

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, the 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, corporate frictions, and constraints on aggregate credit supply 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.

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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 another set of 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 is:

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

¹The basic insight that corporate debt can be viewed as risk-free debt plus a short put option is due to Merton (1974). We distinguish between this Merton *insight* – which requires no assumptions about the distribution 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.

²SPXSM 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 $\hat{Z}_t(T)$ is the risk-free discount factor at time t corresponding to maturity T , and $\hat{P}_t^{SPX}(K, T)$ is the value of an SPX put option at t with strike price K and maturity T . We denote these quantities with “hats” to indicate that their prices are observable from Treasuries and traded option prices, which comprise the “observed” value of the liabilities of the pseudo firm, $\hat{B}_t(K, T)$. Although the pseudo firm is fictitious, we can nonetheless observe both the value of assets and the value of its debt from traded securities and thus we have a fully observable balance sheet.

To illustrate, Panel A of Figure 1 plots the time series of two pseudo bond prices $\hat{B}_t(K_i, T)$ 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 levels 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 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-leveraged pseudo firm would have lost 5% of principal value.

Panel C plots the time series of credit spreads implied by the two pseudo bonds prices $\hat{B}_t(K_i, T)$ and Treasuries. Their dynamics highlight the variations in credit spreads during the financial crisis, a topic further discussed in the paper. 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 to shocks in asset values resulting from leverage.

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

\mathcal{F}_t is the information set at t . Panel D of Figure 1 plots these default probabilities for the two pseudo firms discussed earlier. 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 in our quest 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 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.³ 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

³We 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 be 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.⁴ 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 of the size 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 shaped the credit spreads around the business cycles, especially during the 2008 - 2009 financial crisis. In particular, we follow Gilchrist and Zakrajsek (2012)

⁴The 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.

in their analysis of corporate credit spreads (the “GZ spread”) and show that our index of pseudo credit spreads (*i.e.* the “CNV spread”) strongly covaries with the business cycle and that higher spreads strongly predict lower future economic growth. Again following Gilchrist and Zakrajsek (2012), we further show that the “excess bond premium” (EBP), measured as the difference between pseudo credit spreads and spreads implied by the lognormal Merton model, also predicts lower future economic growth, especially for long time horizons. Impulse response functions from the SPX-based CNV EBP, moreover, indicate that a positive shock to EBP is followed by lower future consumption and GDP growth and lower real investments.

Our results are broadly consistent with the findings of Gilchrist and Zakrajsek (2012) for corporate credit spreads, but suggest a different interpretation. Namely, the ability of the pseudo EBP to predict future growth negatively calls into question the interpretation of the same result by GZ for their EBP as evidence that credit supply shocks are causally responsible for contractions in future economic activity. Indeed, because options are cleared through highly rated central counterparties and their prices are less likely to be directly affected by credit supply contractions, our results suggest that the predictability of future economic growth may be due to reverse causality, as suggested in Philippon (2009). In other words, as the economy deteriorates, credit spreads increase in anticipation of bad economic outcomes. We offer additional supporting evidence for this interpretation of the data in the body of the paper. Overall, our empirical results suggest an alternate view to the one that excessive credit supply makes credit markets “frothy” in good times and hence sews the seeds for future crises, which are amplified by credit contractions (*e.g.* Krishnamurthy and Muir (2016)). Instead, variations in the insurance premium agents require to hold securities with large tail risk is consistent with the evidence from both credit spreads and options.

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 a strong comovement 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. The approaches of all of these papers, however, are very different from ours, as we do not use any parametric model, but instead go straight to the data and analyze the credit spreads of our pseudo firms through traded options.

A small number of papers 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 frictionless 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.⁵

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 numerous extensions.

⁵Our paper is also related to the literature that compares corporate bonds to "synthetic" corporate bonds, as given by risk free bonds plus credit default swaps (*e.g.* Duffie (1999), Longstaff, Mithal and Neis (2005)). Such synthetic bonds, however, do not facilitate the same kind of analysis that we undertake here.

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 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 finally 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 CDS spreads from Markit. We use price/spread data on both the U.S. 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 $\hat{p}_{i,t}(\tau) = Pr[A_\tau < K_i | \mathcal{F}_t]$. 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); and
- (iv) We utilize the historical shock distributions to estimate probabilities of default $\hat{p}_{i,t}(\tau) = Pr[A_{t+\tau} < K_i | \mathcal{F}_t] = Pr[\varepsilon_\tau < X_i | \mathcal{F}_t]$ (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 $\hat{p}_{i,t}(\tau)$ with historical average default frequencies across credit rating bins estimated from Moody’s historical bond default dataset to reflect booms and recessions and horizons τ .⁶

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.⁷ Moreover, corporate bond quotes are unreliable at short maturities and we thus rely on 30- and 91-day commercial paper, which is 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

⁶We rely solely on the methodology described herein – and not rating agency criteria – for this exercise.

⁷For 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.

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 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 compares 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 0.74% 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 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, 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 despite claims to the contrary. 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 four indices (*i.e.*, two pseudo bonds, actual corporate bonds, and the CDX indices) 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 assets of 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 (LGD) 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 LGD (in Panels C and D). We discuss these results more precisely in Section 5.1.

Second, Panel B of Table 2 shows that the LGDs 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 credit default swap (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.⁸ 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 sound and robust.

⁸We 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.

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 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 LGDs of pseudo bonds are smaller than LGDs 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) “bid-ask bounce” as a measure of market liquidity. The Roll measure reflects the degree to which bid and ask prices bounce up and down, with the logic being that large reversals indicate relatively less market liquidity and higher sensitivities of bid and offer prices to large orders. To quantify the bid-ask bounce, the Roll measure uses the negative autocovariance of log price changes.

Specifically, the market illiquidity measure for pseudo bond i in month t is

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

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 ob-

servations in a month.⁹ We calculate the portfolio-level Roll measure as the kernel-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

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

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. 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.¹⁰

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 data from 1970 to 2014.¹¹

⁹This formula slightly differs from Roll (1984) (unlike equation (3), in which we use Roll’s exact formulation.) 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).

¹⁰Panel 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.

¹¹We 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

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.¹² Nevertheless, the overall evidence shows that our *ex ante* default probabilities are not too high 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. The novelty of our approach is to document 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.¹³

each probability p on the x -axis of Figure 4 we back out the threshold $K_{i,t}$ so that the *ex ante* probability $\hat{p}_{i,t}(\tau) = p$. 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.

¹²Intuitively, 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.

¹³Out-of-the-money equity put options became especially expensive after the October 1987 market crash. 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.

What types of risks are implicit in corporate credit spreads? 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, the convexity of the max function implies:

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

Thus, for 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 probabilities of the SPX bond may be lower than the average default probability of single-stock pseudo bonds, and hence 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.

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 LGD, and the risk premium.¹⁴ 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 values from the standard deviation of the residuals from the basic market model. 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.

¹⁴For instance, Chen et al. (2009) show that within a lognormal Merton model, modified to have a given LGD in case of default (as opposed to $K - A_{i,t+\tau}$), it is possible to write the credit spread as

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

where $N(\cdot)$ 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.

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 LGDs, where the latter are computed as the realized average losses $(K_{i,t} - A_{i,T})/K_{i,t}$ conditional on default at T (*i.e.* $A_{i,T} < K_{i,t}$). Given the result in Panel B, higher idiosyncratic volatility is correlated with a fatter left-tail of the asset distribution, which in turn increases the LGD for a given default probability.

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

$$\widehat{PCS}_{i,t} = 0.109 + 0.532 \widehat{p}_{i,t} + 0.007 \widehat{LGD}_{it} + 0.045 \log(\text{IdioVol}_{it}) + \varepsilon_{i,t}$$

(2.97) (10.92) (0.13) (3.89)

where $\widehat{PCS}_{i,t}$ 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* LGD, 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* LGD, 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 idiosyncratic risk impacts spreads over and beyond how they impact default probabilities and LGDs. 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, $R_t = \text{Average IdioVol}_t / \text{Average TotalVol}_t$, as shown in the following time-series regression:

$$\text{Single-Stock Average HY } \widehat{PCS}_t = 0.71 + 0.65 \text{ SPX Average HY } \widehat{PCS}_t + 0.04 R_t + \varepsilon_t$$

(0.54) (9.70) (2.40)

In other words, the average credit spread of the HY pseudo-bond portfolio is strongly dependent on the HY SPX pseudo spread, 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 spreads between the portfolio and the SPX onto the ratio 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 but the difference between the two dropped, highlighting that the dramatic increases in credit spreads during the crisis was 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. Credit Spreads, Economic Growth, and Credit Supply Shocks

We now exploit our pseudo bonds to discuss and shed further light on recent findings in the empirical macro-finance literature about the impact of credit supply shocks on 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. A measure of the excess bond premium (EBP), computed as the difference between the GZ spread and a predicted spread, also contains important and independent information

about future economic growth. GZ’s interpretation of their results is that EBPs are measures of credit constraints on financial intermediaries, and conclude that the predictive power of their GZ spread on future economic growth is evidence of the causal impact of credit constraints on growth. Similarly, Krishnamurthy and Muir (2016) show that credit spreads are especially low *before* financial crisis, which they interpret as evidence of “excessive credit supply.” They contend that excessive credit supply spurs too much lending, which increases the fragility of the financial system and exacerbates the impacts of financial crises.

In contrast to real firms, our pseudo firms are not directly affected by credit supply and do not take on leverage to finance risky investments. The credit spreads of our pseudo firms thus are attributable only to *ex ante* expected losses and the risk premia embedded in put options. Yet, we now show that our pseudo credit spreads predict future economic growth as well as the GZ spreads.

4.1. Pseudo Credit Spreads and Future Economic Growth

To compare our results to GZ spreads and excess bond premiums, we use our previous results to build a simple pseudo spread index, that, as noted earlier, we call the CNV spread. We calculate this spread index as the equally weighted average of IG and HY spreads in Table 1 for pseudo bond maturities of 180, 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. We construct this index both for SPX and single-stock pseudo bonds.

Panel A of Figure 5 plots the time series of the GZ spread as compared to CNV SPX and CNV single-stock spreads. 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. The high correlation between pseudo spreads and GZ spreads may already highlight that the variation in credit spreads may be largely attributable to genuine variations in risk premia and expected losses rather than the result of a contraction in credit supply.

Following GZ, we run the following predictive regression

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

where Δ_h is the “ h -period” lag operator, and the number of lags p is determined by the

Akaike Information Criterion. CNV CS_t is our CNV credit spread and GZ CS_t is the GZ credit spread. 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 but rather tail risk.

Table 4 shows that, like the GZ spread, a high CNV spread predicts lower future growth, especially at the 12-month horizon. In particular, the CNV spread is significant across all specifications with no controls (besides lags) for payroll growth (Panel A), unemployment changes (Panel B), and industrial production growth (Panel C). 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.) Adding GZ spreads increases the R^2 of the regression, and both the GZ and CNV spreads are mostly significant across all specifications. On a few occasions, the CNV spread loses statistical significance, and in fewer still instances the GZ spread is not significant.

Overall, the evidence in Table 4 shows that both the GZ and CNV spreads are significant predictors of business cycle variation and future economic activity. Tables A10 and A11 in the Technical Appendix, moreover, show that these results are not due to the special economic environment around the 2008 - 2009 financial crisis, but they also hold in subsamples – especially the subsample ending in June 2005 before the financial crisis.

4.2. Excess Pseudo Bond Premiums

In order to further our understanding of the impact of credit supply shocks and credit spreads on future economic growth, we compute the analog of the GZ excess bond premium from our option prices. GZ measures a form of “mispricing” embedded into credit spreads that may be a proxy for credit constraints. For each firm i and month t , GZ exploit the lognormal Merton model to compute a predicted GZ spread $\widehat{GZ} SP_{it}$ by regressing (over the whole sample) firm-specific credit spreads onto Merton’s (1974) “Distance to Default” measure and several other firm characteristics. The EBP for each firm is the size of the fitted residual from the panel regression $GZ EBP_{it} = GZ SP_{it} - \widehat{GZ} SP_{it}$, and the index is the average of EBSs across firms. We note that because the methodology uses the full sample, the GZ EBP is in-sample and thus is affected by a forward-looking bias – *i.e.*, the GZ EBP cannot be used for *ex ante* predictions of economic growth, but rather is only useful for inferences

about potential sources of excess credit spreads.

The simplicity of our pseudo-bond approach enables us to compute a CNV EBP in the same spirit as GZ, but from a clean *ex ante* perspective. Indeed, because our pseudo bonds are simple securities with explicitly defined maturities and payoffs, we can calculate simple and unbiased EBPs by substituting traded put option values into the computation of pseudo bond values for put option values computed from the Black, Scholes, and Merton formula – *i.e.*, we compute:

$$\text{CNV EBP}_{i,t} = \widehat{PCS}_{it} - \widehat{PCS}_{it}^{\text{Merton}} \quad (5)$$

where \widehat{PCS}_{it} and $\widehat{PCS}_{it}^{\text{Merton}}$ are the pseudo credit spreads computed from the pseudo bond as in equation (1) using either traded put options (*e.g.*, $P_t^{\text{SPX}}(K, T)$) and the corresponding Black, Scholes, Merton theoretical value, respectively. The Black, Scholes, and Merton formula uses predicted volatilities that we also use to compute *ex ante* default probabilities, and thus is consistent with our previous computations of pseudo credit spreads. As for the pseudo spreads discussed in the previous section, we construct an equally weighted index as the average of the six indices that we can compute across the two credit qualities (IG and HY) and the three maturities (180, 365, and 730 days).

Table 5 shows the results of the same predictive regressions as in Table 4, except that, as in GZ, we now decompose the CNV spread into CNV EBP and the residual $\widehat{PCS}_t^{\text{Merton}} = \text{CNV SP}_t - \text{CNV EBP}_t$. The results show that, except for SPX pseudo bonds at the three-month horizon (Panel B, left columns), the CNV EBP exhibits a strong independent predictive ability of future economic growth.

Figure 6 plots impulse response functions from the estimation of a vector auto regression (VAR) as in GZ, using the SPX-based CNV EBP as the excess bond premium measure.¹⁵ The figure shows results that are very similar to the results of GZ. As in GZ, we find that the CNV EBP is negatively associated with future economic and consumption growth and future investment, and is contemporaneously related to negative stock returns. Our EBP, however, is fully computed on *ex ante* basis, given that \widehat{PCS}_t uses only current Treasuries and traded option prices and $\widehat{PCS}_t^{\text{Merton}}$ only uses the predicted volatility at time t (across firms), which depends exclusively on past returns.

Our empirical results help us to better interpret the information contained in the GZ EBP. Although credit constraints can indeed generate corporate bond spreads that are “too high” compared to some benchmark, we find that the reason why spreads may be too high

¹⁵The results using single-stock CNV EBP are provided in Figure A2 in the Technical Appendix. Impulse responses show the same pattern as shown for SPX in Figure 6, but they have larger confidence bands and hence they are mostly insignificant, possibly due to a shorter sample or more noisy EBP measures.

is instead because of an increase in investors' willingness to pay for tail risk insurance, which bids up the value of securities that pay in extreme negative states (and hence bids down the value of securities that do not pay in such states, such as bonds).

To evaluate how much of the variation in the GZ EBP can be explained by our benchmarks, we run the following contemporaneous regressions:

$$\begin{array}{l} \text{SPX :} \quad GZ\ EBP_t = -0.64 + 0.79 \widehat{PCS}_t^{Merton} + 0.17\ CNV\ EBP_t + \varepsilon_t; \quad R^2 = 54.81\% \\ (1/1990 - 6/2015) \quad \quad \quad (-6.41) \quad (8.05) \quad \quad \quad (2.86) \end{array}$$

$$\begin{array}{l} \text{Single - Stock :} \quad GZ\ EBP_t = -1.76 + 0.54 \widehat{PCS}_t^{Merton} + 0.31\ CNV\ EBP_t + \varepsilon_t; \quad R^2 = 63.96\% \\ (1/1996 - 6/2015) \quad \quad \quad (-9.30) \quad (8.50) \quad \quad \quad (5.11) \end{array}$$

Our results indicate that between 55% (SPX) and 64% (single-stocks) of the variation in the GZ EBP can be explained by a combination of Merton's pseudo credit spreads (\widehat{PCS}_t^{Merton}) and the *ex ante* pseudo bond EBP. This result may be interpreted as indicating that much of the variation that it is ascribed to credit contractions, which GZ proxy with the excess bond premium, may actually be due to fundamentals (\widehat{PCS}_t^{Merton} , which only depends on predicted volatility) or a risk premium demanded by investors to cover their tail risks (CNV EBP).

4.3. Credit Supply and Pseudo Bonds Spreads

The previous sections shows that option-based CNV spreads and the CNV EBP – a fully *ex ante* measure – predict future economic growth as well as GZ spreads and the GZ EBP. Over 50% of the variation of the latter, moreover, can be explained through CNV EBP and Merton-based credit spreads \widehat{PCS}_t^{Merton} .

One interpretation of these empirical results is that credit spreads, leverage, and business cycles are related to each other through some unobservable factor, such as the level of risk aversion of investors, which generates comovements of these observables.¹⁶

To validate our interpretation, we project the CNV and GZ credit spreads on the three monthly fundamental variables in Table 4, and then run the same predictive regression as

¹⁶A similar theoretical argument has been recently made in the heterogeneous habit formation model of Santos and Veronesi (2016), in which the amount of aggregate credit supply to the economy is shown to depend negatively on aggregate risk aversion and hence is procyclical. Santos and Veronesi (2016) do not investigate credit spreads, but previous literature (e.g. Chen, Collin-Dufresne and Goldstein (2009)) shows that a similar habit formation model explains the dynamics of aggregate credit spreads, thereby providing a link between aggregate leverage, credit spreads, and aggregate risk aversion.

in that table, except that we use the fitted values $\widehat{CNV} CS_t$ and $\widehat{GZ} CS_t$ instead of observed credit spreads. Table 6 shows the results. The fitted values of our projections indicate that future economic growth can be predicted with roughly the same R^2 when using either the CNV or GZ spread. An index of the business cycle – *i.e.*, the fitted value of the projection regression – thus is able to predict future economic growth and clearly co-varies with both corporate bond- and option-based credit spreads.

4.4. Intermediary Credit Constraints and Pseudo Bond Spreads

Although the results in the previous sections suggest strongly that a credit supply channel may not be as important as previously thought from earlier research and that time-varying aversion to tail risk may also or better explain the behavior of credit spreads, there is an important caveat to this inference. In particular, put options themselves may also be affected by credit supply shocks. Because options trading is often undertaken by intermediaries and dealers, it is possible that intermediaries’ credit constraints may impact the quoted prices of the put options on which our CNV 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. As such, there could be a link between intermediary credit constraints and put prices.

Although possible, this interpretation of the increase in put option prices resulting from intermediaries’ hedge purchases is consistent with our interpretation of time varying premia for tail risk. 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 an increases in risk or risk aversion. Either way, higher credit spreads reflect an increase in demand for downside insurance risk, *i.e.* tail risk.

To further support this 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, which cast some doubts on the interpretation of excessive credit supply. In fact, 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 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, $\hat{P}_t^{oil}(K, T)$, instead of an SPX option, $\hat{P}_t^{SPX}(K, T)$. 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 premiums are negligible.

In addition to oil, we consider corn, soybeans, natural gas, and gold, 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 observations remains in the data.

Foreign Currencies. Assume that our pseudo firm purchases foreign currency, such as Euros, 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, $\hat{P}_t^{Euro}(K, T)$, instead of SPX options, $\hat{P}_t^{SPX}(K, T)$. 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) with a unitary notional amount, fixed swap rate c , maturity T and tenor $M - T$.¹⁷ 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

¹⁷We assume the credit quality of the swaption counterparty and underlying swap counterparty are also LIBOR-equivalent.

pseudo credit spreads across the five asset classes (*i.e.*, SPX, single stocks, commodities, currencies, and fixed income).¹⁸ Regressions of individual IG spreads on the factor yield R^2 s that range from 52% (fixed income) to 66% (SPX). The comovement is even higher for HY spreads, with R^2 s 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 class) affecting credit spreads.¹⁹

Figure 7 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 LGDs of real corporate bonds and pseudo bonds. Real corporate bonds have around 60% losses on average in case of default. We compute the LGD of each pseudo bond with *ex ante* default probability $\hat{p}_{i,t}(T)$ as the average percentage loss $(K_i - A_{i,T})/K_i$ conditional on a default (*i.e.*, $A_{i,T} < K_i$).²⁰ We find that LGDs 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 LGDs of corporate bonds are higher than the LGDs of pseudo bonds. As a second extension, we now introduce bankruptcy costs and find a portfolio of put options to yield LGDs 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

¹⁸Because 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.

¹⁹Recent 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.

²⁰We 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.

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 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 approximate the pseudo bond value by

$$\hat{B}_t(T, K) = K \hat{Z}_t(T) - (1 - \kappa_i) \hat{P}_t^{SPX}(K, T) - \kappa_i K \frac{\hat{P}_t^{SPX}(K, T) - \hat{P}_t^{SPX}(K', T)}{K - K'} \quad (6)$$

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 LGDs reported by Moody's. We take into account business cycle variations in LGDs 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 LGDs of pseudo firms are now similar to the corporate LGDs shown in the second column. Our *ex ante* methodology to compute bankruptcy costs thus works well. Second, Panel C shows that 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

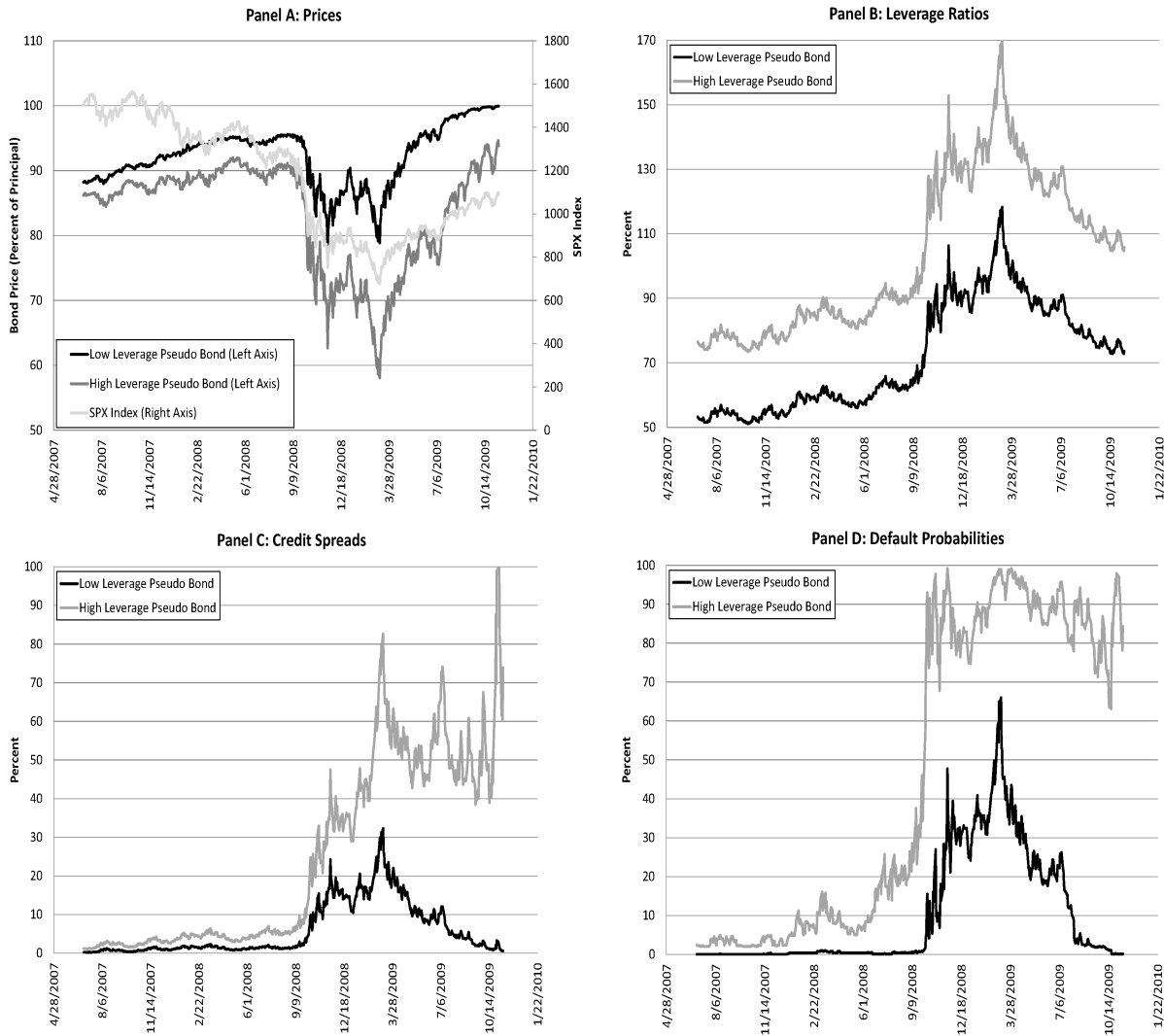
empirical properties of pseudo bonds issued by such firms and the pseudo spreads on such bonds.

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 good deal of integration between corporate bond and options markets, and the existence of similar risk premiums 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 LGDs.

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.²¹ 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.

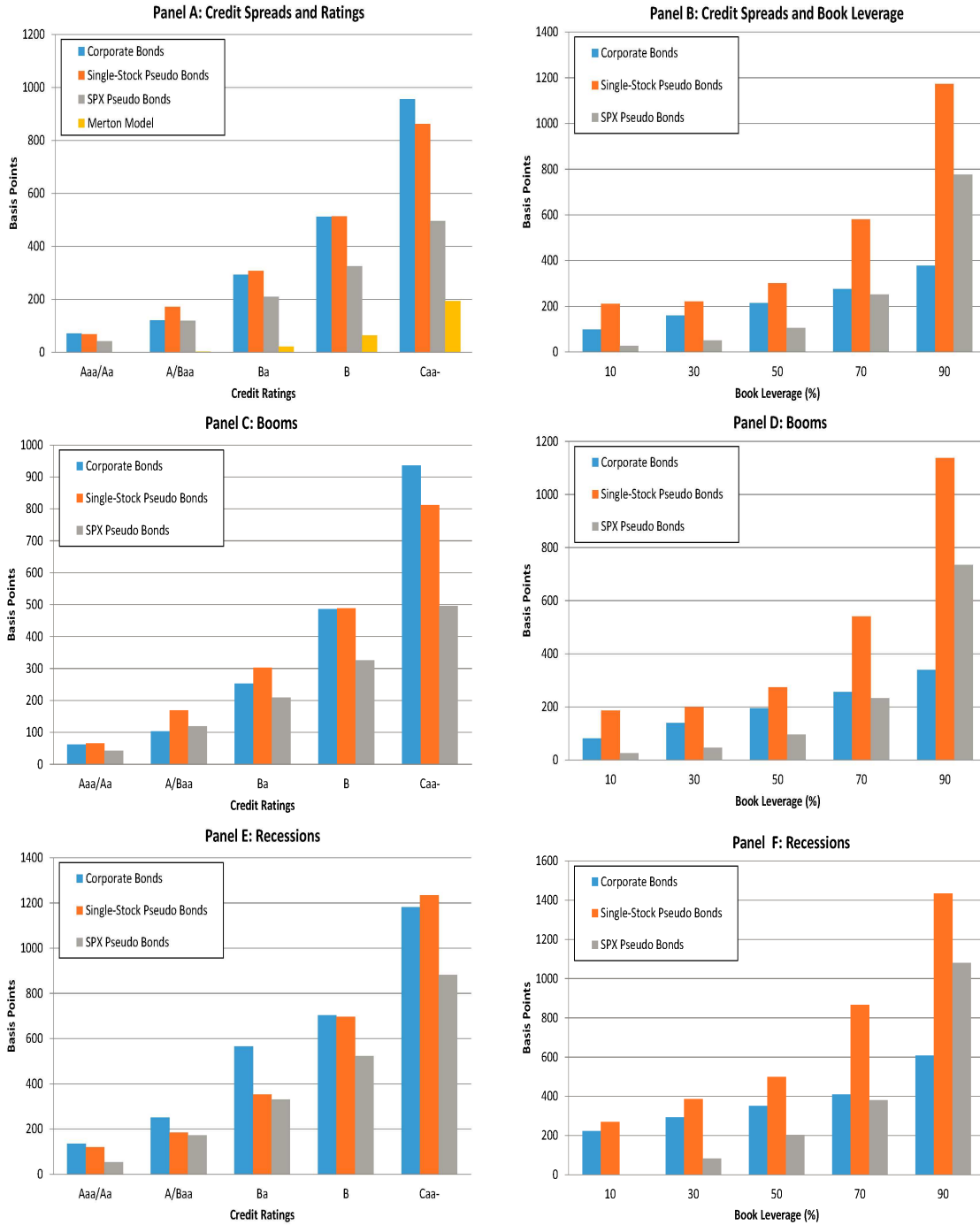
²¹Some of these applications of pseudo firms are contained on the web site “Credit Risk Laboratory” available at http://faculty.chicagobooth.edu/pietro.veronesi/research/Credit_Risk_Lab/

Figure 1: Two SPX Pseudo Bonds



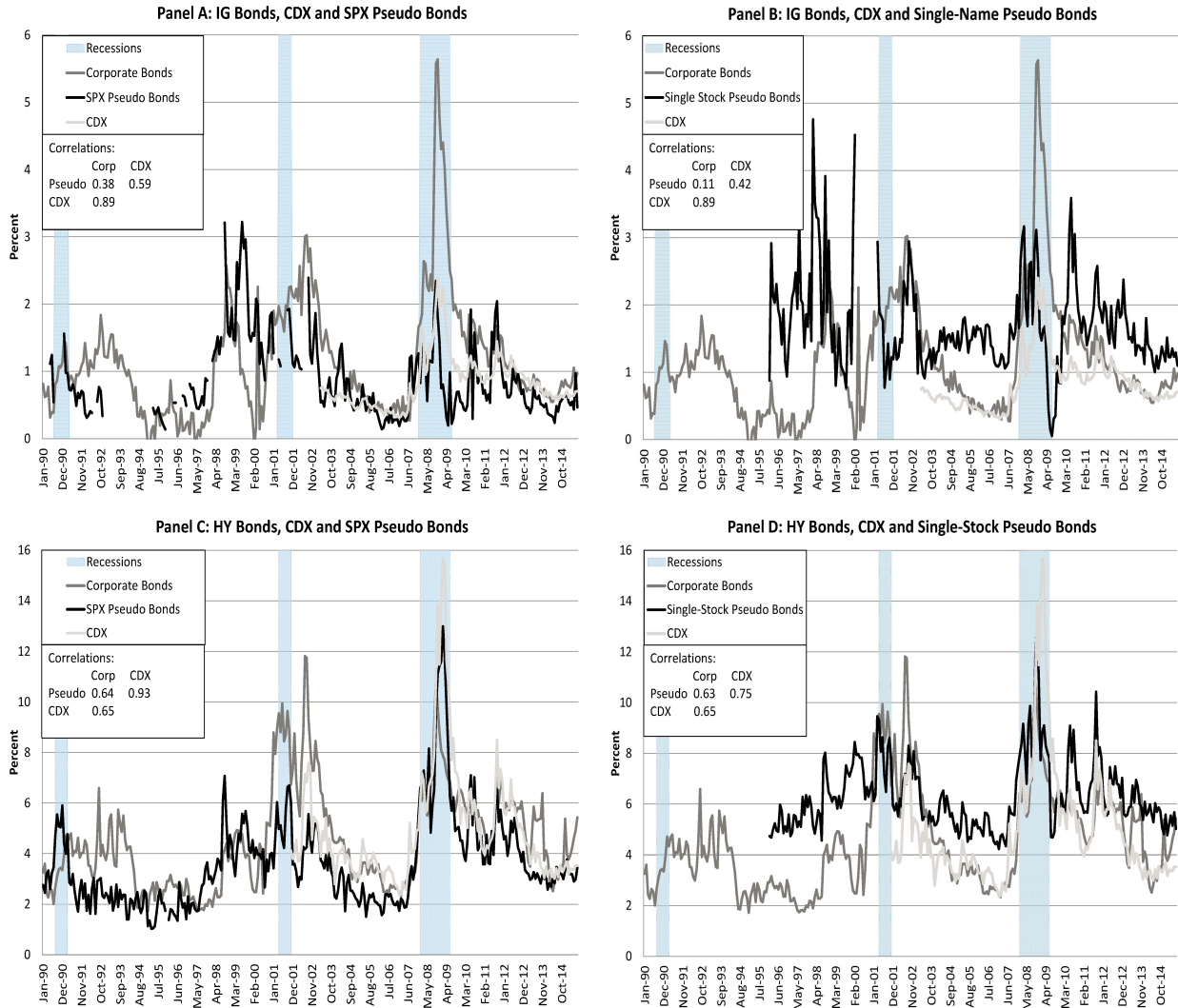
Notes: Panel A reports the no-arbitrage prices of two SPX pseudo bonds from June 2007 to November 2009 as percent of principal. The pseudo bonds are issued by two pseudo firms, one with low leverage (black line) and one with high leverage (dark grey line). The figure also reports the values of assets 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



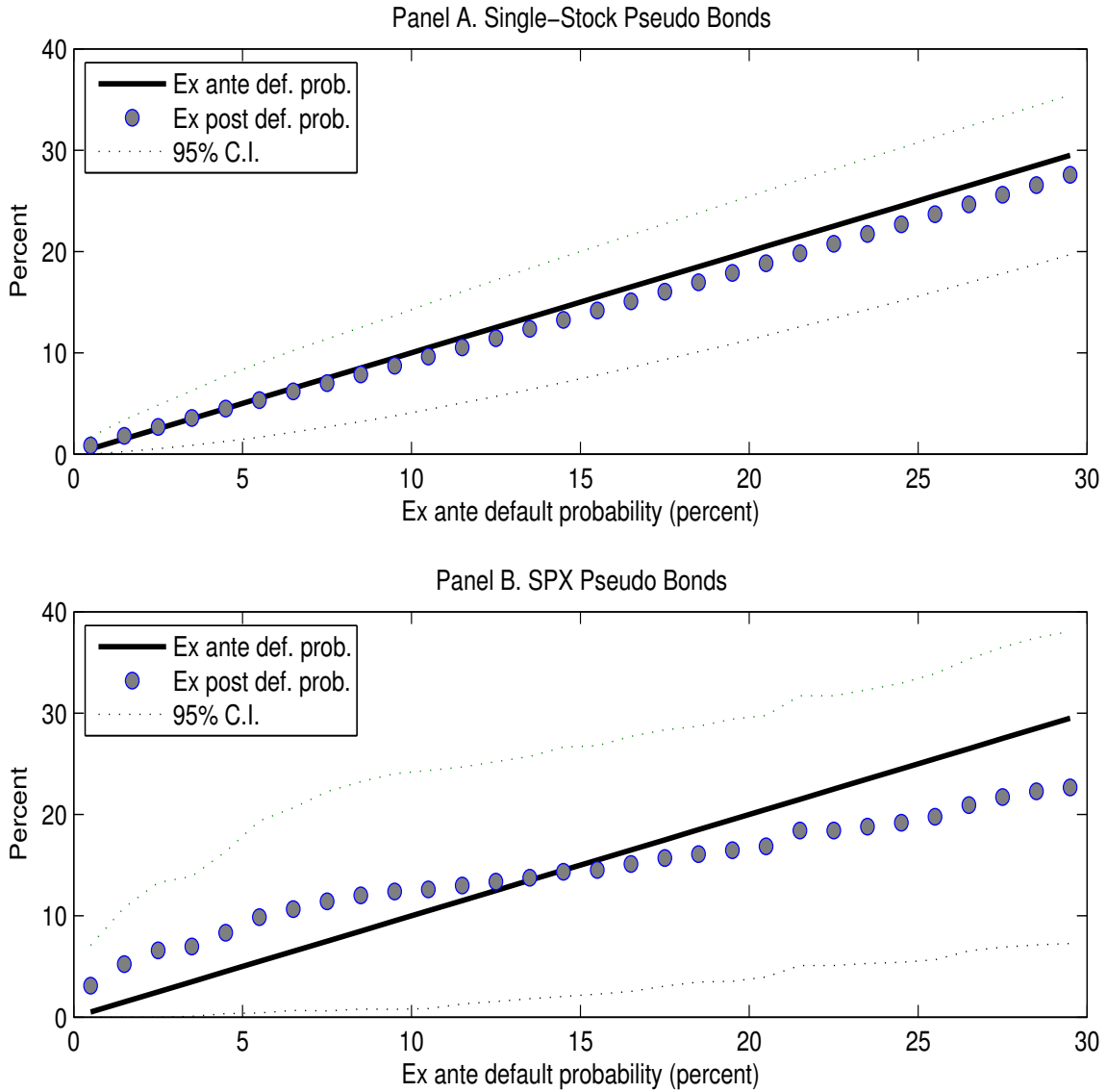
Notes: Credit spreads are shown for corporate bonds, single-stock pseudo bonds, SPX pseudo bonds, and implied by the lognormal Merton model (in Panel A). For corporate bonds, the credit ratings are from Moody's. For pseudo bonds, the credit ratings are imputed by comparing their *ex ante* default probabilities 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



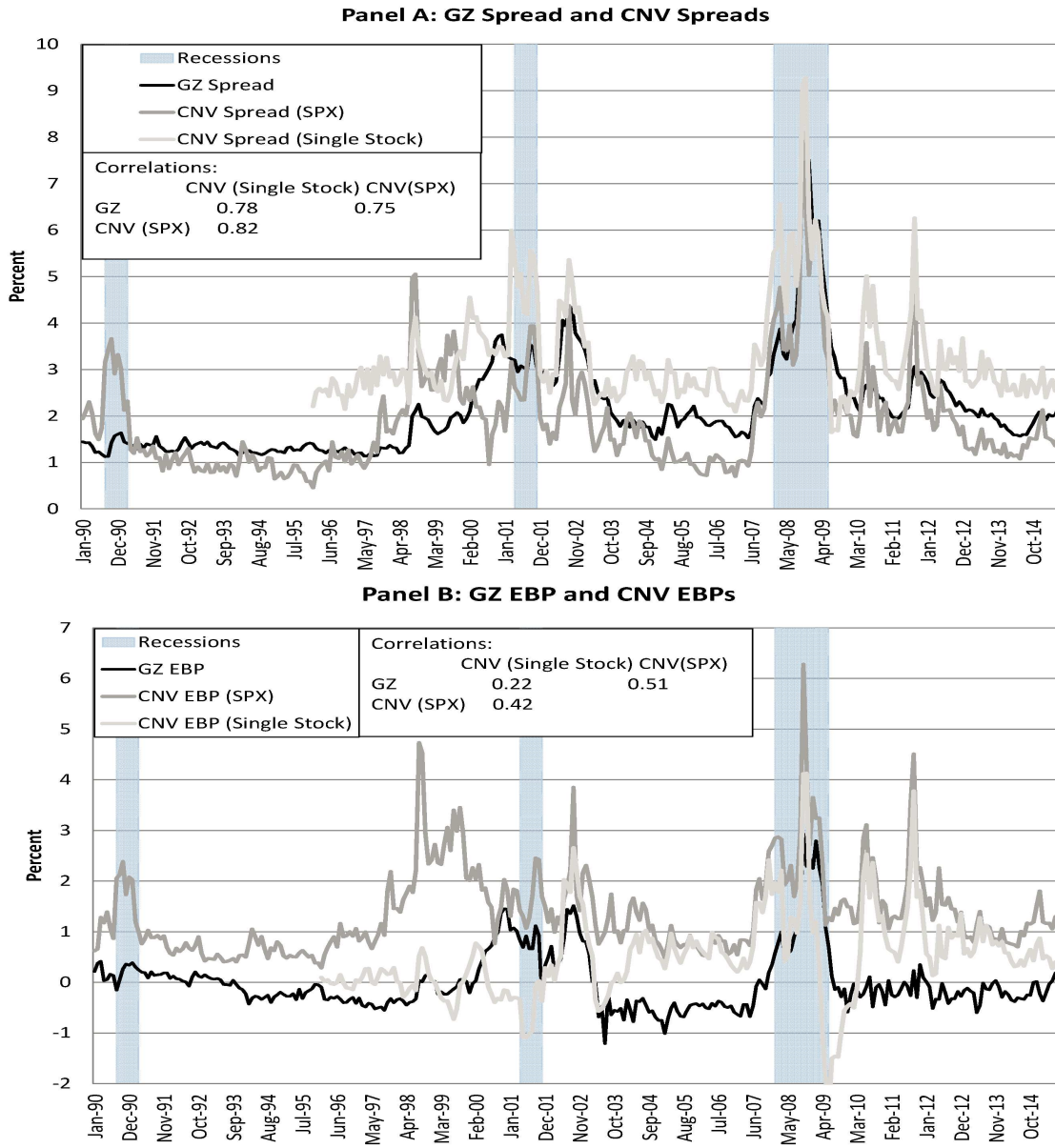
Notes: Credit spreads are shown for two-year pseudo and corporate bonds. Pseudo bonds are constructed from risk-free debt minus put options on individual stocks, or put options on SPX index. Investment Grade (IG) and High Yield (HY) pseudo credit ratings of pseudo bonds are assigned based on their *ex 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



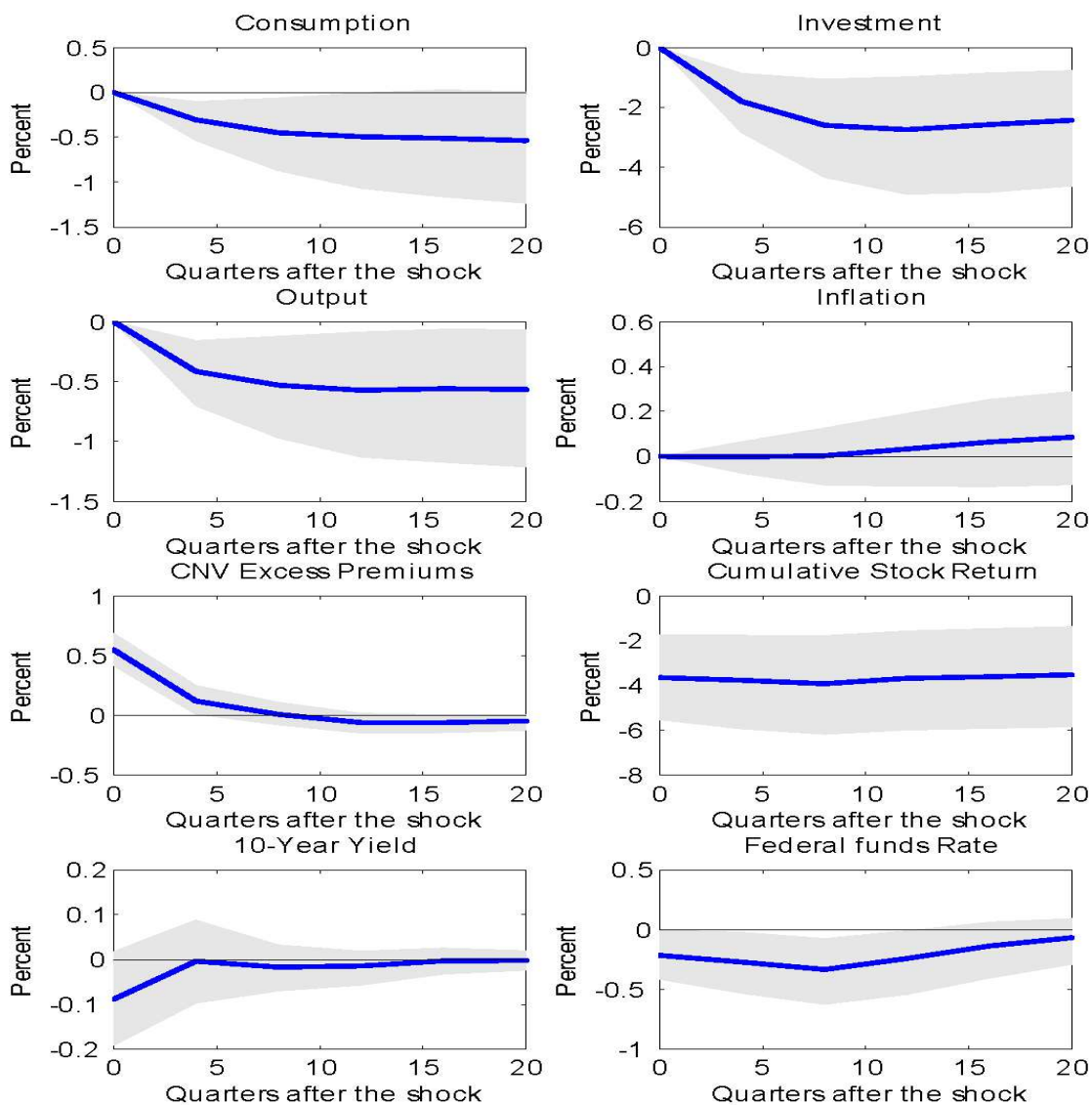
Notes: Panel A plots the estimated *ex post* default frequencies of pseudo bonds based on single-stock (circles) together with their 95% confidence intervals (dotted lines) against the 45 degree line, which represent the *ex ante* default probability for each of the pseudo bonds. The sample is 1970 to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

Figure 5: GZ versus CNV Spreads



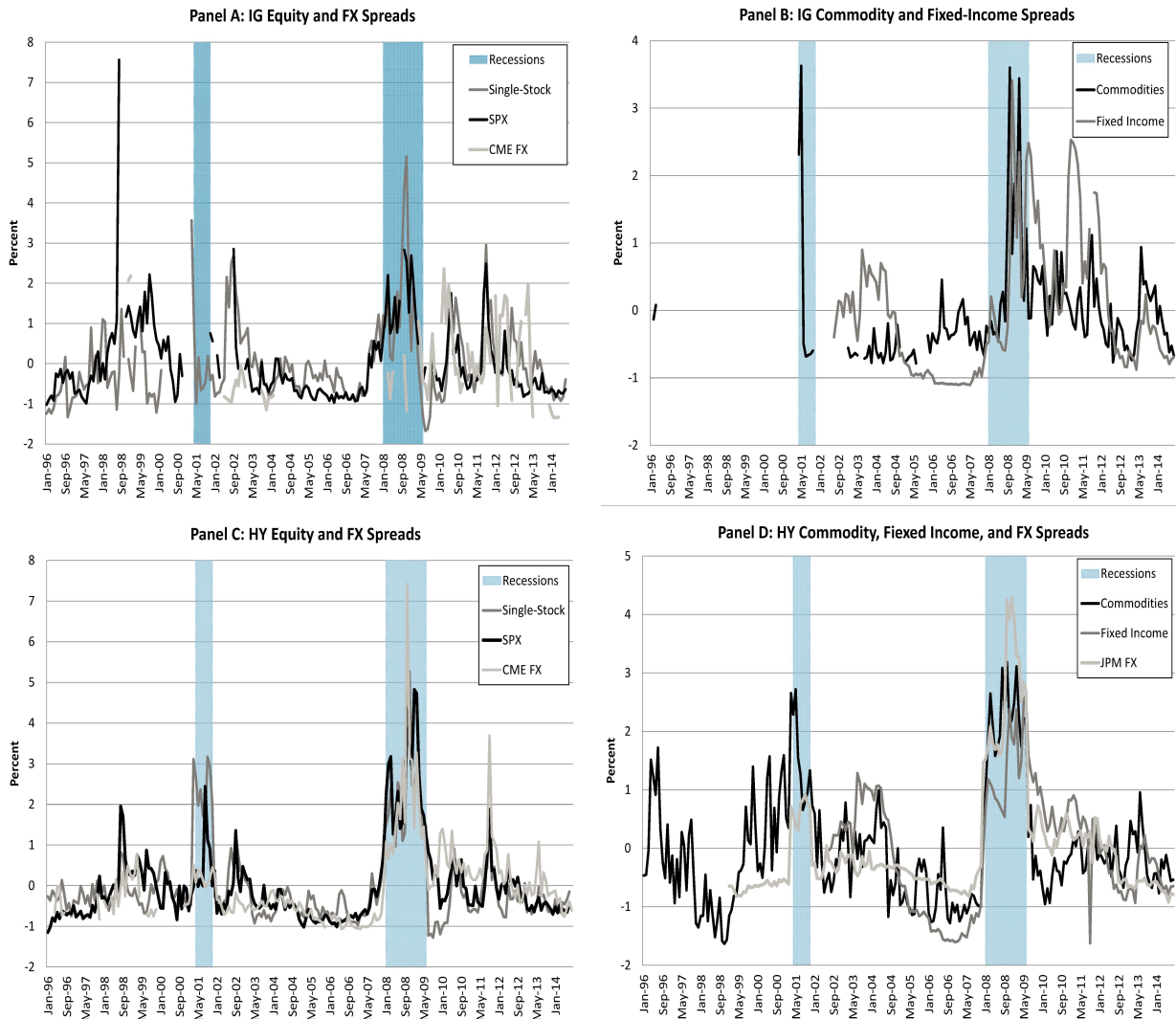
Notes: Panel A plots the time series of the GZ and CNV spreads computed from single stocks or the SPX index. The GZ spread is from Gilchrist and Zakajreks (2012, updated series). Panel B plots the time series of GZ and CNV EBPs. The GZ EBP equals the GZ spread minus the in-sample predicted spread. The CNV EBP is computed as an *ex ante* measure computed as the difference between the CNV spread and the one obtained by using the lognormal Merton model with predicted volatility. The CNV spreads (EBP) are computed as the equally weighted average of IG and HY pseudo bond spreads (EBP) 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: Impulse Response Functions for a Shock to CNV EBP



Notes: This figure plots the impulse response from a shock to the SPX-based CNV EBP. The CNV EBP is computed as the difference between the SPX-based pseudo spread and the analogous spread computed from the lognormal Merton model, which uses the Black, Scholes, and Merton put option pricing formula computed using the predicted volatility. The sample is January 1990 to July 2015.

Figure 7: 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 $\sqrt{-Cov_t(\Delta p_{i,t,d}^{Bid \rightarrow Ask}, \Delta p_{i,t,d+1}^{Ask \rightarrow Bid})}$ 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 Rating	Credit Spreads (bps)					2-year Bonds			
	Days to Maturity					Credit Spreads (bps)		Illiquidity Measures	
	30	91	181	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, LGDs, and Bankruptcy Costs

Credit spreads and losses-given-defaults (LGDs) 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: <i>Ex Post</i> LGDs (%)							
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: <i>Ex Post</i> LGDs 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

Table 4: CNV Spreads and Future Economic Growth

This table reports the results of the following predictive regression:

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

where Δ_h is the “ h -period” lag operator, CNV CS $_t$ is the CNV credit spread, GZ CS $_t$ is Gilchrist Zakrajsek (2012) GZ spread, 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 CNV 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. 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: Payroll Growth												
	Single-Stock						SPX					
	h = 3 months			h = 12 months			h = 3 months			h = 12 months		
CNV Spread	-0.18	-0.19	-0.10	-0.78	-1.11	-0.72	-0.12	-0.16	-0.14	-0.56	-0.99	-0.85
t-stat	(-3.05)	(-3.13)	(-1.58)	(-4.32)	(-4.32)	(-2.92)	(-2.82)	(-2.49)	(-2.10)	(-3.94)	(-3.11)	(-2.82)
GZ Spread			-0.24			-1.05			-0.16			-0.91
t-stat			(-2.26)			(-5.27)			(-1.96)			(-3.96)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
R ²	0.80	0.81	0.84	0.64	0.71	0.77	0.74	0.75	0.78	0.54	0.61	0.68
Panel B: Unemployment Rate Change												
CNV Spread	13.26	14.41	6.10	51.38	75.48	50.74	9.71	12.97	10.75	34.32	72.65	63.14
t-stat	(2.70)	(2.74)	(1.09)	(3.97)	(3.97)	(2.72)	(2.51)	(2.26)	(1.91)	(3.14)	(3.06)	(2.78)
GZ Spread			20.11			61.30			14.79			61.77
t-stat			(2.81)			(3.62)			(2.54)			(3.58)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
R ²	0.50	0.51	0.58	0.46	0.60	0.67	0.42	0.44	0.50	0.33	0.48	0.59
Panel C: Industrial Production Growth												
CNV Spread	-0.76	-0.99	-0.73	-2.59	-4.40	-3.71	-0.52	-0.84	-0.81	-1.62	-4.33	-4.16
t-stat	(-3.62)	(-3.70)	(-2.62)	(-3.78)	(-3.98)	(-3.39)	(-3.28)	(-2.62)	(-2.55)	(-3.09)	(-3.00)	(-2.93)
GZ Spread			-0.85			-2.34			-0.79			-2.97
t-stat			(-3.03)			(-3.11)			(-3.20)			(-3.63)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
R ²	0.55	0.59	0.64	0.30	0.45	0.49	0.39	0.42	0.48	0.18	0.31	0.41
Panel D: GDP Growth												
CNV Spread	-0.21	-0.44	-0.37	-0.52	-1.38	-1.18	-0.10	-0.39	-0.37	-0.38	-1.66	-1.59
t-stat	(-1.86)	(-2.13)	(-1.60)	(-2.07)	(-3.26)	(-2.70)	(-1.23)	(-1.20)	(-1.14)	(-1.60)	(-2.41)	(-2.33)
GZ Spread			-0.20			-0.54			-0.21			-0.69
t-stat			(-1.31)			(-1.39)			(-1.87)			(-2.03)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
R ²	0.20	0.29	0.31	0.14	0.35	0.36	0.13	0.17	0.19	0.09	0.29	0.32

Table 5: CNV Excess Bond Premiums

This table reports the results of the following predictive regression:

$$\Delta_h Y_{t+h} = \alpha + \sum_{i=1}^p \beta_i \Delta Y_{t-i} + \gamma_1 \widehat{\text{PCS}}_t^{\text{Merton}} + \gamma_2 \text{CNV EBP}_t + \text{Controls}_t + \varepsilon_{t+h}$$

where Δ_h is the “ h -period” lag operator, $\widehat{\text{PCS}}_t^{\text{Merton}}$ is the option-based pseudo spread obtained from the Black, Scholes and Merton formula to compute credit spreads (instead of traded options), and $\text{CNV EBP}_t = \widehat{\text{PCS}}_t - \widehat{\text{PCS}}_t^{\text{Merton}}$ is the EBP from using traded options instead of the lognormal Merton model to compute credit spreads. “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 $\widehat{\text{PCS}}_t^{\text{Merton}}$ (CNV EBP_t) 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 spreads (EBP) with 6-months, 1-year, and 2-year maturities (6 series). 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
$\widehat{\text{PCS}}^{\text{Merton}}$	-0.20	17.12	-0.97	-0.46	-1.04	74.66	-3.91	-1.34
t-stat	(-3.06)	(2.97)	(-3.14)	(-2.25)	(-4.31)	(4.00)	(-3.89)	(-3.41)
CNV - EBP	-0.18	11.87	-1.01	-0.43	-1.16	76.25	-4.70	-1.41
t-stat	(-2.64)	(2.05)	(-3.34)	(-2.04)	(-4.26)	(3.54)	(-3.70)	(-2.76)
TERM	0.05	-6.54	0.37	0.15	0.11	-11.47	0.90	0.66
t-stat	(1.00)	(-1.37)	(1.94)	(1.25)	(0.94)	(-0.83)	(1.39)	(1.55)
RFFR	0.02	-1.46	0.18	0.08	-0.12	11.41	0.12	0.28
t-stat	(0.76)	(-0.51)	(1.55)	(1.26)	(-1.77)	(1.31)	(0.32)	(0.82)
VIX	0.00	-0.16	0.04	0.04	0.08	-4.81	0.34	0.14
t-stat	(0.52)	(-0.37)	(1.17)	(1.74)	(3.54)	(-2.65)	(3.20)	(2.88)
R^2	0.81	0.52	0.59	0.28	0.73	0.62	0.45	0.34
Panel B: SPX (January 1990 - June 2015)								
	PAY	UNEMP	IPG	GDP	PAY	UNEMP	IPG	GDP
$\widehat{\text{PCS}}^{\text{Merton}}$	-0.49	45.68	-1.75	-0.59	-1.64	151.38	-5.27	-1.75
t-stat	(-3.00)	(3.79)	(-3.44)	(-1.67)	(-3.00)	(3.95)	(-2.92)	(-2.55)
CNV - EBP	-0.03	-1.55	-0.53	-0.29	-0.67	37.24	-3.98	-1.62
t-stat	(-0.31)	(-0.17)	(-1.29)	(-0.82)	(-2.48)	(1.75)	(-2.77)	(-2.00)
TERM	0.08	-3.89	0.44	0.14	0.32	-15.04	1.47	0.69
t-stat	(1.44)	(-1.02)	(2.91)	(1.81)	(2.97)	(-1.21)	(2.96)	(2.37)
RFFR	0.00	2.42	0.14	0.04	-0.05	15.51	0.33	0.26
t-stat	(0.20)	(1.03)	(1.99)	(1.14)	(-0.87)	(1.89)	(1.58)	(1.73)
VIX	0.00	0.49	0.04	0.04	0.06	-3.59	0.41	0.20
t-stat	(-0.36)	(0.49)	(0.56)	(0.97)	(1.83)	(-1.44)	(2.41)	(2.21)
R^2	0.78	0.54	0.47	0.18	0.62	0.55	0.33	0.27

Table 6: Projected CNV and GZ Spreads and Future Economic Growth

This table reports the results of the following predictive regression

$$\Delta_h Y_{t+h} = \alpha + \sum_{i=1}^p \beta_i \Delta Y_{t-i} + \gamma \text{Proj CS}_t + \text{Controls} + \varepsilon_{t+h}$$

where Δ_h is the “ h -period” lag operator, Proj CS_t is the projection of either the CNV spread or the GZ spread onto the macro variables “PAY”, “UNEMP”, and “IPG”. The “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 CNV spread is computed separately for SPX-pseudo bonds and Single-Stock pseudo bonds, and for each case, it equals the equally weighted average of HY and IG spreads with 6 months, 1 year, and 2 year maturity (6 series). The prediction horizon is either $h = 3$ month 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. 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: Payroll Growth								
	Single-Stock				SPX			
	h = 3 months		h = 12 months		h = 3 months		h = 12 months	
Proj CNV CS	-0.31		0.00		-0.32		-1.16	
t-stat	(-3.14)		(-4.42)		(-3.85)		(-4.98)	
Proj GZ CS		-0.25		0.00		-0.27		-1.00
t-stat		(-3.35)		(-4.77)		(-3.76)		(-5.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.79	0.79	0.58	0.57	0.78	0.78	0.59	0.59
Panel B: Unemployment Rate Change								
Proj CNV CS	28.71		0.00		28.23		83.61	
t-stat	(3.86)		(4.73)		(4.50)		(5.48)	
Proj GZ CS		24.81		0.00		26.72		75.21
t-stat		(4.13)		(5.03)		(4.80)		(5.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.56	0.57	0.48	0.47	0.53	0.55	0.48	0.49
Panel C: Industrial Production Growth								
Proj CNV CS	-0.74		0.00		-0.56		-1.58	
t-stat	(-2.31)		(-3.24)		(-3.12)		(-3.54)	
Proj GZ CS		-0.49		0.00		-0.52		-1.45
t-stat		(-2.19)		(-3.27)		(-3.24)		(-3.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.47	0.47	0.20	0.19	0.41	0.41	0.20	0.20
Panel D: Real GDP Growth								
Proj CNV CS	-0.35		-0.69		-0.29		-0.62	
t-stat	(-2.64)		(-1.82)		(-2.21)		(-2.19)	
Proj GZ CS		-0.32		-0.72		-0.30		-0.57
t-stat		(-3.27)		(-2.55)		(-2.95)		(-2.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.20	0.22	0.16	0.18	0.155	0.17	0.15	0.15

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