Option-Based Credit Spreads

On-Line Appendix

Christopher L. Culp
Johns Hopkins Institute for Applied Economics
and Swiss Finance Institute

Yoshio Nozawa
Federal Reserve Board

Pietro Veronesi
University of Chicago, NBER, and CEPR

This On-Line Appendix contains additional material that did not find space in the main text. The Appendix is divided in six sections:

A. Data description and filters

B. Default frequencies from Moody's data

C. Methodology

D. Pseudo bond returns

E. Parametric reference models

F. Tables and figures

Appendix A. Data Description and Filters.

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

Risk Free Securities. We construct the risk-free zero coupon bonds from 1-, 3-, and 6-month T-bill rates and 1-, 2-, and 3-year constant maturity Treasury yields obtained from the

Federal Reserve Economic Data ("FRED") database. We convert constant maturity yields into zero-coupon yields and linearly interpolate to match option maturities. We also obtain commercial paper rates from FRED, which we use to compute credit spreads for short-term debt.

Corporate Bonds. We construct the panel data of corporate bond prices from the Lehman Brothers Fixed Income Database, TRACE, the Mergent FISD/NAIC Database, and DataStream, prioritized in this order when there are overlaps among the four databases. Detailed descriptions of these databases and the effects of prioritization are discussed in Nozawa (2014). In addition, we remove bonds with floating coupon rates and/or embedded option features.

We apply several filters to remove observations that may be subject to erroneous recording. Following Duffee (1998), we remove bonds with buy-in prices greater than twice and less than 1/100 of their par amounts. We also remove observations for bonds that show large bounce-backs. Specifically, we compute the product of adjacent monthly returns and remove both observations if the product is less than -0.04. For example, if the price of a given bond jumps up by more than 20 percent in one month and then comes down by more than 20 percent in the following month, we assume that the price observation in the middle is recorded with errors and exclude that observation.

Credit Default Swap Indices. We obtained five-year CDX indices for investment grade ("IG") and high yield ("HY") from Markit. The samples start in November 2001 for HY and April 2003 for IG, and ends in August 2014.

Stock Options. We use the OptionMetrics Ivy DB database for daily prices on SPX index options and options on individual stocks from January 4, 1996, through August 31, 2014. In addition, we use SPX options from the MDR data of Market Data Express to cover the 1990 to 1995 sample. To minimize the effects of quotation errors in SPX options, we generally follow Constantinides, Jackwerth and Savov (2013) ("CJS") to filter the data. As in CJS, we apply the filters only to the prices to buy – not to the prices to sell – so that our portfolio formation strategy is feasible for real-time investors. As in CJS, we apply the following specific filters:

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

2. *Level 2 and Level 3 Filters:* Because we need quotes for long-term, deep out-of-the-money puts and deep in-the-money calls, we do not apply filters based on moneyness or maturity, but we remove all options with zero open interest. Following CJS, we also remove options with less than seven days to maturity. We also apply "implied interest rate < 0," "unable to compute IV," "IV," and "put-call parity" filters.[1]

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

Commodity Futures and Options. We obtain monthly settlement prices for commodity futures option for West Texas intermediate light, sweet crude oil, natural gas (Henry Hub), gold, corn and soybeans from the CME group ("CME"). The sample periods vary depending on the underlying commodity futures contract, and are shown in Table A1. We also obtain the underlying futures settlement prices from CME, and the spot prices from Global Financial Data. The expiry date for futures is close to that of options (typically they are apart less than a month), and we assume for our analysis that they expire at the same time. We use the convenience yield backed out from spot and futures prices as a predictor to compute the *ex ante* probabilities of default.

CME commodity futures options are American options, but we treat them as European options in computing the price of pseudo bonds, because they are so deep out of the money, that the early exercise premium is likely negligible. We remove the observations if *i*) the price does not satisfy the put-call parity bound, *ii*) open interest is zero, or *iii*) the number of days to maturity is less than or equal to seven days. In computing the put-call parity

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

bound, we use LIBOR and swap rates obtained from FRED and Barclays, while the pseudo bond prices are computed based on Treasury yields. (We use swap rates to compute the put-call parity bound, since CJS show that the risk-free rate that investors use to evaluate options is higher than T-bill rate.)

Currency Futures and Options. We use two different datasets.

1. We obtain prices for currency futures options for GBP, EUR, JPY, CHF, AUD and CAD from CME, and the corresponding spot exchange rates from Global Financial Data. We apply the same cleaning procedure as we do for the other commodity futures options, as described above.

2. We also use the monthly currency option data from JP Morgan for 9 currencies (CAD, EUR, NOK, GBP, SEK, CHF, AUD, JPY and NZD) from 1999 to 2014. The exchange rates are relative to US dollar. The quoted implied volatility for 1-, 3-, 6-, 12- and 24-month options are used to compute the price of currency options. The strike prices for currency options are expressed in terms of deltas, and we use at-the-money (50-delta) options, 10-delta calls and puts, and 25-delta calls and puts. When converting implied volatilities into a prices, we follow Jurek (2014) and use LIBOR and swap rates for each currency. The pricing of pseudo bonds are computed based on US Treasury yields (FRED). To estimate the *ex ante* and *ex post* probabilities of default, we also use spot exchange rates obtained from JP Morgan.

Swaptions. We use monthly swaption price data obtained from ICAP from July 2002 through December 2014. The data provides the premium for the right to enter the interest rate swap contract (in USD) in which investors pay or receive a fixed rate in exchange for 3-months LIBOR. We use the option expiries of 3, 6, 12 and 24 months on swaps with 5-, 10- and 20-year tenors. The available strike prices are at-the-money and $\pm 300, \pm 200, \pm 150, \pm 100, \pm 75, \pm 50, \pm 25, \pm 12.5$ basis points from at-the-money swap rate. The option premium in the data is an end-of-the-day aggregate quote in the interdealer market run by ICAP. To compute the underlying forward swap rate, we use the interest rate swap rate from JP Morgan.

Appendix B. Default Frequencies for Real Corporate Bonds.

As explained in the text, our goal is to construct pseudo bonds that match the realized default frequencies of the actual corporate bonds used as our main empirical benchmark. To that end, we employ a large dataset of corporate defaults spanning the 44-year period from 1970 to 2013 obtained from Moody's Default Risk Service. For each credit rating assigned by Moody's to our universe of firms, we estimate *ex post* default frequencies at various horizons from 30 days up to two years. We use our own estimates rather than the original Moody's default frequencies for three main reasons. First, we are interested in the variation of default frequencies over the business cycle, whereas Moody's historical default frequencies are only available as unconditional averages. Second, we are interested in the default frequencies at horizons of below one year, and default frequencies are not provided by Moody's for such short time horizons. And third, we need default frequencies for coarser categories (such as Aaa/Aa, A/Baa) as options' strike prices at often lack the sufficient granularity to differentiate across such credit ratings.

Table A2 reports historical default rates from 1970 through 2013 from our sample of firms across credit rating categories and time horizons. We compute historical default frequencies separately for international and U.S. firms. Our results are directly comparable to Moody's historical default rates (reported in Moody's (2014)) for one- and two-year horizons. As Table A2 shows, our estimated default rates closely match the Moody's global default rates for those horizons.

The last two columns of Table A2 report default rates for U.S. firms in NBER-dated booms and recessions. Predictably, we find that default frequencies are higher in recessions than in booms across all credit ratings. At the 1-year horizon, for instance, A-rated bonds have a default frequency of only 0.02% in booms but 0.13% in recessions (as compared to an unconditional U.S. average of 0.04%). Default frequencies for speculative-grade bonds also show large variations over the business cycle. For example, a B-rated bond has a 3.57% default rate at the 1-year horizon during booms but more than twice that in recessions (as compared to an unconditional average of 4.01%).

Table A2 also shows default frequencies at short horizons of 30, 91, and 183 days. At the 30-day horizon, all IG bonds have essentially zero historical default frequencies (although, in recessions, the historical default rate ticks up 0.01% for bonds rated A- and Baa). Some more action for these bonds is observable at the 91- and 183-day horizons, especially during recessions. For example, Baa-rated bonds have defaulted with 0.04% and 0.12% frequencies at the 91- and 183-day horizons (respectively) during recessions, which are much higher than the corresponding unconditional default frequencies of 0.02% and 0.05%. HY bonds, by contrast, exhibit relatively substantial historical default activity even at short horizons. For instance, B-rated bonds have 0.22%, 0.75%, and 1.69% unconditional default frequencies over 30, 91, and 183 days, respectively, which increase to 0.43%, 1.48%, and 3.33%, respectively, during recessions.

Appendix C. Methodology.

C.1. Pseudo Credit Ratings of Pseudo Bonds

In this section we describe the results of the pseudo credit rating assignment for two-year pseudo bonds introduced in Section 4.2. of the main text.

Panel A of Table A3 presents the default frequencies, both average and over the business cycle, estimated from Moody's dataset on corporate defaults for the credit ratings reported in the first column. The last two columns report break points in booms and recessions, computed as the middle points of the corresponding default probabilities in columns three and four.[2] So, for every month t, we compare the probability of each bond i, $\widehat{p}_{i,t}(\tau)$, to the corresponding thresholds in the last two columns, depending on whether month t is a boom or recession, and obtain a classification into a credit rating category.

Panels B and C report the results of our credit rating classification methodology for pseudo bonds based on single stocks and the SPX, respectively. In both panels, for each credit rating in the first column, the second and the third columns show the weighted average *ex ante* default probabilities for pseudo bonds in each rating category. According to the procedure, these probabilities should be close to the historical default frequencies reported in columns three and four of Panel A, and indeed they are. Columns four to six of Panels B and C of Table A3 test whether *ex post* default frequencies are close to the *ex ante* default probabilities. We cannot reject that *ex ante* and *ex post* default probabilities are equivalent.

The second-to-last column in Panels B and C reports the average moneyness of the options ($\overline{K/A}$). The options used for highly rated pseudo bonds are deeply out-of-the-money to be consistent with low default probabilities. As noted, we sometimes lack sufficient data to compute any default rate for the Aaa/Aa category because options that far out-of-the-money are excluded by our minimum liquidity filters (*see* On-Line Appendix A).

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

The last column of Panels B and C report the average maturities $\overline{\tau}$ of the options used by credit rating category. Across the two panels, these averages are between 620 and 674 days (*i.e.*, 1.69 and 1.85 years). Times to maturities thus are a bit smaller than the two-year (730-day) target mainly due to lack of data in the early part of the historical sample. Even so, the lower average maturity biases the empirical results against us, given that shorter maturities imply lower probabilities for the put options to end up in-the-money at maturity. We continue to refer to these pseudo bonds as two-year bonds for expositional simplicity.

C.2. Default Probabilities for Other Asset Classes

The general methodology to compute default probabilities for SPX and single-stock pseudo bonds is explained in Section 2.1. in the main text. The same methodology is applied for other asset classes, with some minor modifications, as explained next.

Futures options. The price of pseudo bonds based on futures options is computed in the same way as SPX and single-stock pseudo bonds:

$$B_t\left(t+\tau, K_{i,t}\right) = K_{i,t} Z_t\left(t+\tau\right) - P_t^{Option}\left(t+\tau, K_{i,t}\right),$$

as are the yields. To compute the probability of default, we assume that the dynamics of the spot price of the underlying asset follows

$$\log S_{t+1} - \log S_t = \mu_t + \sigma_t \varepsilon_{t+1}.$$

The parameters μ_t and σ_t are estimated using the available history of log spot prices up to time t. Specifically, μ_t is the cumulative average log price change, and σ_t is estimated using GARCH(1,1) except for natural gas. For natural gas, the available spot price starts only about a year before the beginning of the options data, and thus there is not enough spot price data available to estimate the out-of-sample forecast for the volatility at the beginning of the options data. Thus, we simply use the monthly volatility estimated from daily changes in log spot prices. The methodologies are summarized in Table A1.

The *ex ante* probability of default is computed by

$$p_t\left(L_{i,t}\right) = \Pr\left[\varepsilon_{t+\tau} < X_{i,t}\right] \quad \text{where} \quad X_{i,t} = \frac{\ln L_{i,t} - \left(\mu_{t,\tau} - r_{t,\tau} + q_{t,\tau}\right)}{\sigma_{t,\tau}}$$

where $q_{t,\tau}$ is a convenience yield. We adjust the leverage by $r_{t,\tau} - q_{t,\tau}$ since the leverage for options on futures is defined using a futures price rather than a spot price.

For currency futures options, we compute the pseudo bond price and probability of default in the same way as other commodity options, except that we estimate the conditional mean log spot rate changes by regressing the changes onto the difference in 3-month T-bill rates between US and the other country.

JP Morgan FX options. The FX options from JP Morgan are for spot currency exchanges. Thus, we apply the same procedure to these FX options as we do for stock options. In estimating the conditional mean log price change parameter, we forecast the changes in exchange rates using the difference in three-month interbank rates between the two currencies. We estimate the conditional volatility using GARCH(1,1).

Swaptions. As discussed in Section 6.1., the price of the swaption-based pseudo bond is

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

and the probability of default is given by

$$\Pr\left(\mathcal{B}_{t+\tau}\left(c,M\right)<1|\mathcal{F}_t\right).$$

In order to estimate the probability of default, we estimate the parameters in the following dynamics of the pseudo firm assets:

$$\log\mathcal{B}_{t+\tau}\left(c,M\right)-\log\mathcal{B}_t\left(c,M\right)=\mu_t+\sigma_t\varepsilon_{t+\tau}. \tag{10}$$

From the term-structure of swap rates, we compute the historical price of pseudo firm's assets, $\mathcal{B}_t\left(c,M\right)$. Then we forecast its change over the period up to the option expiry using the forecasting regression. Specifically, we run the forecasting regression

$$\log\mathcal{B}_{t+\tau}\left(c,M\right)-\log\mathcal{B}_t\left(c,M\right)=a+b\cdot\left(Swap\left(t,M\right)-LIBOR_t\right)+\varepsilon_{t+\tau},$$

where $Swap\left(t,M\right)$ is the swap rate at time t for maturity $M-t$, and $LIBOR_t$ is 3-month LIBOR.Then the estimated mean parameter is given by

$$\hat{\mu}_t=\hat{a}+\hat{b}\cdot\left(Swap\left(t,M\right)-LIBOR_t\right).$$

We use the 60-month rolling volatility of $\log\mathcal{B}_{t+\tau}\left(c,M\right)-\log\mathcal{B}_t\left(c,M\right)$ to account for time-varying volatility.

C.3. Matching LGDs between Corporate and Pseudo Bonds

From Section 6.2., the expected payoff from bonds scaled by a face value conditional of default is given by

$$E\left[\text{Bond Payoff at } t+\tau\,|A_{t+\tau}<K_{i,t}\right]/K_{i,t}=1-\left(1-\kappa_i\right)\kappa_i^{Put}-\kappa_i,$$

where κ_i is the bankruptcy cost of pseudo-firm i, and $\kappa_i^{Put} \equiv E\left[1 - A_{t+\tau}/K_{i,t} \,|A_{t+\tau} < K_{i,t}\right]$. We compute the *ex ante* values for $E\left[1 - A_{t+\tau}/K_{i,t} \,|A_{t+\tau} < K_{i,t}\right]$ for each option in our sample using the historical data of underlying assets and the parameter values of their dynamics based on the information up to time t. Specifically, based on the histogram of $\varepsilon_{t+\tau}$ and parameters $\mu_{t,\tau}$ and $\sigma_{t,\tau}$, we construct the histogram of $A_{t+\tau}$. We then take the average of $1 - A_{t+\tau}/K_{i,t}$ if $A_{t+\tau} < K_{i,t}$.

Our goal is to find the value of κ_i which equates the *ex ante* LGD of pseudo bonds to the corporate LGD in the data, κ_i^{Corp}. Thus, we impose

$$E\left[\text{Bond Payoff at } t+\tau \,|A_{t+\tau} < K_{i,t}\right]/K_{i,t} = 1 - \kappa_i^{Corp},$$

which yields

$$\kappa_i = 1 - \frac{1 - \kappa_i^{Corp}}{1 - \kappa_i^{Put}}.$$

We use Moody's data, shown in Table A4, to find κ_i^{Corp}.

As Chen (2010) documents, corporate LGDs vary over business cycle. Using the Moody's data at the aggregate level, we find that the recovery rate from senior unsecured debt is 5% higher during booms compared with the overall average, whereas it is 27% lower during recessions. Thus, we multiply the recovery rate for each rating by 1.05 and 0.73 depending on business conditions to obtain time-varying recovery rate, $1 - \kappa_i^{Corp}$, for each rating and each month.

Appendix D. Extensions

D.1. Pseudo Bond Excess Returns

In this section we take a different approach to the analysis of credit risk and focus on pseudo bond excess returns. The use of excess returns of portfolios allow us to perform standard asset pricing tests and thus provide further evidence on the source of the large credit spreads.

Table A5, columns five through nine report summary statistics for monthly excess returns of pseudo bonds (Panels A and B), corporate bonds (Panel C), and the lognormal Merton model (Panel D). Highly rated pseudo bonds display lower average excess returns than lower-rated pseudo bonds. Similarly, highly rated pseudo bonds exhibit lower volatility than lower-rated pseudo bonds. Both results are qualitatively consistent with the implications of the Merton model (Proposition 1(b) in Appendix E.1) because both average excess returns and volatility are increasing in market leverage K/A.

Sharpe ratios for pseudo bonds, however, are substantially different across credit ratings. These differences in Sharpe ratios of pseudo bonds are in contrast with the testable implications of the lognormal Merton model, which implies that all zero-coupon corporate bonds should have the same Sharpe ratio (see Proposition 1(d) in Appendix E.1).

Panel C of Table A5 shows that real corporate bonds also display higher excess returns and volatility for lower ratings, which is consistent with the Merton model. Similar to pseudo bonds, moreover, real corporate bonds also have Sharpe ratios that differ across credit ratings, with the highest Sharpe ratios occurring for lower rated bonds.

Panel D of Table A5 shows that even taking into account the influence of time-varying volatility on return series and monthly sampling of returns, the lognormal Merton model does not produce the kind of returns displayed in the first three panels. In particular, average returns and volatility estimates obtained for the lognormal Merton model with Monte Carlo simulations have much smaller magnitudes than are apparent in the data, and the simulated Sharpe ratios exhibit higher values for highly rated bonds than for lower-rated bonds.

The last two columns of Table A5 contain two other important statistics of excess bond returns – skewness and excess kurtosis.[3] For both pseudo bonds and real corporate bonds, excess returns are leptokurtic, although real corporate bonds show a higher excess kurtosis. No obvious pattern of skewness or kurtosis is visible across credit ratings, however, for both pseudo and real corporate bonds.

D.1.1. Excess Bond Returns and Pseudo Firm Assets or Equity

We now examine the determinants of excess bond returns in more detail. Specifically, the second and third columns of Table A6 report average excess returns and t-statistics by rating category. According to the lognormal Merton model, the average excess return on bonds should be explained by the firm's excess return on assets (Proposition 1(b) in Appendix E.1). Because the market values of assets for actual firms are unobservable, we cannot analyze this relation empirically using real corporate bonds. But we can conduct such an analysis on pseudo bonds, whose values are based on *observable* market values of our pseudo firms' assets. For both real corporate bonds and pseudo bonds, however, we can observe excess returns on *equity*. Again, according to the lognormal Merton model the average excess return on bonds should be explained by excess returns on the firms' equity,

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

and this we can do for both pseudo bonds and corporate bonds.

Specifically, we run the following monthly regressions and report the results in Table A6:

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

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

Column four in Panel A shows that single-stock pseudo bond returns display a significantly positive α across most credit ratings when excess returns are regressed on the pseudo firm's excess return on assets. The alphas are larger for lower credit ratings. This result is consistent with the assets of the pseudo firms being subject to systematic (*i.e.,* priced) jumps and stochastic volatility – see Appendix E.2 for a simple demonstrative model.

Columns nine to 13 of Panel A show the results when we regress pseudo bond excess returns on pseudo equity excess returns (given by returns on corresponding equity call options). In this case, only two alphas are significantly positive. Regression betas are increasing with leverage. Both the betas and the R^2 of the regressions on pseudo equity, however, are lower than the results of the regressions on assets, which is consistent with the non-linear relation between asset values and equity.

Turning to SPX pseudo bonds, column four in Panel B shows that in a regression of excess pseudo bond returns on excess returns on assets, all of five portfolio alphas are significantly different from zero. This result is consistent with a model with jumps and stochastic volatility, when they are systematic in nature. Similarly, the regression of pseudo bond excess returns on pseudo equity excess returns (given by returns on corresponding call options) show that most alphas are significantly different from zero.

How do these results for pseudo bonds compare with real corporate bonds? As mentioned, we cannot test whether excess returns of corporate bonds can be explained by excess returns on firms assets. But we can test whether they can be explained by excess returns on firms' equity, and we present the results of those tests in columns nine through 13 of Panel C.

The results are similar to those for the pseudo bond regressions shown in Panel B for SPX pseudo bonds. In particular, the corporate bond alphas (like the SPX pseudo bond alphas) are positive and increasing in credit quality. Actual corporate bond excess return betas with respect to equity are also similar to their pseudo bond counterparts and are significant. R^2's are a bit smaller for real corporate bonds than for pseudo bonds. Overall, we see some strong similarities between the behavior of excess returns of corporate and pseudo bonds *vis-a-vis* excess equity returns.

Panel D of Table A6 presents the same results as in Panels A and B, but in this case for simulations of excess bond returns based on the lognormal Merton model. When we run the same regressions based on simulated excess returns using the Merton model, estimated alphas are much smaller than alphas estimated using real and pseudo bonds and are not significantly different from zero. Betas are again increasing with leverage, but are now much smaller than those estimated using the empirical observations.

D.1.2. Asset Pricing Tests

An important question is whether or not the excess returns for both pseudo bonds and corporate bonds can be explained by priced, systematic risk factors. Accordingly, Table A7 examines whether a number of common risk factors help explain the positive estimated alphas in our pseudo bond and real corporate bond portfolios.

We run the regression

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

where $R^e_{i,t}$ is the excess return on portfolio i, $RMRF_t$ is the excess return on the value-weighted stock market portfolio,[4] $TERM_t$ is the return on the long-term Treasury bonds in excess of T-bill rates, DEF_t is the return on the aggregate long-term corporate bond market portfolio from Ibbotson in excess of the return on long-term Treasury bonds, $dVIXSQ_t$ is the excess return on the option portfolio that underlies the VIX index, $dTED_t$ is the return on a portfolio that replicates the Treasury-Eurodollar ("TED") spread, and $Tail_t$ is the return on the tail-risk factor of Kelly and Jiang (2014). All of these factors are constructed to mimic traded portfolios, thereby enabling us to interpret alpha as an excess return.[5]

Panel A of Table A7 shows the results for pseudo bonds based on the single-stock pseudo firm. Even controlling for these six systematic risk proxies, the alphas are significant across

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

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

credit rating categories. In other words, these six systematic factors do not fully explain the average excess return of pseudo bonds. In terms of factor loadings, pseudo bonds load significantly on the market excess return, while the loadings on other factors vary depend on pseudo credit rating. The volatility factor, $dVIXSQ_t$, features though prominently, especially for lower rated pseudo bonds.

Panel B of Table A7 documents the results for pseudo bonds created from options on the SPX. The results are consistent with those in Panel A, except that now factor loadings are larger and with higher t-stats. In particular, the $TERM_t$ factor is now significant across credit ratings.

Somewhat surprisingly, the TED spread liquidity proxy does not seem to have much impact on pseudo bond returns.[6] One reason could be that the TED spread reflects variations in both liquidity and credit risk across corporate and government bonds, and, to the extent the TED spread is indicating credit risk over the sample period, the risk may already be reflected in other variables.[7] Tail risk, by contrast, enters significantly for some credit ratings, possibly due to the jump probability in the underlying SPX. Yet, the estimated alphas of pseudo bonds are still strongly significant, showing that there are other sources of risk not captured in the risk factors above.

Panel C of Table A7 shows the results of similar regressions for real corporate bonds. Like Panels A and B, the estimated alphas are strongly significant across all credit ratings, showing that the proposed risk factors do not explain the corporate bonds' risk premia. The main explanatory variables for corporate bond excess returns are the term premium $TERM_t$ and (not surprisingly) the corporate default risk factor DEF_t. The volatility risk factor $dVIXSQ_t$ mostly enters negatively in the regressions (as in Panels A and B) but is not significant. The R^2s of the regressions, moreover, are smaller for actual corporate bonds than for the pseudo bonds, perhaps due to the additional noise introduced by the lower liquidity of lower-rated corporate bonds.[8]

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

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

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

D.2. Robustness and Additional Results

This section shows the results discussed in Section 4. but for other maturities. In particular:

- Table A8 shows the *ex ante* and *ex post* default frequencies of pseudo bonds and corporate bonds for the mautities T =30 days, 91 days, 183 days, and 364 days.
- Table A9 presents the credit spread and return statistics of short-horizon pseudo bonds and corporate bonds.
- Table A10 indicates the results about credit spreads and excess returns of single-stock pseudo bonds when we use equivalent European options as opposed to the American traded options.
- Table A11 shows the average credit spreads and LGDs for 1-year pseudo bonds of firms whose assets are the SPX, single stocks, commodities, foreign currencies, fixed income securities, and single stocks with negligible leverage.
- Table A12 reports the results of a factor analysis of credit spreads of pseudo bonds of pseudo firms whose assets are the SPX, single stocks, commodities, foreign currencies, and fixed income securities.

Appendix E. Reference Parametric Models

E.1. The Lognormal Merton Model and Testable Predictions

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

$$dA_t = \mu_A A_t dt + \sigma_A A_t dW_{A,t} \tag{11}$$

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

$$CF_T = K - \max(K - A_T, 0) \tag{12}$$

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

$$B_t(T, K) = KZ_t(T) - P_t(T, K) \tag{13}$$

where $Z_t(T)$ is the price of a zero-coupon bond at t with maturity T, and $P_t(T,K)$ is the price of a European put option at t with maturity T and strike price K. From the assumptions about A_t, the value of the put option $P_t(T,K)$ can be computed and the bond prices in equation (13) analyzed.[9] The corporate bond yield under the Merton model is given by

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

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

Proposition 1. Under the asset dynamics in equation (11), the bond price $B_t(T,K)$ in expression (13) has the following properties:

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

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

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

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

$$\mu_B - r = \beta\,(\mu_A - r);\ \text{and}\ \sigma_B = \beta\sigma_A \tag{14}$$

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

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

$$\mu_B - r = \beta_E\,(\mu_E - r) \tag{15}$$

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

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

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

Note, in particular, that in the lognormal Merton model the bond inherits the properties of expected excess returns from the firm's underlying assets through its beta β, and that the Sharpe ratio of corporate bonds is the same as for the firm's underlying assets. The Merton model thus implies that the Sharpe ratio for the firm's debt is independent of the bond's maturity or face value. Expression (15) for the bond's excess returns, moreover, is

[9] The dynamics of assets in (11) is only convenient inasmuch as it provides a closed-form solution for the value of the put option in equation (13).

often convenient because, in analyzing real corporate bonds, we cannot observe the value of the firm's assets but do observe the value of its equity. For such securities, (15) thus has an empirical counterpart.[10]

Much of the literature that has expanded the original lognormal Merton model has focused on generalizing the asset dynamics in equation (11) – *e.g.*, by adding a jump process, incorporating stochastic volatility, stochastic interest rates, and endogenous default, allowing a firm to experience insolvency prior to maturity, etc. In this paper, we make no assumptions about A_t and instead use U.S. Treasuries and traded options to analyze the properties of bonds directly. In Appendix E.2., we discuss one specific modification of the Merton model in which the market value of the firm's assets A_t follows a jump-diffusion process with stochastic volatility. Although we do not estimate this model, the discussion and a related Proposition 2 in Appendix E.2. shed light on some of our empirical results.

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

(b) From Ito's lemma:

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

The Black and Scholes pricing Partial Differential Equation has

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

Substitution into the previous equation proves the claim, with

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

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

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

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

The results for the lognormal Merton model reported in Figure 2 and Tables A5 , A6, and A7 correct for the influence of any bias generated by time-varying stock return volatility

[10]Note in this connection that we are *not* assuming that the CAPM has to hold under the lognormal Merton model. Indeed, under process (11) the normalized shock $dW_{A,t}$ could itself load on several pricing factors, which then would affect the level of the asset's expected return μ_A.

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

E.2. Jumps and Stochastic Volatility in the Merton Framework.

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

$$dA_t = \left[\mu_A - \lambda E(J_A - 1)\right] A_t dt + \sigma_{A,t} A_t dW_{A,t} + (J_A - 1) A_t dQ_t \quad (16)$$

$$d\sigma_{A,t} = \mu_\sigma\left(\sigma_{A,t}\right) dt + s\left(\sigma_{A,t}\right) dW_{\sigma,t} \quad (17)$$

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

Proposition 2. Under the asset dynamics in Equations (16) and (17), the bond price $B_t(T, K)$ in expression (13) has a risk premium given by

$$\mu_B - r = \left[\alpha_B - \beta_A \, \alpha_A + \beta_\sigma \xi s\left(\sigma_{A,t}\right)\right] + \beta_A \, \left(\mu_A - r\right) \quad (18)$$

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

Expression (18) illustrates how the violations of Merton's lognormality assumption manifest themselves in the risk premium. Because generally $\alpha_B \neq \beta \, \alpha_A$, we should expect a non-zero estimated intercept in a regression of excess bond returns on excess asset returns if jumps reflect an important component of the bond's excess returns and/or volatility dynamics are priced.[11]

[11] As discussed in Broadie et al. (2009, Appendix B), additional alpha may result from discretization bias

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

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

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

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

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

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

or

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

where

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

Q.E.D.

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and the covariance between asset value and volatility.

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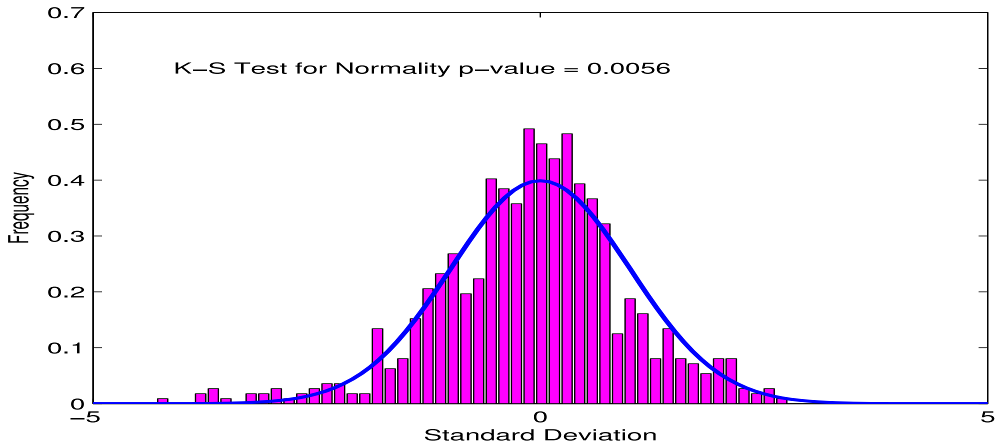
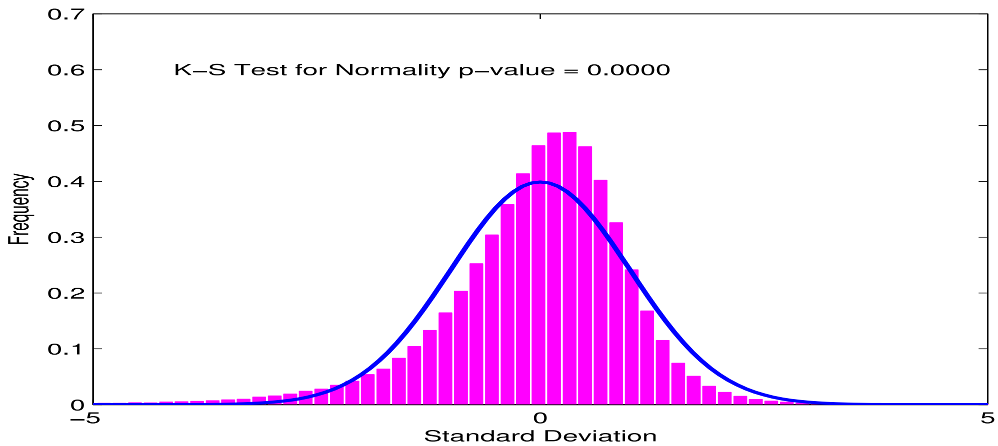
Appendix F. Additional Figures and Tables.

Figure A1: Normalized Monthly Shocks to Two-Year Pseudo Bonds

Panel A: S&P500 Index as Assets



Panel B: Individual Firms as Assets



Notes: Histograms of residuals computed as

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

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

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

Table A1: Options Data

	Spot Price Starts	Option Data Starts	Option Data Ends	Conditional Mean Model	Conditional Vol Model
SPX	194601	199601	201408	Dividend yields	GARCH(1,1)
Individual	194601	199601	201408	Cumulative average	Monthly vol
Commodities:					
Crude oil	197702	198611	201502	Cumulative average	GARCH(1,1)
Natural gas	199004	199210	201502	Cumulative average	Monthly vol
Gold	197402	198601	201502	Cumulative average	GARCH(1,1)
Corn	190002	198502	201502	Cumulative average	GARCH(1,1)
Soybeans	191312	198410	201502	Cumulative average	GARCH(1,1)
FX (CME):					
GBP	197201	198801	201502	Yield difference	GARCH(1,1)
EUR	197201	199901	201502	Yield difference	GARCH(1,1)
JPY	197201	198603	201502	Yield difference	GARCH(1,1)
CHF	197201	198502	201502	Yield difference	GARCH(1,1)
AUD	197201	198801	201502	Yield difference	GARCH(1,1)
CAD	197201	198606	201502	Yield difference	GARCH(1,1)
FX (JPM):					
9 Currencies (*1)	199001	199901	201412	Yield difference	GARCH(1,1)
Swaptions:					
5-, 10-, 20-yr tenor	199105	200207	201412	Forward swap rate	Monthly vol

*1 CAD, EUR, NOK, GBP, SEK, CHF, AUD, JPY, NZD

Table A2: Corporate Bond Historical Default Rates: 1970 — 2013

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

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

Table A3: Default Frequencies of Two-Year Corporate Bonds and Pseudo Bonds

Panel A of this table reports *ex post* default frequencies of corporate bonds by credit rating category (shown in the first column.) The second column is the aggregate average, while columns 3 and 4 report default frequencies during NBER booms and recessions, respectively. The last two columns report the cutoff points used to assign pseudo credit ratings to pseudo bonds, which equal the mid-points of the default frequencies in columns 3 and 4. The exception is the final cut off for Caa- ratings, that is chosen as 150% the historical default rate for Caa- bonds. Panels B and C report the results of our credit rating system for single-stock and SPX pseudo bonds, respectively. Pseudo bonds are constructed from a portfolio of risk-free debt minus single-stock (Panel B) or SPX (Panel C) put options. Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability, *i.e.* the probability the put option is in-the-money at maturity during booms and recessions. The *ex ante* default probabilities of pseudo bonds are computed from the empirical distribution of underlying asset returns. The first two columns of each Panel B and C report the *ex ante* average default probabilities for bonds in each pseudo credit rating category. The next three columns show the actual *ex post* default frequencies of the pseudo bonds across the pseudo credit ratings and their confidence intervals. The *ex post* default frequency is computed as the fraction of times that the two-year return (excluding dividends) on stock prices falls below the given moneyness of the pseudo bonds in each portfolio. The last two columns report the average moneyness of the options $\overline{K/A}$, and the average maturity $\overline{\tau}$ in days. *Ex ante* probabilities of default are computed using asset prices from 1946 to the prediction date, while *ex post* frequencies are from 1970 to 2014.

Panel A: Corporate Bonds

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

Panel B: Pseudo Bonds (Single-Stock)

	Ex ante Def. Prob.		*Ex post* Def. Prob.				
	Boom	Recession	Mean	C.I.(2.5%)	C.I.(97.5%)	$\overline{K/A}$	$\overline{\tau}$
Aaa/Aa	0.12	0.21	0.16	0.00	0.34	0.46	620
A/Baa	1.21	1.59	0.62	0.00	1.27	0.53	625
Ba	3.98	5.75	3.32	0.82	5.83	0.62	642
B	10.49	17.36	8.58	3.94	13.22	0.76	657
Caa-	22.74	36.39	23.69	17.31	30.08	0.93	668

Panel C: Pseudo Bonds (SPX)

	Ex ante Def. Prob.		*Ex post* Def. Prob.				
	Boom	Recession	Mean	C.I.(2.5%)	C.I.(97.5%)	$\overline{K/A}$	$\overline{\tau}$
Aaa/Aa	0.02	0.01	1.94	0.00	4.65	0.40	674
A/Baa	0.99	1.27	2.13	0.00	5.18	0.61	621
Ba	3.49	4.95	6.98	0.07	13.89	0.73	627
B	10.16	18.08	12.60	1.24	23.96	0.83	638
Caa-	23.81	45.03	19.57	5.31	33.83	0.94	644

Table A4: Corporate LGDs: 1982 - 2013

The average corporate recovery rate for senior unsecured bonds, based on rating 2 years before the default. As Aaa-rated bonds have a few defaults, the recovery rate for Aaa/Aa is based on Aa bonds. The recovery rate of A/Baa is the average between A and Baa. The recovery rate in booms is 1.05 multiplied by the average, while the recovery rate in recessions is 0.73 multiplied by the average.

	Recovery rates for Corporate Bonds			LGDs for Corporate Bonds		
	Average	Boom	Recession	Average	Boom	Recession
Aaa/Aa	0.39	0.41	0.28	0.61	0.59	0.72
A/Baa	0.42	0.44	0.31	0.58	0.56	0.69
Ba	0.44	0.46	0.32	0.56	0.54	0.68
B	0.37	0.39	0.27	0.63	0.61	0.73
Caa-	0.37	0.39	0.27	0.63	0.61	0.73

Table A5: Credit Spreads and Returns of Two-Year Pseudo Bonds

Credit spreads and summary statistics are shown for pseudo bonds (Panels A and B), corporate bonds (Panel C), and the lognormal Merton model (Panel D). Pseudo bonds are constructed from a portfolio of risk free debt minus put options on individual stocks (Panel A) or put options on SPX index (Panel B). Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability, i.e. the probability the put option is in the money at maturity. The default probability and the loss-given-default (LGD) are computed from the empirical distribution of asset returns, i.e. the individual stocks or SPX for Panel A and B, respectively. Corporate bonds are non-callable, level-coupon corporate bonds with times to maturity between 1.5 and 2.5 years. LGDs for corporate bonds are from Moody's. The sample period is January 1996 to August 2014. The lognormal Merton model's statistics are averages over 1,000 Monte Carlo simulations of 224 months of asset values. Simulations are designed to replicate the time-variation in volatility and predictability found in the SPX data.

Credit Rating	Credit Spreads (%)			Monthly Excess Returns (%)				
	Average	Boom	Recession	Mean	Std	Sharpe Ratio	Skew	Excess Kurtosis
Panel A: Pseudo Bonds (Single-Stock)								
Aaa/Aa	98	98	103	0.07	0.48	0.15	-0.44	0.86
A/Baa	218	217	223	0.25	1.23	0.20	-1.32	10.35
Ba	346	338	400	0.30	1.32	0.23	-1.44	6.65
B	569	540	769	0.43	1.88	0.23	-1.78	8.80
Caa-	920	862	1324	0.79	2.39	0.33	-1.05	3.12
Panel B: Pseudo Bonds (SPX)								
Aaa/Aa	51	47	74	0.12	0.70	0.18	-3.39	26.15
A/Baa	126	118	191	0.23	1.03	0.23	-2.63	21.69
Ba	214	192	355	0.32	1.30	0.24	-2.03	15.89
B	315	281	547	0.35	1.65	0.21	-1.76	12.05
Caa-	469	409	884	0.40	2.12	0.19	-1.45	7.84
Panel C: Corporate Bonds								
Aaa/A	62	56	106	0.14	0.71	0.20	-2.75	30.28
A/Baa	115	95	249	0.23	0.59	0.39	0.03	1.86
Ba	316	255	706	0.35	1.30	0.27	-1.73	19.15
B	556	502	913	0.77	2.34	0.33	2.25	21.35
Caa-	1382	1221	2632	1.10	4.24	0.26	0.95	5.25
Panel D: Lognormal Merton Model								
Aaa/Aa	0	0	1	0.07	0.47	0.15	0.40	1.75
A/Baa	2	2	7	0.07	0.46	0.15	0.38	1.74
Ba	21	17	45	0.07	0.53	0.13	-0.33	3.46
B	63	51	144	0.09	0.79	0.11	-0.94	6.01
Caa-	194	148	511	0.12	1.46	0.09	-0.59	5.22

Table A6: Returns on Two-Year Pseudo Bonds and Corporate Bonds

This table reports the results of the regression specification

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

where $R^e_{B,t}$ is the excess return of pseudo bonds (Panels A and B), corporate bonds (Panel C), and simulated bonds from the lognormal Merton model (Panel D). The explanatory variable $R^e_{i,t}$ is the excess return on assets ($i = A$, Columns 4 to 8) or equity ($i = E$, Columns 9 to 13). In all cases, bonds are sorted monthly into credit rating categories, and portfolio returns in excess of the U.S. Treasury bill rate are computed over the following month. The sample is January 1996 to August 2014. Statistics for the lognormal Merton model in Panels D are averages of 1,000 Monte Carlo simulations of 224 months of underlying asset values. Simulations are designed to replicate the time-variation in volatility and predictability found in the data.

Credit	Average		Bonds on Assets					Bonds on Equities				
Rating	$\overline{R}$	$t(\overline{R})$	α	$t(\alpha)$	β	$t(\beta)$	R^2	α	$t(\alpha)$	β	$t(\beta)$	R^2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
					Panel A: Pseudo Bonds (Single-Stock)							
Aaa/Aa	0.07	(2.22)	0.04	(0.83)	0.05	(3.57)	0.22	0.06	(1.16)	0.02	(2.07)	0.09
A/Baa	0.25	(3.06)	0.11	(2.00)	0.18	(9.51)	0.65	0.16	(2.31)	0.08	(6.19)	0.50
Ba	0.30	(3.38)	0.12	(2.24)	0.25	(11.64)	0.69	0.15	(2.40)	0.11	(11.41)	0.61
B	0.43	(3.39)	0.12	(1.77)	0.38	(14.41)	0.80	0.08	(0.86)	0.15	(11.89)	0.67
Caa-	0.79	(4.92)	0.19	(2.71)	0.51	(25.99)	0.86	0.09	(0.76)	0.16	(15.84)	0.67
					Panel B: Pseudo Bonds (SPX)							
Aaa/Aa	0.12	(2.05)	0.06	(0.87)	0.10	(3.08)	0.33	0.05	(0.59)	0.06	(2.60)	0.27
A/Baa	0.23	(3.44)	0.12	(2.11)	0.18	(6.80)	0.53	0.13	(1.77)	0.07	(5.22)	0.39
Ba	0.32	(4.05)	0.16	(2.98)	0.24	(10.03)	0.65	0.17	(2.25)	0.08	(8.58)	0.50
B	0.35	(3.61)	0.14	(2.52)	0.33	(12.92)	0.73	0.16	(2.16)	0.09	(10.98)	0.54
Caa-	0.40	(3.24)	0.11	(1.75)	0.45	(17.48)	0.81	0.13	(1.48)	0.10	(14.09)	0.60
					Panel C: Corporate Bonds							
Aaa/Aa	0.14	(3.30)						0.13	(2.91)	0.03	(1.57)	0.08
A/Baa	0.23	(6.45)						0.20	(5.64)	0.03	(3.62)	0.07
Ba	0.35	(4.35)						0.26	(3.65)	0.10	(4.96)	0.36
B	0.77	(5.01)						0.68	(4.46)	0.06	(3.20)	0.09
Caa-	1.10	(2.82)						0.99	(2.64)	0.08	(3.71)	0.13
					Panel D: Lognormal Merton Model							
Aaa/Aa	0.07	(2.30)	0.07	(1.88)	0.00	(0.20)	0.00	0.07	(1.92)	0.00	(-0.67)	0.01
A/Baa	0.07	(2.19)	0.07	(1.81)	0.01	(1.08)	0.01	0.07	(1.83)	0.00	(0.08)	0.00
Ba	0.07	(2.00)	0.06	(1.71)	0.05	(5.05)	0.15	0.06	(1.55)	0.01	(4.13)	0.10
B	0.09	(1.65)	0.06	(1.51)	0.12	(7.21)	0.43	0.04	(1.08)	0.03	(7.28)	0.34
Caa-	0.12	(1.29)	0.06	(1.21)	0.28	(8.56)	0.69	0.01	(0.23)	0.05	(9.89)	0.53

Table A7: Time Series Regression on Risk Factors

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

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

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

	α_i	$RMRF_t$	$TERM_t$	DEF_t	$dVIXSQ_t$	$dTED_t$	$Tail$	$\bar{R}^2$
				Panel A: Pseudo Bonds (Single-Stock)				
Aaa/Aa	0.19	0.06	0.07	-0.09	-0.03	-0.47	-0.04	0.31
	(2.61)	(2.06)	(3.68)	(-1.87)	(-0.21)	(-2.05)	(-1.75)	
A/Baa	0.23	0.15	0.04	0.00	-0.22	-0.11	0.13	0.48
	(3.13)	(6.08)	(1.94)	(0.04)	(-1.09)	(-0.62)	(2.43)	
Ba	0.31	0.17	0.04	0.06	-0.67	-0.35	0.01	0.64
	(3.49)	(7.09)	(1.44)	(1.30)	(-3.74)	-1.67	(0.69)	
B	0.40	0.26	0.04	0.14	-0.89	-0.21	0.00	0.75
	(4.03)	(7.95)	(1.57)	(2.97)	(-4.32)	(-0.90)	(-0.02)	
Caa-	0.68	0.35	0.03	0.19	-0.97	-0.05	0.03	0.78
	(6.77)	(11.28)	(1.10)	(3.56)	(-4.00)	(-0.15)	(0.88)	
				Panel B: Pseudo Bonds (SPX)				
Aaa/Aa	0.11	0.10	0.04	-0.03	-0.12	0.08	0.01	0.34
	(1.75)	(3.07)	(2.66)	(-1.15)	(-0.85)	(0.40)	(0.40)	
A/Baa	0.23	0.15	0.03	0.01	-0.38	-0.08	0.01	0.55
	(3.83)	(5.68)	(2.09)	(0.19)	(-2.50)	(-0.46)	(0.95)	
Ba	0.31	0.19	0.04	0.06	-0.55	-0.08	0.02	0.66
	(5.13)	(8.10)	(2.33)	(1.60)	(-3.46)	(-0.46)	(1.92)	
B	0.32	0.26	0.04	0.10	-0.78	-0.09	0.02	0.76
	(4.58)	(9.85)	(2.29)	(2.31)	(-4.53)	(-0.49)	(2.00)	
Caa-	0.27	0.38	0.04	0.12	-0.71	-0.16	0.02	0.82
	(4.03)	(13.32)	(2.18)	(2.58)	(-3.80)	(-0.78)	(1.71)	
				Panel C: Corporate Bonds				
Aaa/Aa	0.34	-0.03	0.07	0.09	-0.41	-0.74	0.02	0.29
	(7.32)	(-1.50)	(6.24)	(1.80)	(-1.43)	(-3.85)	(1.18)	
A/Baa	0.41	0.01	0.08	0.07	-0.16	-0.26	0.02	0.28
	(10.23)	(0.75)	(7.42)	(3.33)	(-1.87)	(-2.37)	(1.87)	
Ba	0.49	0.10	0.09	0.19	-0.26	-0.17	-0.06	0.29
	(6.44)	(3.35)	(4.58)	(4.82)	(-1.52)	(-0.75)	(-1.87)	
B	0.78	0.14	0.06	0.20	-0.09	-0.37	-0.05	0.10
	(6.07)	(2.19)	(1.27)	(2.39)	(-0.22)	(-0.80)	(-0.99)	
Caa/C	0.92	0.09	-0.08	0.38	-0.64	-0.26	-0.04	0.07
	(1.91)	(0.70)	(-0.84)	(1.75)	(-0.60)	(-0.15)	(-0.31)	

Table A8: Default Frequencies of Short-Term Corporate Bonds and Pseudo Bonds

The left-hand-side of this table reports *ex post* default frequencies of corporate bonds with Moody's credit ratings reported in the first column across maturities. The mean is the aggregate average and columns 3 and 4 report default frequencies during NBER booms and recessions, respectively. The two panels on the right-hand-side report the results of our credit rating methodology for SPX and single-stock pseudo bonds. Pseudo bonds are constructed from a portfolio of risk-free debt minus put options on the SPX index or individual stocks. Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bonds *ex ante* default probabilities (i.e. the probabilities that the put options are in the money at maturity) during booms and recession. In each subpanel, the first two columns report the *ex ante* average default probabilities for pseudo bonds in booms and recessions, respectively, for each pseudo credit rating. The next three columns show the actual *ex post* default frequencies of the pseudo bonds across the pseudo credit ratings, and their confidence intervals. The *ex post* default frequency is computed as the fraction of times the stock return (excluding dividends) drops below the portfolio moneyness in the sample. The last two columns collect the average leverage K/A of pseudo bonds, and their average time to maturity (days). The sample of underlying asset price for *ex post* default frequency is 1970 to 2013.

	Corporate Bonds			Pseudo Bonds (Single-Stock)							Pseudo Bonds (SPX)						
				Ex ante Def. Prob.		*Ex post* Default Frequency					*Ex ante* Def. Prob.		*Ex post* Default Frequency				
	Mean	Boom	Bust	Boom	Bust	Mean	C.I. (2.5%)	C.I. (97.5%)	$\overline{K/A}$	$\overline{\tau}$	Boom	Bust	Mean	C.I. (2.5%)	C.I. (97.5%)	$\overline{K/A}$	$\overline{\tau}$
							Target Maturity: 30 days										
IG	0.00	0.00	0.01								0.00	0.00	0.37	0.00	0.90	0.77	33
Ba	0.05	0.04	0.11	0.07	0.19	0.10	0.03	0.17	0.70	50		0.18	0.37	0.00	0.90	0.8	33
B	0.22	0.19	0.43	0.58	1.23	0.34	0.16	0.52	0.78	50	0.32	0.82	0.56	0.00	1.20	0.86	31
Caa-	1.89	1.61	3.47	1.65	3.64	1.96	1.48	2.44	0.83	50	1.55	3.52	2.41	1.09	3.73	0.91	33
							Target Maturity: 91 days										
IG	0.01	0.01	0.03	0.05	0.14	0.02	0.01	0.04	0.54	147	0.00	0.01	0.56	0.00	1.20	0.67	119
Ba	0.19	0.16	0.38	0.27	0.63	0.29	0.10	0.48	0.61	139	0.23	0.68	0.56	0.00	1.20	0.74	108
B	0.75	0.65	1.48	1.43	3.23	0.94	0.42	1.47	0.70	128	1.24	2.87	1.68	0.00	3.43	0.82	90
Caa-	4.90	4.07	9.51	4.16	9.66	4.39	2.98	5.79	0.78	119	4.27	9.86	7.26	3.52	11.01	0.88	85
							Target Maturity: 183 days										
Aaa/Aa	0.00	0.00	0.03	0.01	0.04	0.01	0.00	0.02	0.32	280	0.00	0.00	0.75	0.00	1.91	0.59	197
A/Baa	0.03	0.02	0.09	0.14	0.35	0.08	0.02	0.13	0.50	233	0.15	0.25	0.94	0.00	2.46	0.68	192
Ba	0.47	0.40	0.91	0.60	1.45	0.65	0.18	1.12	0.57	215	0.48	1.16	2.06	0.00	4.72	0.73	193
B	1.69	1.47	3.33	2.69	6.51	1.79	0.75	2.82	0.68	195	2.35	5.83	2.25	0.00	5.13	0.80	189
Caa-	8.88	7.25	17.73	7.59	18.25	7.32	4.87	9.76	0.79	182	7.63	18.34	8.24	2.56	13.92	0.87	183
							Target Maturity: 365 days										
Aaa/Aa	0.01	0.00	0.05	0.03	0.12	0.03	0.00	0.07	0.33	372	0.00	0.05	1.14	0.00	3.01	0.47	355
A/Baa	0.10	0.08	0.24	0.38	0.76	0.21	0.00	0.41	0.46	372	0.31	0.70	2.08	0.00	4.91	0.61	348
Ba	1.19	1.08	1.91	1.50	3.16	1.30	0.24	2.37	0.55	361	1.37	2.37	3.22	0.00	7.45	0.71	352
B	4.01	3.57	7.31	5.16	11.84	3.61	1.43	5.80	0.69	348	4.62	10.48	6.82	0.40	13.24	0.80	353
Caa-	15.37	12.63	29.49	13.29	29.78	13.04	8.73	17.36	0.84	329	13.02	33.33	13.45	3.25	23.64	0.87	348

Table A9: Credit Spreads and Returns of Short-Term Pseudo and Corporate Bonds

Credit spreads and excess returns summary statistics are shown for short-term single-stock pseudo bonds (columns 2 to 7), SPX pseudo bonds (columns 8 to 13), and corporate bonds (columns 14 to 19). Pseudo bonds are constructed from a portfolio of risk-free debt minus SPX put options or put options on individual stocks. Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability (i.e. the probability the put option is in the money at maturity) in booms and recessions. Corporate bonds are non-callable, level-coupon corporate bonds with time to maturity close to the one reported in the Panel's heading. The sample is monthly and runs from 1996 to 2014.

Credit Rating	Credit Spread	Monthly Returns in Excess of T-bill (%)					Credit Spread	Monthly Returns in Excess of T-bill (%)					Credit Spread	Monthly Returns in Excess of T-bill (%)				
		Mean	Std	Sharpe Ratio	Skew	Ex. Kurt.		Mean	Std	Sharpe Ratio	Skew	Ex. Kurt.		Mean	Std	Sharpe Ratio	Skew	Ex. Kurt.
	Pseudo Bonds (Single-Stock)						Pseudo Bonds (SPX)						Corporate Bonds					
Target Maturity: 30 Days																		
IG							79	0.03	0.13	0.19	0.28	6.34						
Ba	255	-0.20	0.75	-0.26	-4.26	23.43	280	0.02	0.62	0.03	-2.97	12.00						
B	387	-0.18	0.78	-0.23	-3.00	13.96	206	0.03	0.56	0.06	-9.84	129.14						
Caa-	582	-0.10	1.02	-0.10	-5.83	54.96	424	0.09	0.97	0.09	-6.22	55.33						
Target Maturity: 91 Days																		
IG	133	-0.06	0.62	-0.09	2.71	30.93	61	0.08	0.25	0.31	-5.55	56.11						
Ba	164	-0.05	0.46	-0.10	-2.21	14.69	120	0.13	0.38	0.33	-3.84	38.96						
B	297	0.03	0.71	0.05	-2.66	21.04	222	0.16	0.59	0.28	-4.23	35.81						
Caa-	525	0.13	1.04	0.13	-2.30	15.09	418	0.27	0.95	0.29	-3.64	31.60						
Target Maturity: 183 Days																		
Aaa/Aa	68	-0.07	0.41	-0.18	-4.20	21.15	46	0.06	0.46	0.13	-10.36	136.14	37	0.06	0.24	0.26	1.86	17.99
A/Baa	106	-0.03	0.38	-0.08	-1.94	8.94	90	0.09	0.52	0.17	-5.55	45.73	124	0.14	0.25	0.54	-0.45	14.12
Ba	164	0.01	0.53	0.02	-1.70	11.71	150	0.13	0.69	0.19	-4.59	39.96	290	0.26	0.70	0.37	1.78	13.30
B	327	0.05	0.93	0.06	-2.78	19.75	255	0.22	0.90	0.24	-2.87	21.25	631	0.34	1.39	0.25	-1.17	15.35
Caa-	650	0.13	1.44	0.09	-2.04	11.60	420	0.30	1.30	0.23	-2.67	19.09	1190	0.41	2.52	0.16	-1.40	5.10
Target Maturity: 365 Days																		
Aaa/Aa	71	0.06	0.52	0.12	-0.82	12.11	39	0.04	0.51	0.08	-7.56	78.69	55	0.11	0.42	0.27	0.62	10.12
A/Baa	112	0.06	0.59	0.10	-2.04	15.23	83	0.13	0.62	0.20	-4.64	43.94	114	0.17	0.45	0.38	-1.67	18.24
Ba	193	0.06	0.87	0.07	-2.90	20.28	166	0.21	0.89	0.24	-2.65	23.39	310	0.33	0.75	0.45	1.30	6.64
B	424	0.17	1.40	0.12	-2.86	20.03	270	0.27	1.20	0.22	-2.43	18.77	597	0.75	2.15	0.35	2.42	12.11
Caa-	867	0.39	1.94	0.20	-1.57	7.40	424	0.33	1.69	0.19	-2.05	13.77	1196	1.18	4.20	0.28	0.64	3.63

Table A10: Assets as Shares of Individual Firms in the SPX Index: Equivalent European Options

This table contains several results for pseudo bonds constructed from individual stocks as presented in the paper, except that pseudo bonds are computed from European-equivalent put options. European-equivalent put options are obtained from the implied volatilities reported from OptionsMetrics. Panel A reports summary statistics of the pseudo bond portfolios. Columns 2 to 4 report the Gaussian-kernel weighted average credit spread of pseudo bonds. Column 5 reports the equal weighted average credit spread of pseudo bonds in each credit rating category, while the next several columns report summary statistics of portfolio bond returns. For each credit rating, Panel B reports the time-series regression of the pseudo bond portfolio excess returns on the average excess returns of pseudo assets (i.e. stocks of underlying individual firms). For each credit rating, Panel C reports the time-series regression of the pseudo bond portfolio excess returns on the average excess returns of pseudo equity (i.e. call options of the underlying individual firms).

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

	Credit Spreads			Monthly Returns in Excess of T-bill (%)				
	Average	Boom	Recession	Mean	Std	SR	Skew	Ex. Kurt
Aaa/Aa	97	97	103	0.07	0.48	0.14	-0.47	0.90
A/Baa	214	213	224	0.25	1.11	0.23	-0.58	4.98
Ba	341	332	399	0.29	1.29	0.22	-1.47	6.94
B	559	530	764	0.41	1.84	0.22	-1.81	9.13
Caa-	899	840	1311	0.75	2.32	0.32	-1.06	3.35

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

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	0.07	(2.17)	0.04	(0.80)	0.05	(3.53)	0.22
A/Baa	0.25	(3.41)	0.12	(2.46)	0.16	(11.72)	0.64
Ba	0.29	(3.35)	0.12	(2.17)	0.24	(11.73)	0.68
B	0.41	(3.36)	0.12	(1.70)	0.37	(13.85)	0.79
Caa-	0.75	(4.82)	0.17	(2.46)	0.49	(24.01)	0.85

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

	Mean (%)	$t(Mean)$	α	$t(\alpha)$	β	$t(\beta)$	R^2
Aaa/Aa	0.07	(2.17)	0.06	(1.13)	0.02	(2.02)	0.09
A/Baa	0.25	(3.41)	0.17	(2.67)	0.07	(6.70)	0.47
Ba	0.29	(3.35)	0.15	(2.35)	0.11	(11.10)	0.59
B	0.41	(3.36)	0.08	(0.86)	0.14	(11.53)	0.66
Caa-	0.75	(4.82)	0.08	(0.72)	0.16	(15.12)	0.66

Table A11: Extensions: Types of Assets and Bankruptcy Costs. 1-year Pseudo Bonds.

Credit spreads and LGDs are shown for corporate bonds and for pseudo bonds with one year to maturity. Pseudo bonds are constructed from a portfolio of risk-free debt minus put options on the SPX index (column "SPX"), on individual stocks (column "Single Stocks"), on commodity futures (column "Commodities"), on foreign currency (column "Currencies"), swaptions (column "Fixed Income"), or single stocks for underlying firms with negligible leverage (column "Low Leverage"). Pseudo credit ratings of pseudo bonds are assigned based on the pseudo bond *ex ante* default probability, i.e. the probability the put option is in the money at maturity. In Panel B the 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 are non-callable, level-coupon corporate bonds with times to maturity between 0.5 and 1.5 years. LGDs for corporate bonds are from Moody's. Sample periods vary: SPX and single stocks – 1/1996 to 8/2014; commodities – mid 1980s to 2/2015; foreign currencies – 1/1999 to 12/2014; swaptions – 7/2002 to 12/2014.

Credit Rating	Corporate	SPX	Single Stocks	Commodities	Currencies CME	Currencies JPM	Fixed Income	Low Leverage
				Panel A: Credit Spreads across Types of Assets (bps)				
Aaa/Aa	55	39	71	22	21	-	30	94
A/Baa	114	83	112	39	53	-	68	169
Ba	310	166	193	68	69	83	97	319
B	597	270	424	174	119	75	138	658
Caa-	1196	424	867	341	196	152	261	1194
				Panel B: Ex-Post Loss-Given-Default (%)				
Aaa/Aa	63.0	6.3	32.6	9.6	4.3	-	4.1	26.1
A/Baa	68.0	7.2	32.8	9.6	4.2	0.1	4.1	22.5
Ba	60.0	16.0	26.0	12.7	5.4	5.6	3.8	24.3
B	54.0	11.7	21.0	12.0	4.8	4.6	2.2	20.9
Caa-	62.0	12.5	17.6	14.0	6.1	5.1	3.5	18.3
				Panel C: Credit Spreads adjusted for Loss-Given-Default (bps)				
Aaa/Aa	62	130	124	124	206	-	318	-
A/Baa	115	288	244	190	675	-	665	713
Ba	316	491	488	325	688	1086	762	985
B	556	911	1237	859	1391	1213	1239	1990
Caa-	1382	1431	2651	1733	2272	1350	2505	3506
				Panel D: Ex-Post Loss-Given-Default with adjustment (%)				
Aaa/Aa	63.0	-	50.9	-	-	-	-	41.6
A/Baa	68.0	70.0	67.1	70.9	69.31331	67.0	69.3	60.3
Ba	60.0	62.9	60.4	61.4	60.70613	60.2	61.1	58.2
B	54.0	55.4	52.8	53.0	54.33577	53.9	54.3	51.4
Caa-	62.0	63.6	59.8	61.8	62.4795	61.7	62.1	59.1

Table A12: Common Factors in Pseudo Bonds of Pseudo Firms with Heterogeneous Assets

Regression result of credit spreads of pseudo bonds issued by pseudo firms with assets defined in the first row on a pseudo credit spread factor. The credit spread factor is equal to the average of standardized credit spreads across the asset classes in the first column. Panel A reports the results for IG pseudo bonds, and Panel B reports results for HY pseudo bonds. The left panels use 1-year pseudo bonds while right-hand panels use 2-year pseudo bonds. The sample periods is from January 1996 to August 2014, except for foreign currencies (start January 1999) and fixed income (start July 2002).

Panel A. IG Pseudo Bonds						
	1-year			2-year		
	b	$t(b)$	R^2	b	$t(b)$	R^2
SPX	1.07	8.36	0.62	1.02	7.36	0.66
single-stock	1.12	5.25	0.53	0.98	12.01	0.65
commodity	1.03	6.90	0.71	0.94	3.9	0.55
cme fx	0.51	2.47	0.12			
jpm fx						
fixed income	1.01	5.70	0.41	1.29	6.45	0.52

Panel B. HY Pseudo Bonds						
	1-year			2-year		
	b	$t(b)$	R^2	b	$t(b)$	R^2
SPX	1.09	17.29	0.80	1.09	11.97	0.83
single-stock	1.06	13.24	0.76	1.01	12.13	0.71
commodity	0.99	14.86	0.67	0.97	13.36	0.65
cme fx	0.98	10.45	0.71			
jpm fx	1.07	11.46	0.87	1.05	13.8	0.79
fixed income	0.80	5.49	0.57	0.89	5.99	0.65