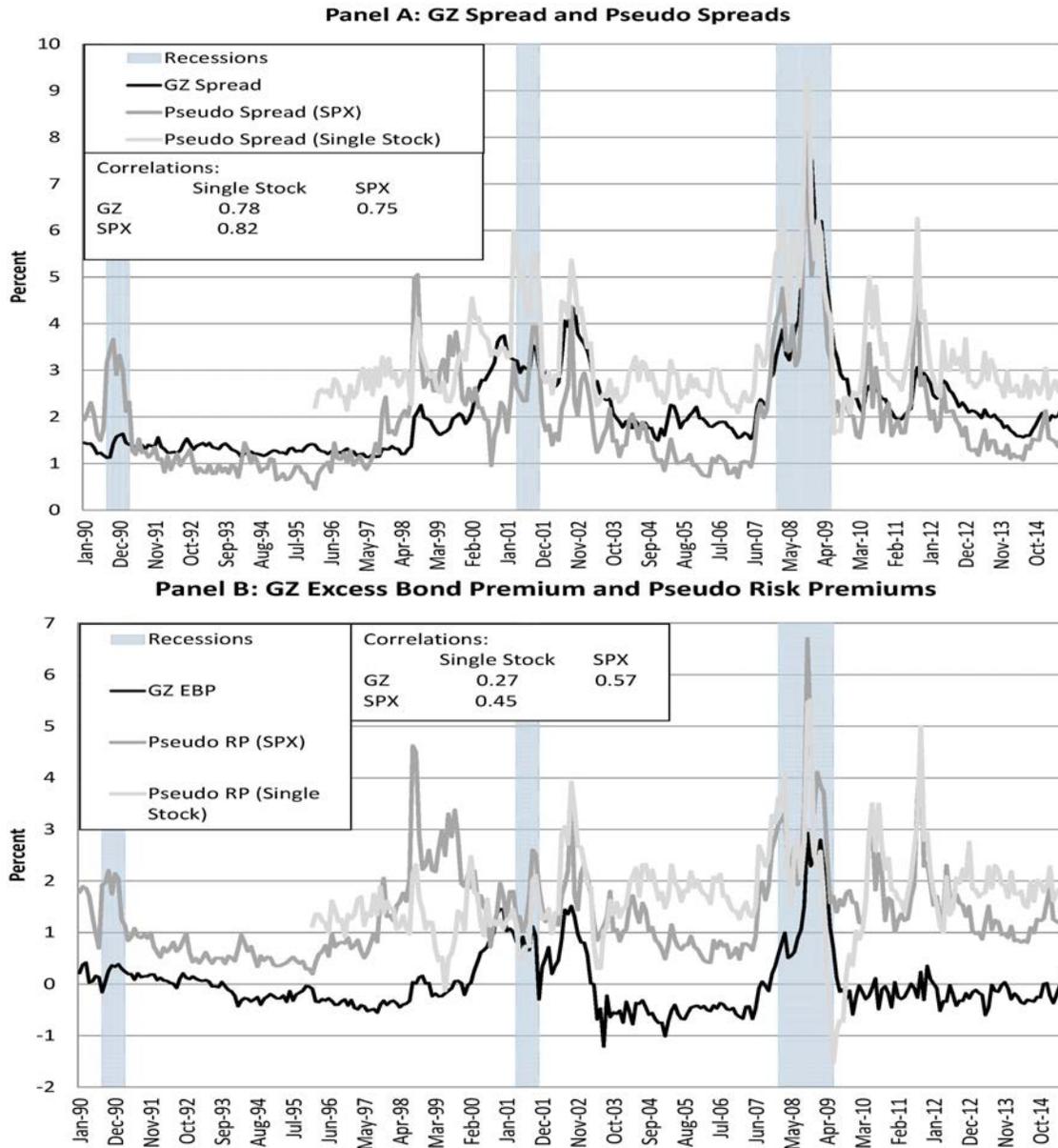
Notes: Panel A plots the time series of the GZ spread and the pseudo spread indices computed from single stocks or the SPX index. The GZ spread is from Gilchrist and Zakajreks (2012, updated series). Panel B plots the time series of GZ excess bond premium (EBP) and the pseudo bond risk premia. The GZ EBP equals the GZ spread minus the in-sample predicted spread. The pseudo risk premium equals the pseudo spread minus the "expected loss spread," an *ex ante* estimate of the actuarialy fair compensation for expected losses. The pseudo spread index and pseudo risk premium index are are computed as the equally weighted average of IG and HY pseudo bond spreads and pseudo risk premia for pseudo bonds with maturities of 6 months, 1 year, and 2 years (six series). The pseudo bonds' credit ratings are imputed by comparing their *ex ante* default probabilities to Moody's default frequencies in booms and in recessions. For each pseudo bond, we compute its default probability from the empirical distribution of asset returns. The sample is 1990 – 2015 for SPX pseudo bonds and real corporate bonds, and 1996 – 2015 for single-stock pseudo bonds.

Figure 6: The Comovement of Pseudo Spreads
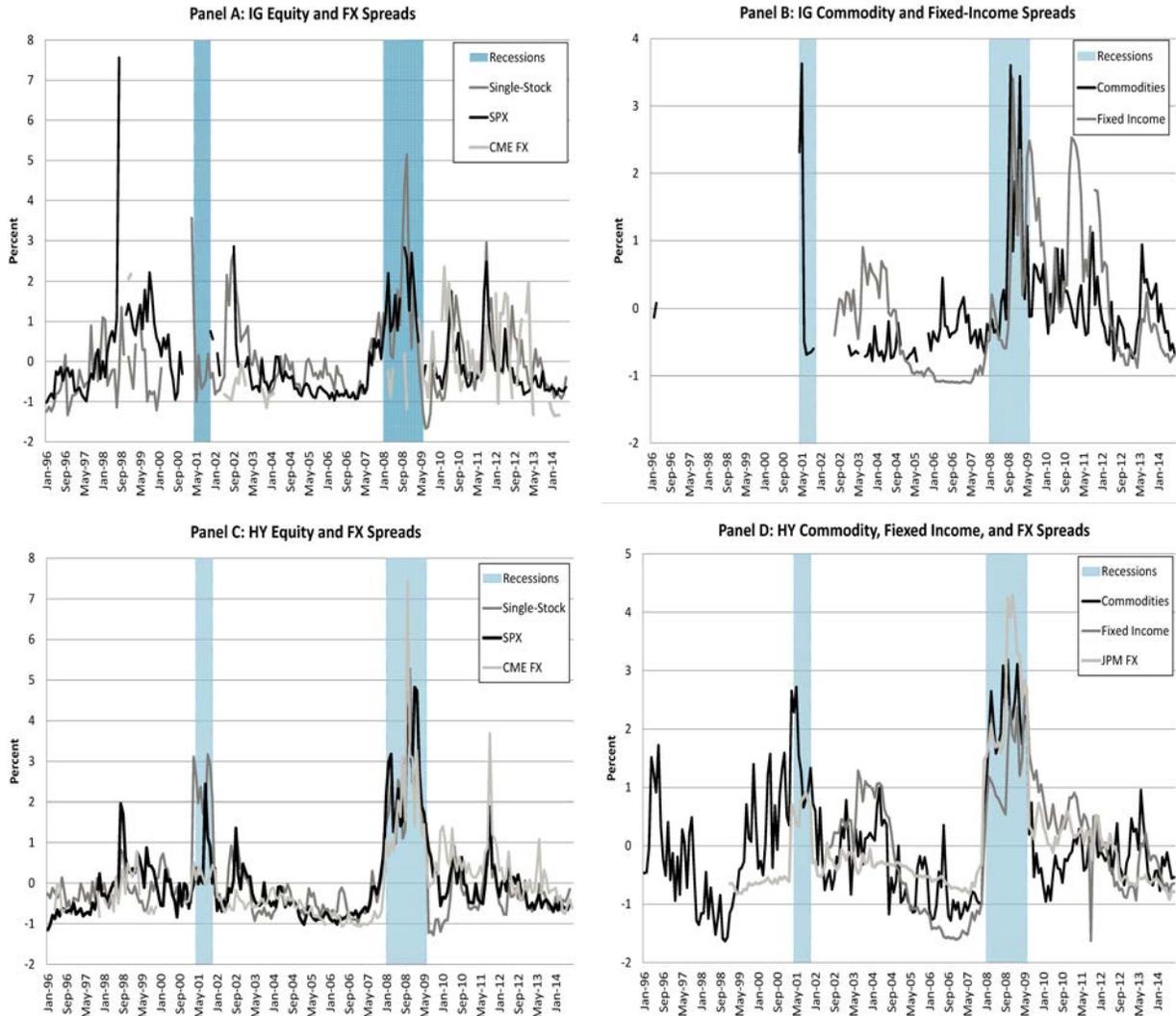
Notes: The four panels in this figure plot the standardized average credit spreads of pseudo firms with different types of assets and credit rating categories (IG and HY). The type of assets underlying the pseudo firms are the (i) the SPX index; (ii) single stocks; (iii) commodities; (iv) foreign exchange (CME dataset); (v) foreign exchange (JPM dataset); and (vi) fixed-income, through swaptions. 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 are shown 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 both callable and non-callable bonds, except for 30 and 91 days for which we use commercial paper. Callable bonds' spreads are adjusted for the option to call as in Gilchrist and Zakrajsek (2012). 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 Spreads (bps)					2-year Bonds			
						Credit Spreads (bps)		Iliquidity Measures	
Credit Rating	Days to Maturity					Boom	Recession	B/A (%)	Roll (%)
	30	91	183	365	730	Boom	Recession	B/A (%)	Roll (%)
Panel A. Single-Stock Pseudo Bonds (Jan 1996 – Jul 2015)									
IG		75	67	74	170	168	184	1.01	0.34
HY	392	340	436	577	632	601	865	1.44	0.50
Aaa/Aa			42	49	68	66	119	0.86	0.29
A/Baa			67	74	171	169	184	1.01	0.34
Ba	148	109	113	147	308	303	352	1.14	0.38
B	274	217	258	372	514	489	697	1.31	0.46
Caa-	447	425	570	800	862	812	1234	1.48	0.57
Panel B. SPX Pseudo Bonds (Jan 1990 – Jul 2015)									
IG	52	45	53	59	90	86	118	0.30	0.10
HY	226	250	285	294	362	319	675	0.34	0.16
Aaa/Aa			38	32	42	41	53	0.29	0.09
A/Baa			82	81	119	113	172	0.33	0.11
Ba	187	91	140	162	209	192	330	0.34	0.12
B	178	195	246	266	325	299	522	0.34	0.14
Caa-	398	394	401	426	496	442	881	0.33	0.18
Panel C. Corporate Bonds (Jan 1990 – Jul 2015)									
IG	61	60	103	107	115	98	237		1.10
HY			334	389	452	421	674		1.97
Aaa/Aa	29	27	47	57	71	62	135		0.85
A/Baa	65	64	112	119	121	103	250		1.18
Ba			226	252	293	253	566		1.77
B			418	469	512	486	703		2.15
Caa-			761	978	956	936	1181		3.15

Table 2: Types of Assets, Loss-Given-Default, and Bankruptcy Costs

Credit spreads and losses-given-defaults (LGD) are shown for corporate bonds and pseudo bonds. Pseudo bonds are constructed from a portfolio of risk-free debt minus put options on the SPX index (column "SPX"), individual stocks (column "Single Stocks"), individual stocks for underlying firms with negligible leverage (column "Low Leverage"), commodity futures (column "Commodities"), foreign currency (column "Currencies"), and swaptions (column "Fixed Income"). 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 LGDs are computed from the empirical distributions 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 have times to maturity between 1.5 and 2.5 years. LGDs for corporate bonds are from Moody's. Sample periods vary – *i.e.*, Corporate and SPX: 1/1990 to 7/2015; single stocks: 1/1996 to 7/2015; commodities: mid 1980s to 2/2015; Foreign currencies: 1/1999 to 12/2014; Swaptions: 7/2002 to 12/2014.

Credit Rating	Corporate	Single Stock	SPX	Un-levered Equity	Commodities	Currencies	Fixed Income
Panel A: Credit Spreads across Types of Assets (bps)							
Aaa/Aa	71	68	42	199	32	51	33
A/Baa	121	171	119	297	70	52	73
Ba	293	308	209	468	147	51	87
B	512	514	325	728	263	87	159
Caa-	956	862	496	1069	435	175	278
Panel B: Ex Post Loss-given-default(%)							
Aaa/Aa	61.0	49.6	10.2	49.6	10.9		
A/Baa	57.0	44.7	10.2	43.0	12.1		
Ba	59.0	32.0	14.9	31.4	15.5	3.6	1.3
B	56.0	27.3	15.1	27.4	17.0	5.5	2.4
Caa-	63.0	25.0	18.0	25.1	15.4	8.0	4.0
Panel C: Credit Spreads with Bankruptcy Costs (bps)							
Aaa/Aa	71		66	228	121		238
A/Baa	121	486	216	698	207		436
Ba	293	845	400	1036	396	544	627
B	512	1149	668	1456	942	641	1085
Caa-	956	1727	1121	1984	1513	953	1789
Panel D: Ex Post Loss-given-default with Bankruptcy Costs (%)							
Aaa/Aa	61.0	69.2	64.4	67.6			
A/Baa	57.0	57.8	60.1	52.8	59.5		
Ba	59.0	58.7	60.8	56.3	59.0	58.8	58.8
B	56.0	54.0	58.1	52.0	55.8	56.1	55.4
Caa-	63.0	60.3	65.6	58.7	62.3	63.2	62.5

Table 3: Idiosyncratic Asset Volatility and Credit Spreads

This table shows the impact of idiosyncratic asset volatility on pseudo spreads. For each time t, we first sort pseudo bonds according to their pseudo credit rating, and then according to the idiosyncratic volatility of pseudo-firm assets (individual stocks). Idiosyncratic volatility is computed from the residuals of a market model regression. Panel A reports the average credit spreads for each credit rating/volatility bin, while Panels B and C report the average leverage K/A and the average loss given default (LGD) for each credit rating/volatility combination, respectively. The LGD for each pseudo bond is computed on an *ex ante* basis from the empirical distribution of asset returns. The sample is January 1996 to July 2015.

Credit Rating	A. Average Credit Spread			B. Average K/S			C. Loss Given Default		
	Idiosyncratic Volatility			Idiosyncratic Volatility			Idiosyncratic Volatility		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Aaa/Aa	85	57	63	0.51	0.44	0.37	0.35	0.32	0.32
A/Baa	135	188	205	0.53	0.54	0.49	0.40	0.44	0.49
Ba	233	306	395	0.65	0.63	0.59	0.28	0.32	0.38
B	436	497	610	0.80	0.76	0.71	0.25	0.30	0.36
Caa-	798	836	946	0.97	0.93	0.87	0.25	0.29	0.36

This table reports the results of the following predictive regression:

$$\Delta_h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \gamma_1 \text{ Pseudo Spread}_t + \gamma_2 \text{ GZ Spread}_t + Controls_t + \varepsilon_{t+h}$$

where Δ_h is the "h-period" lag operator, Pseudo Spread$_t$ is the option-based pseudo spread index, GZ Spread$_t$ is Gilchrist Zakrajsek (2012) spread, or its orthogonal component to the Pseudo Spread$_t$ when the latter is in the same regression, and "Controls" include the term spread, the real Federal Funds rate, and the option-implied "fear gauge" VIX. The number of lags p is determined by the Akaike Information Criterion. The pseudo spread is computed separately for SPX pseudo bonds and single-stock pseudo bonds, and for each case reflects the equally weighted average of HY and IG spreads with 6-months, 1-year, and 2-year maturities (6 series). The prediction horizon is either $h = 3$ months or $h = 12$ months. The predicted economic variables are in the title of each panel. Frequency is monthly except for Panel D, where it is quarterly. All regression coefficients are multiplied by 100. Hodrick-adjusted t-statistics are in parenthesis.

Panel A: Single Stocks Pseudo Spreads (January 1996 to June 2015)

A1: Payroll Growth

	h = 3 months						h= 12 months					
Pseudo Spread	-0.18		-0.22	-0.19		-0.28	-0.78		-0.91	-1.11		-1.51
t-stat	(-3.05)		(-2.91)	(-3.13)		(-3.47)	(-4.32)		(-4.87)	(-4.32)		(-5.28)
GZ Spread		-0.28	-0.19		-0.33	-0.24		-1.11	-0.57		-1.66	-1.05
t-stat		(-2.79)	(-1.71)		(-3.33)	(-2.26)		(-5.06)	(-3.20)		(-5.80)	(-5.27)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.80	0.82	0.83	0.81	0.83	0.84	0.64	0.63	0.66	0.71	0.70	0.77

A2: Unemployment Rate Change

	h = 3 months						h= 12 months					
Pseudo Spread	13.26		15.36	14.41		21.29	51.38		52.94	75.48		97.03
t-stat	(2.70)		(2.73)	(2.74)		(3.45)	(3.97)		(3.95)	(3.97)		(4.58)
GZ Spread		17.81	11.58		24.78	20.11		51.14	8.85		98.06	61.30
t-stat		(2.64)	(1.66)		(3.62)	(2.81)		(3.62)	(0.60)		(4.85)	(3.62)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.50	0.51	0.53	0.51	0.57	0.58	0.46	0.37	0.46	0.60	0.59	0.67

A3: Industrial Production Growth

	h = 3 months						h= 12 months					
Pseudo Spread	-0.76		-0.89	-0.99		-1.37	-2.59		-2.61	-4.40		-5.48
t-stat	(-3.62)		(-3.68)	(-3.70)		(-4.53)	(-3.78)		(-3.95)	(-3.98)		(-4.55)
GZ Spread		-0.97	-0.52		-1.29	-0.85		-2.10	-0.10		-4.25	-2.34
t-stat		(-3.44)	(-1.72)		(-4.49)	(-3.03)		(-3.58)	(-0.15)		(-4.65)	(-3.11)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.55	0.54	0.58	0.59	0.57	0.64	0.30	0.19	0.29	0.45	0.30	0.49

A4: GDP Growth

	h = 3 months						h= 12 months					
Pseudo Spread	-0.21		-0.22	-0.44		-0.54	-0.52		-0.48	-1.38		-1.63
t-stat	(-1.86)		(-2.08)	(-2.13)		(-2.62)	(-2.07)		(-2.01)	(-3.26)		(-3.45)
GZ Spread		-0.16	-0.02		-0.39	-0.20		-0.28	0.17		-1.14	-0.54
t-stat		(-1.89)	(-0.12)		(-2.68)	(-1.31)		(-1.19)	(0.46)		(-2.88)	(-1.39)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.20	0.16	0.18	0.29	0.22	0.31	0.14	0.10	0.13	0.35	0.24	0.36

Table 4: (cntd.) Pseudo Spreads and Future Economic Growth

Panel B: SPX Pseudo Spreads (January 1990 to June 2015)

B1: Payroll Growth

	h = 3 months						h = 12 months					
Pseudo Spread	-0.12		-0.14	-0.16		-0.25	-0.56		-0.67	-0.99		-1.48
t-stat	(-2.82)		(-2.66)	(-2.49)		(-3.11)	(-3.94)		(-4.13)	(-3.11)		(-3.73)
GZ Spread		-0.16	-0.11		-0.17	-0.16		-0.77	-0.54		-1.02	-0.91
t-stat		(-2.24)	(-1.49)		(-2.18)	(-1.96)		(-4.10)	(-3.09)		(-4.10)	(-3.96)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.74	0.75	0.76	0.75	0.76	0.78	0.54	0.56	0.57	0.61	0.63	0.68

B2: Unemployment Rate Change

	h = 3 months						h = 12 months					
Pseudo Spread	9.71		10.59	12.97		21.10	34.32		36.32	72.65		106.34
t-stat	(2.51)		(2.48)	(2.26)		(2.96)	(3.14)		(3.11)	(3.06)		(3.67)
GZ Spread		11.24	7.36		16.00	14.79		34.58	17.44		68.97	61.77
t-stat		(2.18)	(1.45)		(2.71)	(2.54)		(2.67)	(1.36)		(3.77)	(3.58)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.42	0.42	0.44	0.44	0.47	0.50	0.33	0.32	0.34	0.48	0.51	0.59

B3: Industrial Production Growth

	h = 3 months						h = 12 months					
Pseudo Spread	-0.52		-0.62	-0.84		-1.37	-1.62		-1.84	-4.33		-6.23
t-stat	(-3.28)		(-3.43)	(-2.62)		(-3.55)	(-3.09)		(-3.33)	(-3.00)		(-3.49)
GZ Spread		-0.70	-0.51		-0.82	-0.79		-2.00	-1.34		-3.14	-2.97
t-stat		(-3.23)	(-2.25)		(-3.27)	(-3.20)		(-3.53)	(-2.41)		(-3.70)	(-3.63)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.39	0.42	0.43	0.42	0.43	0.48	0.18	0.19	0.21	0.31	0.27	0.41

B4: GDP Growth

	h = 3 months						h = 12 months					
Pseudo Spread	-0.10		-0.12	-0.39		-0.52	-0.38		-0.41	-1.66		-2.11
t-stat	(-1.23)		(-1.44)	(-1.20)		(-1.48)	(-1.60)		(-1.84)	(-2.41)		(-2.75)
GZ Spread		-0.13	-0.10		-0.23	-0.21		-0.44	-0.30		-0.79	-0.69
t-stat		(-1.93)	(-1.01)		(-1.94)	(-1.87)		(-2.32)	(-1.09)		(-2.26)	(-2.03)
Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
R^2	0.13	0.13	0.13	0.17	0.14	0.19	0.09	0.10	0.09	0.29	0.19	0.32

Table 5: Pseudo Bond Expected Losses and Risk Premia

This table reports the results of the following predictive regression:

$$\Delta_h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \gamma_1 \text{Expected Loss Spread}_t + \gamma_2 \text{ Risk Premium}_t + Controls_t + \varepsilon_{t+h}$$

where Δ_h is the "h-period" lag operator, Expected Loss Spread$_t$ is the index of actuarially fair, non-risk adjusted pseudo spread to compensate for the expected losses of pseudo bonds, and Pseudo Risk Premium$_t$ is the residual risk premium of individual pseudo bonds, given by Risk Premium$_{it}$ = Pseudo Credit Spread$_{it}$ − Expected Loss Spread$_{it}$. "Controls" include the term spread, the real Federal Funds rate, and the option-implied "fear gauge" VIX. The number of lags p is determined by the Akaike Information Criterion. The Expected Loss Spread$_{it}$ (Pseudo Risk Premium$_{it}$) is computed separately for single-stock pseudo bonds (Panel A) and SPX pseudo bonds (Panel B), and for each case, it equals the equally weighted average of HY and IG pseudo bonds with 6-months, 1-year, and 2-year maturities (6 series). ΔR^2 is the increment in the (adjusted) R^2 from including the Risk Premium$_t$ in the regression. The prediction horizon is either $h = 3$ month or $h = 12$ months. The predicted economic variables are payroll growth (PAY), unemployment rate changes (UNEMP), industrial production growth (IPG), and real GDP growth (GDP). Frequency is monthly except for GDP growth, where it is quarterly. All regression coefficients are multiplied by 100. Hodrick-adjusted t-statistics are in parenthesis. The sample is January 1990 to June 2015 for SPX pseudo spreads, and January 1996 to June 2015 for single stocks pseudo spreads.

Panel A: Single Stocks (January 1996 - June 2015)

	h = 3 months				h = 12 months			
	PAY	UNEMP	IPG	GDP	PAY	UNEMP	IPG	GDP
Expected Loss Spread	-0.23	19.31	-1.02	-0.47	-1.10	78.39	-3.97	-1.41
t-stat	(-3.08)	(2.99)	(-2.89)	(-2.14)	(-4.40)	(4.06)	(-3.78)	(-3.85)
Pseudo Risk Premium	-0.18	11.74	-0.98	-0.43	-1.11	73.95	-4.54	-1.37
t-stat	(-2.70)	(2.07)	(-3.63)	(-2.03)	(-4.05)	(3.50)	(-3.92)	(-2.86)
R^2	0.81	0.52	0.59	0.29	0.71	0.60	0.45	0.34
ΔR^2	0.05	0.05	0.13	0.15	0.18	0.20	0.31	0.18

Panel B: SPX (January 1990 - June 2015)

	h = 3 months				h = 12 months			
	PAY	UNEMP	IPG	GDP	PAY	UNEMP	IPG	GDP
Expected Loss Spread	-0.50	46.07	-1.69	-0.56	-1.46	134.82	-4.02	-1.45
t-stat	(-3.50)	(3.64)	(-2.63)	(-1.49)	(-3.16)	(3.94)	(-2.39)	(-2.49)
Pseudo Risk Premium	-0.06	2.03	-0.62	-0.33	-0.82	51.86	-4.42	-1.73
t-stat	(-0.86)	(0.33)	(-1.89)	(-0.97)	(-2.55)	(2.10)	(-2.98)	(-2.10)
R^2	0.77	0.51	0.43	0.17	0.61	0.51	0.31	0.28
ΔR^2	0.00	0.00	0.02	0.03	0.04	0.04	0.13	0.12

Table 6: Pseudo Spreads and Future Economic Growth

This table reports the results of the following predictive regression:

$$\Delta_h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \gamma_1 \text{ SPX Spread}_t + \gamma_2 \text{ Spread Difference}_t + Controls_t + \varepsilon_{t+h}$$

where Δ_h is the "h-period" lag operator, the "Spread Difference" is either the difference in pseudo spreads between single-stock and SPX indices (Panel A) or the difference in the risk-premium component of these pseudo spreads (Panel B). "Controls" include the term spread, the real Federal Funds rate, and the option-implied "fear gauge" VIX. The number of lags p is determined by the Akaike Information Criterion. The pseudo spread is computed separately for SPX pseudo bonds and single-stock pseudo bonds, and for each case reflects the equally weighted average of HY and IG spreads with 6-months, 1-year, and 2-year maturities (6 series). The risk premium component of a pseudo spread is the difference between the pseudo spread and spread as compensation of expected losses, the latter computed as default probability times the loss-given default. The risk premium index is then computed as the equally weighted average of HY and IG risk premia with 6-months, 1-year, and 2-year maturities (6 series). The prediction horizon is either $h = 3$ months or $h = 12$ months. The predicted economic variables are payroll growth (PAY), unemployment rate changes (UNEMP), industrial production growth (IPG), and real GDP growth (GDP). ΔR^2 is the increment in the (adjusted) R^2 from including the Spread Difference$_t$ in the regression. Frequency is monthly except for Panel D, where it is quarterly. All regression coefficients are multiplied by 100. Hodrick-adjusted t-statistics are in parenthesis. The sample is January 1996 to June 2015.

Panel A: Pseudo Spread Difference

	h = 3 months				h= 12 months			
	PAY	UNEMP	IPG	GDP	PAY	UNEMP	IPG	GDP
SPX Spread	-0.21	18.11	-1.08	-0.53	-1.33	97.91	-5.98	-2.09
t-stat	(-2.64)	(2.55)	(-2.71)	(-1.41)	(-3.36)	(3.30)	(-3.18)	(-2.71)
Pseudo Spread Difference	-0.19	12.57	-0.95	-0.40	-0.99	64.27	-3.73	-0.99
t-stat	(-2.85)	(2.42)	(-3.69)	(-2.37)	(-4.74)	(4.06)	(-4.34)	(-2.52)
R^2	0.81	0.52	0.59	0.29	0.72	0.62	0.48	0.40
ΔR^2	0.06	0.05	0.12	0.10	0.13	0.14	0.19	0.07

Panel B: Pseudo Risk Premium Difference

	PAY	UNEMP	IPG	GDP	PAY	UNEMP	IPG	GDP
SPX Spread	-0.21	18.07	-1.04	-0.51	-1.38	100.98	-5.99	-2.07
t-stat	(-2.58)	(2.42)	(-2.71)	(-1.28)	(-3.24)	(3.17)	(-3.08)	(-2.40)
Pseudo Risk Premium Difference	-0.12	8.00	-0.64	-0.22	-0.69	46.92	-2.69	-0.59
t-stat	(-2.25)	(1.78)	(-3.10)	(-1.57)	(-3.67)	(3.05)	(-3.51)	(-1.57)
R^2	0.78	0.49	0.54	0.23	0.67	0.57	0.44	0.37
ΔR^2	0.03	0.03	0.06	0.04	0.08	0.09	0.14	0.04

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