Default Risk Premia and Asset Returns*

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Abstract

We identify a common default risk premia (DRP) factor in the risk-adjusted excess returns on pure default-contingent claims. Asset pricing tests using almost 50 corporate bond portfolios sorted on rating, maturity or industry suggest that the DRP factor is priced in the corporate bond market. For index put option portfolios sorted on maturity and moneyness, both average returns and DRP beta estimates become more negative with decreasing time to maturity. There is little to no evidence of the DRP factor being priced in equity markets. Most of the variation in DRP is explained by the portion DRP^{JtD} due to common jump-to-default risk premia. A theoretical framework where DRP^{JtD} is part of the pricing kernel supports our empirical findings.

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1 Introduction

Recent empirical studies in financial economics suggest that the price for bearing exposure to U.S. corporate default risk, after controlling for expected default losses, is substantial and that it varies dramatically over short horizons of time. Driessen (2005) finds that instantaneous risk-neutral default probabilities are 1.8 times higher than their rating-based counterparts. He assumes that a firm's default probability is the average historical default frequency of firms with the same credit rating. Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) and Saita (2006) use firm-specific estimates of conditional physical default probabilities instead and estimate the median ratio of risk-neutral to physical default intensities to be 2.0 and 3.7, respectively. Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) show that for a given default probability, credit spreads exhibit substantial time variation. They peaked in the third quarter of 2002 and then declined steadily and dramatically through late 2003 to roughly 50% of the value at their peak.[1]

If credit markets are close to being in equilibrium most of the time, any preference-based asset pricing theory will predict that investors demand risk premia on traded assets to compensate for bearing systematic risk. While investor preferences might change over time, it is quite unlikely that they would change dramatically enough over short horizons to induce a time variation in observed default risk premia of the magnitude reported in the aforementioned studies. Alternatively, investors might demand higher compensation for being more exposed to certain systematic factors which suddenly become more important relative to other systematic factors.

This is the first paper to extract a common risk factor from credit markets and investigate its contribution towards explaining average returns observed in corporate bond, equity and index option markets. Our data consist of weekly at-market credit default swap (CDS) rates provided by Markit for 112 firms from 9 different industries, ranging from January 2002 to October 2006. We use these observation to estimate, for each firm and week, the price of a pure default-contingent claim that pays one unit of account if default does not occur before the maturity of the contract (in our applications, one year), and zero otherwise. We form a credit-market portfolio consisting of these pure credit-contingent claims, equally-weighted across all firms in our sample. The sample correlations between the weekly excess returns on this credit-market portfolio and the three stock-market factors MKT, SMB and HML in Fama and French (1993) are 0.22, 0.21 and 0.16, respectively. To investigate the

[1] Berndt and Obreja (2007) discover similar findings for European credit markets.

marginal contribution of a new credit-market risk factor, we identify that portion of the weekly excess returns on the credit-market portfolio that cannot be explained by linear combinations of systematic risk factors. We refer to it as the default risk premia factor, or simply the DRP factor. Besides the Fama-French stock-market factors we also control for the momentum factor introduced by Jagadeesh and Titman (1993) and the $TERM$ factor in Fama and French (1993) which proxies the common risk in bond returns that arises from unexpected changes in interest rates. The systematic risk factors explain 25% of weekly realized excess returns on the credit-market portfolio. At the firm level, between 4% and 59% of the excess returns on pure default-contingent claims can be associated with known systematic risk factors. For the median firm in our sample, 20.4% of the variation in the residuals can be attributed to the DRP factor.

Results using Bloomberg-NASD corporate bond indices generated from actual transaction prices of actively traded issues suggest that the DRP factor is priced in the corporate bond market. A cross-sectional analysis of Merrill Lynch corporate bond portfolios, sorted on industry, maturity or rating, supports these findings. We also construct 16 portfolios of delta-hedged European put options written on the S&P 500 index, sorted on moneyness and maturity. We find that both average returns and the beta estimates for our default risk premia factor become more negative as time to maturity decreases. Although less pronounced, a similar overall trend can be observed along the moneyness dimension for portfolios of first- and of second-to-expire index put options. The DRP factor contributes little towards explaining the time variation in equity portfolio returns.

To further test the hypothesis that DRP is a priced factor, we implement the two-pass procedure in Fama and MacBeth (1973) using a total of 214 test assets from all three markets. In particular, we include the IG and HY Bloomberg-NASD corporate bond portfolios, a total of 47 Merrill Lynch corporate bond portfolios, the 100 Fama and French equity portfolios sorted on size and book-to-market, the 49 Fama and French industry equity portfolios, and the 16 index put options portfolios sorted on moneyness and time to maturity. Our results show that the weekly risk premia on the DRP factor is about 3 basis points, and that this estimate is statistically significant.

In order to account for the possibility that some of the co-movement in risk-adjusted excess returns on pure default-contingent claims is due to reasons other than the common variation in covariances, we also test for firm characteristics such as the firm's default probability and recovery rate, its leverage ratio and implied volatility. We find that the common variation in default risk premia is not likely to be due to these firm characteristics.

To offer additional insights into our empirical findings we use estimates of conditional default probabilities provided by Moody's KMV to decompose the DRP factor into a portion associated with common changes in expected default losses (DRP^L), a portion due to common variation in jump-to-default risk premia (DRP^{JtD}), and a portion due to common variation in the market price of default risk (DRP^{MPR}). For our model specification, the first two components account for most of the time variation in the DRP factor, with R^2's ranging between 87% for the first quarter of 2003 and almost 100% during the first quarter of 2002 and the second quarter of 2005. For corporate bonds, the loadings on DRP^{JtD} are statistically significant and increase with increasing average excess returns, indicating that market-wide jump to default risk is priced in the corporate bond market. For the equity portfolios, none of the factors by themselves appear to be significant in explaining the time variation of returns. For the index put options, the DRP^{JtD} factor is estimated consistently to have the correct (negative) sign. The beta estimates line up with average excess returns within each moneyness bin. They are estimated to be lower (more negative) for out-of-the-money options than for at-the-money contracts. For short-term index put options, both average returns and the loadings on DRP^L become more negative as options move out of the money. With regard to the cross-sectional results, weekly risk premia on DRP^L, DRP^{JtD} and DRP^{MPR} are estimates to be 1, 2 and 1 basis points, respectively. The latter two are significant at the 5%-level.

Next, we develop a theoretical framework in which DRP^{JtD} arises naturally in the pricing kernel and show that it captures the jump-to-default risk premia associated with market-wide credit events. Within this framework, unlike risk premia on corporate bonds and index put options, equity risk premia are only marginally affected by DRP^{JtD}. This result is based on the observation that DRP^{JtD} has a much stronger impact on the returns of assets with a non-degenerate payoff structure in the default states.

Finally, we address the practical issue of building trading strategies based on the DRP factor. The pure default-contingent claims used to construct the DRP factor are not actually traded. To give the reader a sense of how a trading strategy based on the same motivation as for our default risk premia factor could be implemented, we compute an alternative CDS-based DRP factor, named $CDRP$, by replacing the holding returns on pure default-contingent claims by negative changes in logarithmic default swap rates. Although with different magnitudes, similar conclusions can be drawn from asset pricing tests that use $CDRP$ and its components.

Related Literature

Fama and French (1993), Collin-Dufresne, Goldstein, and Martin (2001) and Elton, Gruber, Agrawal, and Mann (2001), among others, have shown that systematic stock-market factors are insufficient to explain returns on corporate bonds. The first paper introduces a corporate bond market factor DEF to account for shifts in economic conditions that change the price of default risk. It is defined as the difference between the return on a portfolio of long-term corporate bonds and the long-term government bond return. Because returns on corporate bonds are contaminated by tax and liquidity effects (see, for example, Elton, Gruber, Agrawal, and Mann (2001), Delianedis and Geske (2001) and Longstaff, Mithal, and Neis (2005)), DEF is not a clean measure of the reward for exposure to default risk. Our DRP factor, on the other hand, is constructed exclusively using pricing information from credit markets and should be a better measure of the return on default risk. We disentangle DEF into default-related components (DRP^L, DRP^{JtD} and DRP^{MPR}) and a non-default-related component to gain additional insights into the pricing of different classes of assets.

A number of papers have studied whether default risk is priced in equity markets. They differ in the choice of variables used to predict bankruptcy and the methodology employed to estimate the likelihood of default. The Altman Z-score (Altman (1968)) and Ohlson O-score (Ohlson (1980)) are based on accounting variables and have emerged as popular measures of financial distress. They are used, for example, by Dichev (1998), Griffin and Lemmon (2002) and Ferguson and Shockley (2003) to explore the risk and average return of distressed firms. Vassalou and Xing (2004) and Da and Gao (2005) rely on the distance to default, an asset-volatility-adjusted leverage measure of the firm. More recently, Campbell, Hilscher, and Szilagyi (2007) construct their own empirical measure of financial distress by estimating a dynamic panel model using a logit specification. Except for Vassalou and Xing (2004), these studies generally find that the equity market has not properly priced distress risk. Our approach differs from this body of literature in that instead of sorting portfolios on estimates for actual default risk, we construct a risk factor that is based on returns observed in credit markets. Focusing only on expected default losses only ignores the effect of jump-to-default risk on asset returns, which we identify to be important when pricing corporate bonds and index put options.

To date only a few papers have investigated whether jump-to-default risk is priced, and the existing studies focus on solving the credit spread level (and volatility) puzzle. Collin-Dufresne, Goldstein, and Helwege (2003) propose a reduced-form model where jumps to default are priced because they generate a market-wide jump in credit spreads. While this framework is consistent with a counterparty risk interpretation as in Jarrow and Yu (2001), it is more naturally interpreted as an updating of beliefs due to unexpected events. Cremers, Driessen, and Maenhout (2006) use a structural jump-diffusion firm model with systematic and firm-specific jumps to generate option-implied jump-risk premia. By means of a calibration exercise, the authors show that incorporating option-implied jump risk premia brings predicted credit spread levels much closer to observed levels. Amato and Remolona (2005) argue that idiosyncratic jump-to-default risk is highly priced in the corporate bond market because there are not enough liquid names to allow investors to significantly diversify that risk in the sense of Jarrow, Lando, and Yu (2005). They point to the fact that credit indices have only 125 names and argue that there is so much skewness in bond returns that idiosyncratic risk may be difficult to diversify with exposure to less than 500 corporate issuers. In contrast, Saita (2006) documents that there is ample compensation in corporate debt portfolios for skewness and kurtosis, in part because there are indeed significant opportunities for diversification even in moderately sized portfolios, and in part because of the large compensation for the individual issuer risk.

The remainder of this paper is structured as follows. Section 2 describes our data, comprised of credit default swap rates, Moody's KMV EDF estimates for actual default probabilities, OptionMetrics option pricing information and other accounting and market price data. Section 3 introduces our measure of model-implied holding-period returns on pure default-contingent claims, and Section 4 presents a methodology for extracting a latent common factor from the associated firm-specific risk-adjusted excess returns. Section 5 describes our results from the asset pricing tests, and Section 6 takes a closer look at the DRP components. Section 7 proposes a the theoretical framework of the relevant pricing kernel that is consistent with our empirical findings, and Section 8 summarizes our findings and discusses an alternative DRP factor that can be traded.

2 Data

This section describes our data sources for *(i)* default swap rates, *(ii)* conditional default probabilities, *(iii)* returns on equity, option and corporate bond portfolios, and *(iv)* firm characteristics.

2.1 Credit Default Swaps

Credit default swaps (CDS) are over-the-counter credit derivatives that provide bond insurance. Fueled by participation from commercial banks, insurance companies, and hedge funds, CDS markets have grown exponentially over the past ten years, reaching an estimated outstanding notional value of more than $34.4 trillion dollars in 2006.[2] The buyer of protection in a CDS contract pays a quarterly insurance premium until the expiration of the contract or until default by the reference entity, whichever occurs first. In return, the seller of protection pays to the buyer of protection the difference between the face value and the market value of the referenced debt. This compensation can be through physical delivery or cash delivery, with the former being more common.

For our data, default events are triggered by bankruptcy, failure by the obligor to make payments on its debt, or a debt restructuring that is materially adverse to the interests of the creditors. For the latter, the "modified" ISDA contractual standards apply. In the case of physical settlement, modified debt restructuring restricts deliverable obligations to have a maturity within 30 months of the CDS contract's maturity. This significantly decreases heterogeneity at a debt restructuring event in the maturity, and hence the market value, of the various deliverables.

CDS rates are quoted as annualized percentages of the notional value of the debt covered. Using an actual 360-day convention, they are equal to four times the quarterly premia. Default swap data are provided by Markit and consist of weekly (Wednesday) 1-year and 5-year at-market CDS rates for senior-unsecured U.S. dollar-denominated debt with modified restructuring. Here, "at-market" denotes the premium rate at which the market value of the CDS contract at initiation is equal to zero. Our observations are for 112 firms from 9 different industries, including 9 firms from the Basic Materials sector, 15 Consumer Goods firms, 9 Consumer Services firms, 14 Health Care firms, 17 Industrials firms, 17 Oil and Gas firms, 8 Technology firms, 9 Telecommunications firms, and 14 Utilities. The sample period ranges from January 2, 2001 to October 11, 2006, with a total of 250 weeks. Table 1 in Appendix A lists the firms covered in our sample, sorted by industry. For the median firm, the average 1-year and 5-year CDS rates are 41 and 68 basis points, respectively. It has 250 weekly 5-year CDS observations, and 247 1-year CDS observations. Figure 1 shows the distribution of median Moody's senior rating during the sample period. It

[2]According to the ISDA (International Swaps and Derivatives Association) market survey available at http://www.isda.org/statistics/historical.html.

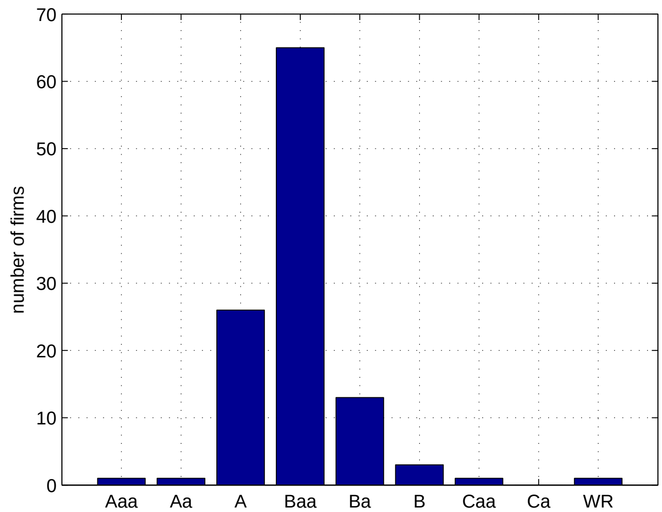

Figure 1: Distribution of firms by median Moody's senior rating during the sample period. Source: Moody's DRS.

indicates that the range of credit scores of the included firms is concentrated around medium credit quality, with the majority of the firms having a Baa rating. Credit ratings at the firm level were obtained from Moody's Default Risk Service (DRS) data base.

Figure 7 in Appendix A displays the time series of median recovery rates by industry as reported by Markit, for each week in our sample period. We find that there is little variation over time in the magnitude of the recovery rates, with median sector recovery rates ranging between 36% and 45%. At the firm level, a similar observation regarding the limited amount of time variation for recovery rates holds true. Our understanding from conversations with Markit is that the reported recoveries are indicative of the values used by their contributors when pricing CDS contracts. We therefore compute firm-specific estimates for the risk-neutral mean fractional loss given default as one minus the average of the recovery rates reported by Markit over the sample period.

The CDS data used in this study are composites. Markit re-distribution rules stipulate that there are at least three contributors to each composite quote.[3] The median firm in our sample has 10 contributors for the 5-year CDS rate quotes. Figure 2 plots the distribution of firms by median number of quote contributors. In our sample, the median firm has a sample median of 10 contributors for the 5-year CDS rate quotes.

[3]See http://www.markit.com for further details on the CDS pricing data.

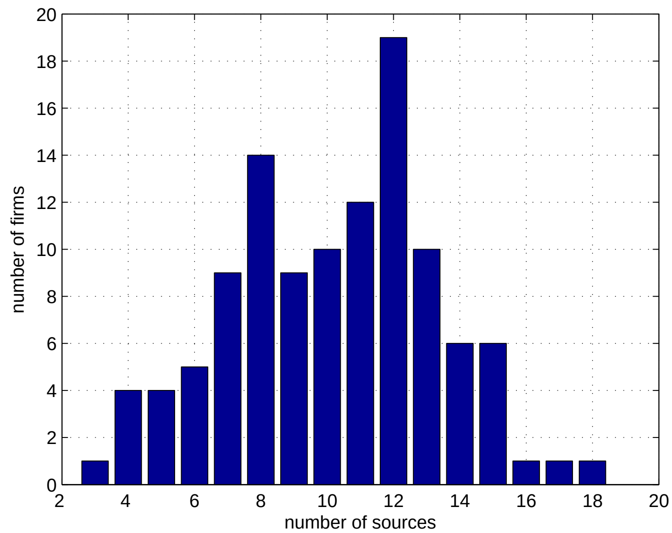

Figure 2: Distribution of firms by median number of quote contributors during the sample period. Source: Markit.

2.2 EDF Data

We use one-year EDF$^{\mathrm{TM}}$ (Expected Default Frequency) data provided by Moody's KMV as our estimates of conditional actual default probabilities. The concept of the EDF measure is based on the structural credit risk framework of Black and Scholes (1973) and Merton (1974). In these models, equity is viewed as a call option on the firm's asset value, with the strike price being equal to the liabilities of the firm. The "distance-to-default", defined as the number of standard deviations of asset growth by which its assets exceed a measure of book liabilities, is a sufficient statistic of the likelihood of default. In the EDF release underlying the default probabilities used in this study, the liability measure is equal to the firm's short-term book liabilities plus one half of its long-term book liabilities. EDF values are reported with a floor of 2 basis points and a cap of 20%.[4]

The Moody's KMV EDF measure is extensively used in the financial services industry as most of the world's 100 largest financial institutions are subscribers. Crosbie and Bohn (2001) and Kealhofer (2003) provide more details on the model implementation and the fitting procedures for distance to default and EDF. Moody's KMV uses a non-parametric mapping from the distance to default to EDF that is based on a rich history of actual defaults, where the same definition of a default event is used

[4]The forthcoming EDF 8.0 release expands the range of meaningful EDF values by lowering the floor to 1 bp and by raising the cap to 35%. For more details, refer to http://www.moodyskmv.com.

as for our default swap data.[5] The EDF measure is therefore less sensitive to model mis-specification. The accuracy of the EDF measure as a predictor of default, and its superior performance compared to rating-based default prediction, is documented in Bohn, Arora, and Korbalev (2005). Duffie, Saita, and Wang (2007) propose a default prediction model in which they construct their own measure of distance to default and include other covariates such as the trailing 1-year stock return of the firm, the current 3-month Treasury rate, and the trailing 1-year return of the S&P 500. The authors find that the variation in their distance-to-default measure has a substantially greater effect on future default hazard rates when compared to a similarly significant change in any of the other covariates, suggesting that EDF is a useful proxy for the physical probability of default.

We obtain weekly (Wednesday) one-year EDF rates from Moody's KMV, for the same set of firms and for the same time period as described in Section 2.1. Table 1 in Appendix A provides summary statistics for the EDF data at the firm level. The median firm in our sample has 247 weekly 1-year EDF observations, and an average 1-year EDF rate of 24 basis points. Figure 3 shows the time series of the median 1-year EDF rates across all firms in our sample, together with the median 1-year and 5-year CDS rates. Both EDF and CDS rates vary considerably over time. EDF rates peaked during the third quarter of 2002 and then declined steadily until the end of our sample period in October 2006. The temporal pattern of CDS rates looks similar, with an additional spike in default swap premia shortly after the Ford and General Motors downgrade in May 2005.

2.3 Returns on Equity, Option and Corporate Bond Portfolios

We obtain daily data on Fama-French portfolios and the stock-market factors from Kenneth French's website. Daily returns are compounded from Wednesday to Wednesday to obtain weekly returns.

We also collect return information for the investment-grade (IG) and high-yield (HY) Bloomberg-NASD corporate bond indices.[6] Rebalanced on a monthly basis,

[5] This is different from the Merton model, where the likelihood of default is the inverse of the normal cumulative distribution function of distance to default.

[6] The name of these indices has recently been changed to FINRA-Bloomberg Corporate Bond Indicies. FINRA stands for Financial Industry Regulatory Authority, and was created in July 2007 through the consolidation of NASD and the member regulation, enforcement and arbitration functions of the New York Stock Exchange.

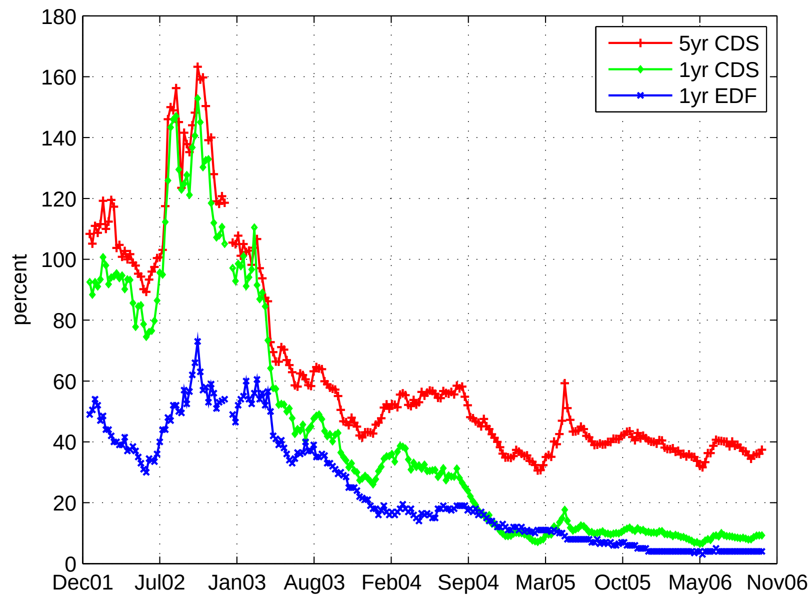

Figure 3: Time series of median 5-year and 1-year CDS rates, and of median 1-year EDF rates across the 112 firms in Table 1. Sources: Markit and Moody's KMV.

these indices are comprised of the most frequently traded fixed-coupon bonds represented by NASD's TRACE (Trade Reporting and Compliance Engine), which collects and publicly disseminates transaction data on all over-the-counter activity in the secondary corporate bond market.[7] Bloomberg-NASD indices are the first and to our knowledge the only corporate bond indices generated solely from the actual transaction prices of actively traded bonds, and do not rely on any quotes or estimated prices. We compute holding-period returns using weekly (Wednesday) index prices that we download from the NASD website at www.nasdbondinfo.com. The Bloomberg-NASD indices are calculated as of 5:15 p.m every trading day. On October 11, 2006, there were 720 bond issues of 161 firms in the NBBI index, and 259 issues of 127 firms in the NBBH index. Using the SIC industry classifications, the majority of firms in the IG index belong to the manufacturing industry (41%), to Transportation Communications Electric Gas and Sanitary Services (TCEGSS, 21%), and to the finance, insurance, and real estate sector (23%). For the high-yield index, the members' industry distribution is somewhat different, with 11%, 41%, 23% and 15% of the corporations represented belonging to the mining-and-construction, manufacturing,

[7]Index membership is comprised of TRACE-eligible fixed-coupon corporate bonds, excluding all zero coupon bonds, 144As, convertible bonds, and bonds set to mature before the last day of the month for which index re-balance occurs. All bonds must have traded on average at least 3 times per day, with at least one trade on 80% of the 60 trading days prior to the re-balance calculation date, and have a total issued amount outstanding available publicly.

TCEGSS, and the services sector, respectively.

Furthermore, we obtain weekly return data for Merrill Lynch corporate bond portfolios. Using Datastream as our source, we download 7 portfolios sorted on Standard & Poor's (S&P) credit rating (AAA, AA, A, BBB, BB, B, and C), 6 portfolios sorted on time to maturity (1-3yrs, 3-5yrs, 5-7yrs, 7-10yrs, 10-15yrs and more than 15yrs), 4 IG portfolios sorted on broad industry (Industrials BBB-A 1-10yrs, Banks BBB-A 1-10yrs, Financials AA-AAA 1-10yrs, and Gas and Electrics BBB-A 1-10yrs), and 30 HY industry portfolios.[8] All corporate bond returns are available throughout our sample period from January 2, 2002 until October 11, 2006, except the Bloomberg-NASD indices which are available only starting October 2002 (index initiation) to September 2005.

Using OptionMetrics as our source for option data, we form portfolios of European put options written on the S&P 500 index based on moneyness and time to maturity. We define moneyness as the present value of the strike price divided by the current value of the S&P 500 index. To form portfolios, we first classify the options into 4 maturity bins consisting of options that expire within one month (first-to-expire options), two months (second-to-expire options), three to five months (third to fifth-to-expire options), and more than five months. Options with less than 10 days remaining until expiration are not used since trading at the very short end occurs less frequently and bid and ask quotes are therefore less reliable. In a second step, we split each maturity bin into 4 sub-bins based on moneyness. The deepest out-of-the-money (OTM) bin consists of options with moneyness between 0.85 and 0.9, followed by bins with moneyness ranging from 0.9 to 0.95, 0.95 to 1, and greater than 1. This results in 16 different portfolios sorted on maturity and moneyness. Every week (Wednesday) t, we assign each index put option to a particular bin based on its maturity and moneyness as of that time, and compute Black-Scholes delta-hedged returns as of one week later. The return of any particular maturity-moneyness portfolio at time $t + h$, where h equals one week, is computed as the value-weighted average of the buy-and-hold returns of all delta-hedged option positions associated with this particular portfolio as of time t. Table 2 in Appendix A shows sample averages for moneyness and time to maturity as well as the number of observations for each of the 16 option portfolios. Average value-weighted portfolio excess returns are reported in the first part of Table 10 in Appendix C. When weighting returns by value, we

[8]The list of Datastream symbols for all ML portfolios is available from the authors upon request. The mnemonic for each of the 30 HY industry portfolios begins with "MLHY", followed by an abbreviation for the industry.

use market prices of the delta-hedged option positions as of time t to compute the weights. Option prices are computed as daily mid prices, that is, the average of the best bid and best offer prices.

We restrict ourselves to options with standard settlement. To eliminate prices with large errors, we only use observations that satisfy all of the following criteria: both the bid and the offer price are positive, the offer price is at least as high as the bid price, open interest is positive, the sum of the option price plus the spread is at least as high as the intrinsic value, the mid price is at least as high as twice the bid-ask spread, and the implied volatility is 1% or higher. The intrinsic value is calculated as the larger of the present value of the strike price plus the present value of future dividends minus the closing value of the S&P 500 index and zero. The price of the option should exceed its intrinsic value based on no-arbitrage arguments. To allow for non-synchronous reporting of the value of the underlying and of the option, we use a looser constraint, and only require that the price plus spread exceeds the intrinsic value. As in Jones (2006), we also use an implied volatility cutoff to remove options prices that appear suspect.

2.4 Firm Characteristics Data

The firm characteristics used in Section 5.5 include firm-level recovery rates, implied volatilities and leverage ratios, all at a weekly (Wednesday) frequency. Recovery rates at the firm level are provided by Markit and were described in Section 2.1. We use the Standardized Options table in OptionMetrics to access firm-specific call-option-implied volatilities with 30 days until expiration. Leverage is computed as book liabilities divided by the market price of equity plus book liabilities. Book liabilities are equal to short-term plus long-term debt, where short-term debt is estimated as the larger of items DATA45 and DATA49 from the quarterly Compustat files. Long-term liabilities are taken from item DATA51. After calculating the leverage ratios at the end of each quarter, we interpolate to obtain leverage ratios at a weekly frequency. The market value of equity is computed using the daily CRSP files. For each week and every firm, we multiply the closing stock price (data item PRC) with the number of outstanding shares recorded in millions (data item SHROUT divided by 1,000).

3 Measuring Returns on Defaultable Debt

This section describes how we measure the compensation that investors in U.S. credit markets demand for taking on default risk. The goal is to compute, at the firm level, holding-period returns on pure default-contingent claims that pay one unit of account if default does not occur before the maturity of the contract (in our applications, 1 year), and zero otherwise. In the existing literature, pricing information for credit risk has either been estimated using corporate bond prices or, more recently, CDS quotes. Firm-by-firm time-series data on realized returns on corporate bonds is very sparse.[9] Even if it were readily available, it is contaminated by tax and liquidity effects (see, for example, Elton, Gruber, Agrawal, and Mann (2001)). The advantage of using at-market CDS rates, on the other hand, is that each of our CDS observations is effectively a new constant-maturity par-coupon credit spread on the underlying firm that is much less corrupted by tax and liquidity issues. It is therefore important to stress that we exclusively use pricing information from the CDS market to estimate returns on defaultable debt. We believe this yields a cleaner measure of the compensation for exposure to default risk than can be extracted from corporate bond price data.

We take as given a probability space $(\Omega, \mathcal{F}, P)$ and an information filtration $\{\mathcal{F}_t : t \geq 0\}$ that satisfies the usual conditions. The default intensity of a firm is the instantaneous mean arrival rate of default, conditional on all current information. More precisely, we suppose that default of an obligor occurs at the first event time τ of a (non-explosive) counting process N with intensity process λ^P, relative to $(\Omega, \mathcal{F}, P)$ and $\{\mathcal{F}_t : t \geq 0\}$. In this case, so long as the firm survives, we say that its default intensity at time t is λ_t^P. Under mild technical conditions this implies that, given survival to time t and all information available at t, the probability of default between times t and $t+\Delta$ is approximately $\lambda_t^P \Delta$ for small Δ. We adopt the simplifying doubly-stochastic, or Cox-process, assumption under which the conditional probability at time t that a currently surviving obligor survives for an additional time Δ is

$$p(t, \Delta) \;\; = \;\; E_t \left(e^{-\int_t^{t+\Delta} \lambda_s^P \, ds} \right). \tag{1}$$

Here, E_t denotes expectation conditional on information available up to and including time t.

[9] Time-series data on realized returns on corporate bonds at the issue level can be accessed via the TRACE (Trade Reporting and Compliance Engine), starting July 2002. In the secondary market, the majority of corporate bonds trade only a few times a year on average.

Under the absence of arbitrage and market frictions, and under mild technical conditions, there exists a "risk-neutral" probability measure, also known as an "equivalent martingale" measure, as shown by Harrison and Kreps (1979) and Delbaen and Schachermayer (1999). In our setting, markets should not be assumed to be complete, so the martingale measure is not unique. This pricing approach nevertheless allows us, under its conditions, to express the price at time t of a security paying some amount, say Z, at some bounded stopping time $\tau > t$, as

$$S_t = E_t^Q \left(e^{-\int_t^\tau r_s \, ds} Z \right), \tag{2}$$

where r is the short-term interest-rate process and E_t^Q denotes expectation conditional on information available up to and including time t with respect to an equivalent martingale measure Q that we fix.[10] One may view (2) as the definition of such a measure Q. The idea is that the actual (or physical) measure P and the risk-neutral measure Q differ by an adjustment for default risk premia.

We measure holding-period returns on pure default-contingent claims by comparing the time-t price $P(t, T-t)$ of a risky zero-coupon zero-recovery bond with maturity $T > t$ to the price of that same security one period h earlier. (Recall that h equals one week in our applications.) From (2) we derive $P(s, \Delta) = E_s^Q \exp(-\int_s^{s+\Delta} r_u + \lambda_u^Q \, du)$, for all s and times to maturity Δ. If the firm has not defaulted by time t, the realized *holding-period return* $R_{t,h}(T)$ over an interval of length h is given by

$$R_{t,h}(T) = \frac{P(t, T-t)}{P(t-h, T-(t-h))} - 1 = \frac{E_t^Q \left(e^{-\int_t^T r_s + \lambda_s^Q \, ds} \right)}{E_{t-h}^Q \left(e^{-\int_{t-h}^T r_s + \lambda_s^Q \, ds} \right)} - 1.$$

Throughout this paper we assume independence between the short-term interest rate process and default times under the risk-neutral measure. Even though the magnitude of the correlation is generally found to be negative (see, for example, Duffee (1998)), we have verified that its role is negligible for our parameter estimates. This allows us to rewrite the last equation as

$$R_{t,h}(T) = \frac{d(t, T-t)}{d(t, T-(t-h))} \frac{E_t^Q \left(e^{-\int_t^T \lambda_s^Q \, ds} \right)}{E_{t-h}^Q \left(e^{-\int_{t-h}^T \lambda_s^Q \, ds} \right)} - 1, \tag{3}$$

[10] Here, r is a progressively measurable process with $\int_0^t |r_s| \, ds < \infty$ for all t, such that there exists a "money-market" trading strategy, allowing investment at any time t of one unit of account, with continual re-investment until any future time T, with a final value of $e^{\int_t^T r_s \, ds}$.

where $d(t, \Delta) = E_t^Q \exp(-\int_t^{t+\Delta} r_s\, ds)$ is the default-free market discount factor.

Given $R_{t,h}(T)$, we are now in a position to compute risk-adjusted excess returns on pure default-contingent claims. In Section 4, we extract our default risk premia factor as the common component in these firm-specific returns, and we describe how to decompose the DRP factor into three different components. The first component captures changes in expected default losses, the second accounts for jump-to-default risk premia, and the third is due to the market price of risk associated with random fluctuations in the risk-neutral default intensity (MPR). To isolate the first component, we compute holding-period returns $R_{t,h}^{PP}(T)$ that would have applied in the absence of any risk premia related to default. They are given by

$$R_{t,h}^{PP}(T) \quad = \quad \frac{d(t, T-t)}{d(t, T-(t-h))} \frac{E_t^P \left(e^{-\int_t^T \lambda_s^P\, ds} \right)}{E_{t-h}^P \left(e^{-\int_{t-h}^T \lambda_s^P\, ds} \right)} - 1. \tag{4}$$

The first P in the double-P superscript for the return variable indicates that there is no jump-to-default risk premia, in other words that λ^Q in (3) is replaced by λ^P. The second P in the superscript points to the fact that the market price of risk associated with random fluctuations in the risk-neutral default intensity is set to zero, implying that the survival probabilities in (3) should now be computed under the P measure.

To separate the MPR component, we compare $R_{t,h}(T)$ to model-implied holding-period returns $R_{t,h}^{QP}(T)$ that would have applied if only the market price of risk associated with random fluctuations in the risk-neutral default process was turned off. The latter are computed as

$$R_{t,h}^{QP}(T) \quad = \quad \frac{d(t, T-t)}{d(t, T-(t-h))} \frac{E_t^P \left(e^{-\int_t^T \lambda_s^Q\, ds} \right)}{E_{t-h}^P \left(e^{-\int_{t-h}^T \lambda_s^Q\, ds} \right)} - 1, \tag{5}$$

where Q in the QP superscript is a reminder of the compensation for jump-to-default risk premia, whereas P has the same interpretation of zero MPR as before.[11] The remaining component of the risk-adjusted excess returns on defaultable bonds, which is due to jump-to-default risk premia, can be also be extracted from $R_{t,h}^{QP}(T)$, after accounting for changes in expected default losses using $R_{t,h}^{PP}(T)$. Details will be provided in Section 4.

If pure default-contingent claims were actively traded, we could observe their prices $P_{t,T-t}$ directly and it would be possible to compute holding-period returns on

[11] According to this notation, $R_{t,h}(T)$ in (3) could also be referred to as $R_{t,h}^{QQ}(T)$. To keep notation simple, we use the former.

defaultable securities as in (3). As this is not the case, we proceed by estimating a time-series model for λ^Q using CDS data, which enables us to compute model-implied returns $R_{t,h}(T)$ according to (3). As a by-product of the estimation, we also obtain estimates for $R_{t,h}^{QP}(T)$ in (5). Using Moody's KMV EDF rates, we then follow a similar procedure to estimate the model-implied returns $R_{t,h}^{PP}(T)$ in (4). Details on the specification of the time-series models for λ^P and λ^Q, as well as our estimation techniques, are discussed in the next section.

4 Extracting the Default Risk Premia Factor

In this section, we first describe the time-series models for both actual and risk-neutral default intensities and explain our estimation procedure. Once the firm-specific model-implied values for λ^Q and λ^P are obtained, in a second step we compute estimates for the realized holding-period returns $R_{t,h}(T)$ in (3). Next we explain how to extract the DRP factor as the common component in firm-specific risk-adjusted excess returns on defaultable debt. Lastly, we turn our attention to decomposing the DRP factor into components that are due to common changes in *(i)* expected default losses, *(ii)* jump to default risk premia, and *(iii)* market price of default risk.

We specify a model under which the logarithm of a firm's physical default intensity λ_t^P satisfies the Ornstein-Uhlenbeck equation

$$d\log(\lambda_t^P) \quad = \quad \kappa(\theta - \log(\lambda_t^P))\, dt + \sigma\, dB_t, \tag{6}$$

where B_t is a standard Brownian motion, and θ, κ, and σ are constants to be estimated. The behavior of λ^P is called a Black-Karasinski (BK) model, according to Black and Karasinski (1991). Berndt (2007) performs a diagnostic analysis of the EDF data and shows that (6) offers a good compromise between goodness-of-fit and model simplicity. The author uses non-parametric specification tests developed in Hong and Li (2005) to evaluate several one-factor reduced-form credit risk models for actual default intensities. She finds that the BK specification outperforms popular affine jump-diffusion models for λ^P, such as the Ornstein-Uhlenbeck or Vasicek model (Vasicek (1977)), the CIR model (Cox, Ingersoll, and Ross (1985)), and the CIR model with jumps in Duffie and Garleanu (2001). For the BK default intensity model, there is generally no closed-form solution available for 1-year EDFs, $1 - p(t, 1)$, from (1). We therefore compute $p(t, 1)$ numerically as a function of λ_t^P by implementing the two-stage lattice-based Hull and White (1994) procedure for constructing trinomial trees.

Using the EDF data described in Section 2.2, we obtain sector-by-sector maximum-likelihood estimates for κ and σ in (6), while allowing for a firm-specific long-run mean parameter θ^i. (The superscript i is used to identify parameters specific to firm i.) Sector-specific parameters have two important advantages over estimating a different set of parameters κ^i and σ^i for each firm i. First, it reduces the small-sample bias in the MLE estimators, especially for the estimates of the mean-reversion parameter κ. (Monte Carlo evidence to that effect was given in Berndt, Douglas, Duffie, Ferguson, and Schranz (2005), Appendix B.) Second, it allows us to model a joint distribution of EDF rates across firms in a given industry sector. In particular, we impose joint normality of the Brownian motions driving each firm's default intensity, with a flat cross-firm correlation structure within the sector. In other words, for each firm i within a given sector we rewrite (6) as

$$d \log \lambda_t^{P,i} \;=\; \kappa \left(\theta^i - \log \lambda_t^{P,i}\right) dt + \sigma \left(\sqrt{\rho}\, dB_t^c + \sqrt{1-\rho}\, dB_t^i\right), \tag{7}$$

where B^c and B^i are independent standard Brownian motions, independent of $\{B^j\}_{j \neq i}$, and ρ denotes the constant pairwise within-sector correlation coefficient.

Routine maximum-likelihood estimation of the sector-by-sector estimates of the extended parameter vector

$$\Theta = \left(\{\theta^i\}, \kappa, \sigma, \rho\right)$$

is not available because of missing data points, and because EDF rates are censored from above at 20%. Both issues are explicitly accounted for by using an EM (Expectation-Maximization) algorithm with Gibbs sampling.[12] As mentioned in Section 2.2, EDF rates are also truncated below at 2 basis points. To avoid the problem of integer-based granularity in the EDFs for firms with exceptionally good credit quality, we removed all firms with a sample average of 1-year EDFs of less than 5 basis points from the data set initially provided by Moody's KMV. They are not part of the 112 names in Table 1. The remaining 2-basis-point observations in our sample are treated as "true" data points. Since the majority of the firms in our sample are of median credit quality (see Figure 1), we do not expect this simplification to introduce any significant bias to the parameter estimates.

Results are shown in Table 3 in Appendix B. To improve the interpretability of our parameter estimates, we have imposed the overriding restriction that $\theta^{Q,i}$ is

[12] Details are available form the authors upon request. The Matlab code is available online at www.andrew.cmu.edu/user/aberndt/software/.

equal to the model-implied sample mean of $\log \lambda_t^{P,i}$, for each firm i. The estimated mean-reversion parameter is lowest for oil-and-gas firms at 10.9%, and highest for consumer-goods firms at 120%, implying a half time of 6 years 4 months and of 7 months, respectively. Annualized volatilities, on the other hand, range between 96.3% for telecommunication firms and 157.4% for consumer-goods firms. Note that the pairwise correlation among the log-default intensities is lowest for health-care firms (17.2%) and almost twice that for utilities (33.5%).

With regard to risk-neutral default intensities, we assume that

$$d\log\lambda_t^{Q,i} \;=\; \kappa^Q(\theta^{Q,i} - \log\lambda_t^Q)\,dt + \sigma^Q\left(\sqrt{\rho^Q}\,dB_t^{Q,c} + \sqrt{1-\rho^Q}\,dB_t^{Q,i}\right), \qquad (8)$$

where $B_t^{Q,c}$ and $B_t^{Q,i}$ are independent standard Brownian motions with regard to the physical measure P, independent of $\{B^{Q,j}\}_{j\neq i}$. The parameters κ^Q, $\{\theta^{Q^i}\}$, σ^Q and ρ^Q are scalars to be estimated. The risk-neutral distribution of $\lambda^{Q,i}$ is specified as

$$d\log\lambda_t^{Q,i} \;=\; \tilde{\kappa}^Q(\tilde{\theta}^{Q,i} - \log\lambda_t^{Q,i})\,dt + \sigma^Q\left(\sqrt{\rho^Q}\,d\tilde{B}_t^{Q,c} + \sqrt{1-\rho^Q}\,d\tilde{B}_t^{Q,i}\right), \qquad (9)$$

with constants $\tilde{\kappa}^Q$ and $\tilde{\theta}^{Q,i}$. $\tilde{B}_t^{Q,c}$ and $\tilde{B}_t^{Q,i}$ are independent standard Brownian motions with regard to Q, independent of $\{\tilde{B}^{Q,j}\}_{j\neq i}$. The market-price-of-default-risk process, Λ^i, characterizes the change in the drift parameter of $d\log\lambda_t^{Q,i}$ when replacing the physical by the risk-neutral measure. It is given by $\sqrt{\rho^Q}\,dB_t^{Q,c} + \sqrt{1-\rho^Q}\,dB_t^{Q,i} = -\Lambda_t^i\,dt + \sqrt{\rho^Q}\,d\tilde{B}_t^{Q,c} + \sqrt{1-\rho^Q}\,d\tilde{B}_t^{Q,i}$. According to (8) and (9), we have

$$d\Lambda_t^i \;=\; \frac{\kappa^Q\theta^{Q,i} - \tilde{\kappa}^Q\tilde{\theta}^{Q,i}}{\sigma^Q} + \frac{\tilde{\kappa}^Q - \kappa^Q}{\sigma^Q}\log\lambda_t^{Q,i}. \qquad (10)$$

Given a set of parameters $(\tilde{\theta}^{Q,i}, \tilde{\kappa}^Q, \sigma^Q)$ for firm i plus its risk-neutral loss-given-default rate, we can compute 1-year and 5-year CDS rates as a function of $\lambda^{Q,i}$. Since estimation of the model (8) and (9) is a necessity but not the focus of our paper, we refer the reader to Section 5.1 in Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) for a detailed explanation of the computations involved. Note, however, that we use firm-specific instead of industry-specific loss-given-default values as discussed in Section 2.1 and listed, for each firm, in Table 1.

Based on 5-year CDS observations, we employ maximum likelihood estimation (MLE) to obtain sector-by-sector estimates for the parameters

$$\Theta^Q = \left(\{\theta^{Q,i}\}, \kappa^Q, \sigma^Q, \rho^Q, \{\tilde{\theta}^{Q,i}\}, \tilde{\kappa}^Q\right)$$

that govern the processes $\{\lambda^{Q,i}\}$. We impose two overriding conditions to improve the interpretability of our parameter estimates. First, we make use of the term-structure information contained in 1-year CDS rates to pin down the risk-neutral long-run-mean parameters $\{\tilde{\theta}^{Q,i}\}$. In particular, given $(\tilde{\kappa}^Q, \sigma^Q)$, we determine $\tilde{\theta}^{Q,i}$ so that the sample mean of the model-implied risk-neutral mean-loss rates for firm i is equal to the sample mean of its 1-year CDS rates. Second, for each firm i, we set $\theta^{Q,i}$ equal to the model-implied sample mean of $\log \lambda_t^{Q,i}$. Note that in contrast to Berndt, Douglas, Duffie, Ferguson, and Schranz (2005), we do not impose a functional form that links risk-neutral to actual default intensities. Besides limiting our exposure to model misspecifications in that regard, it also allows us to estimate the parameters that drive λ^Q and the parameters for λ^P in two separate MLE procedures.

Estimates for the parameters in (8) and (9) are listed in Table 4 in Appendix B. We find that the estimated mean-reversion parameters under the risk-neutral measure, $\tilde{\kappa}^Q$, are substantially smaller than their physical counterparts, κ^Q, except for firms in the telecommunications sector. According to (8) and (9), $d \log \lambda_t^{Q,i}$ has a drift term that is higher under Q than under P whenever the market price of default risk Λ_t^i in (10) is less than zero. For values of $\log \lambda_t^{Q,i}$ close to its long-run mean, this holds true as long as $\tilde{\kappa}^Q \tilde{\theta}^{Q,i} > \tilde{\kappa}^Q \theta^{Q,i}$. This relationship is satisfied, on average, for all industries in our sample except for the health-care and technology sectors. Annualized volatilities range from 125.5% (Consumer Goods) to 183.6% (Consumer Services, whereas within-sector correlations are estimated to be between 8.2% (Health Care) and 35.5% (Telecommunications). For the majority of the sectors, estimates for both σ^Q and ρ^Q are higher than for their physical counterparts.[13]

Figure 4 plots the time series of median yield spreads of pure default-contingent claims with a maturity of one year, across all firms in our sample. Because we assume independence between the short-term interest rate process and default times under the risk-neutral measure, the price $P(t, \Delta)$ corresponds to a yield spread $s(t, \Delta) = -[\log E_t^Q \exp(-\int_t^{t+\Delta} \lambda_s^Q \, ds)]/\Delta$. We find that yield spreads peaked in the third quarter of 2002, and then declined quite dramatically until the end of 2003. They have stayed at fairly low levels since then. A second spike in default insurance rates occurred, however, immediately after Ford and General Motors (GM) debt was reduced to junk bond status in early May of 2005. We also compute the yield

[13]Berndt (2007) shows that the pairwise correlation between $\lambda_{t+h}^{Q,i}$ and $\lambda_{t+h}^{Q,j}$, conditioned on $\lambda_t^{Q,i}$ and $\lambda_t^{Q,j}$, does not depend on $\theta^{Q,i}$, $\theta^{Q,j}$ or the level of $\lambda_t^{Q,i}$ or $\lambda_t^{Q,j}$. It is a function of ρ^Q, σ^Q and h only. A similar observation holds true for their physical counterparts. This implies that within-sector correlations between risk-neutral default intensities are estimated to be higher than correlations between actual default intensities.

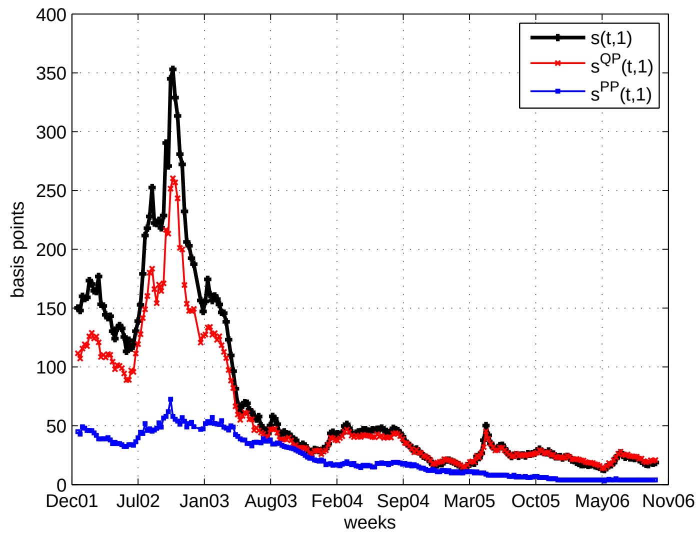

Figure 4: Time series of median yield spreads for pure default-contingent claims with a maturity of one year, across all firms. $s - s^{QP}$ and $s^{QP} - s^{PP}$ measure compensation for exposure to diffusive default risk and to jump-to-default risk, respectively.

spreads $s^{QP}(t,\Delta)$ and $s^{PP}(t,\Delta)$ that would have applied if the market price of risk associated with random fluctuations in λ^Q was turned off and in the absence of any risk premia related to the default event, respectively. They are given by $s^{QP}(t,\Delta) = -[\log E_t^P \exp(-\int_t^{t+\Delta} \lambda_s^Q \, ds)]/\Delta$ and $s^{PP}(t,\Delta) = -[\log E_t^P \exp(-\int_t^{t+\Delta} \lambda_s^P \, ds)]/\Delta$. Figure 4 shows that the time series of $s^{QP}(t,1)$ follows that of $s(t,1)$ closely, in particular after the first 15 months of our sample. According to (10), the drift parameter of $d \log \lambda^Q$ under Q increases relative to that under P as λ^Q increases (for all sectors with $\tilde{\kappa}^Q < \kappa^Q$), which explains why $s(t,1)$ is larger than $s^{QP}(t,1)$ during 2002 and the first quarter of 2003, when credit spreads were high. The yield spreads linked to expected default losses, $s^{PP}(t,1)$, also peaked in the second half of 2002, and subsequently declined steadily to a median of about 4 basis points at the end of our sample. Interestingly, we do not observe any significant widening of conditional default rates in May 2005, implying that the actual downgrade of Ford and GM did not lead to a surprise reaction in EDFs.

Using the model-implied values for λ_t^Q, we can now compute estimates for the realized holding-period returns $R_{t,h}(T)$ in (3), which in turn enables us to compute risk-adjusted excess returns on pure default-contingent claims. We will refer to the latent common component in these firm-specific risk-adjusted excess returns as the *default risk premia* factor, or simply the *DRP* factor. Let F_t^S denote the vector of h-period returns on known systematic factors.[14] Among the factors we account for are those in Fama and French (1993), including their term (but not the default) factor, and the momentum factor introduced by Jagadeesh and Titman (1993). Let RF_t denote the risk-free rate compounded over the interval $[t-h,t]$ from the Fama-French T-bill daily returns. Using superscript i to indicate returns specific to firm i, we regress the excess returns on an equally weighted portfolio on F^S according to

$$\frac{1}{N}\sum_{i=1}^{N} R^i_{t,h}(T) - RF_t \quad = \quad \alpha + \beta^S \cdot F^S_t + \epsilon_t, \tag{11}$$

where N is the number of firms in our sample. In our applications, h equals one week and $T = t - h + 1$.

The residuals ϵ_t absorb any common variation in firm-specific risk-adjusted excess returns on pure default-contingent claims that cannot be explained by linear combinations of the systematic factors F^S. If $\{\hat{\alpha}\}$ and $\{\hat{\epsilon}_t\}$ denote the least-squares estimates for (11), the default risk premia factor is given by

$$DRP_t \quad = \quad \hat{\alpha} + \hat{\epsilon}_t. \tag{12}$$

Figure 5 plots the time series of the DRP factor. It shows that most of the time variation occurs during January and February of 2002 (a record amount of corporate debt fell into default the first month of 2002, led by Kmart and Global Crossing), the second half of 2002 (following the Worldcom scandal), and in May 2005 (in response to the Ford and General Motors downgrade to junk status). This is in line with our observations in Figure 4.

In Section 5, we use the time series of returns on the DRP factor and employ the Fama-MacBeth methodology to test whether this factor is priced in the cross-section of corporate bond, option and stock returns. We offer additional insights into our empirical findings by decomposing the DRP factor into three different components. The goal is to write the default risk premia factor as

$$DRP_t \quad = \quad DRP^L_t + DRP^{JtD}_t + DRP^{MPR}_t, \tag{13}$$

where DRP^L is the portion associated with common changes in expected default losses, DRP^{JtD} accounts for common changes in jump-to-default risk premia and DRP^{MPR} captures the common variation in the market price of default risk.

To this end, we first compute firm-specific estimates for $R^{PP}_{t,h}(T)$ in (4) and for

[14] To simplify notation, we suppress the reference to h and T in the return variables.

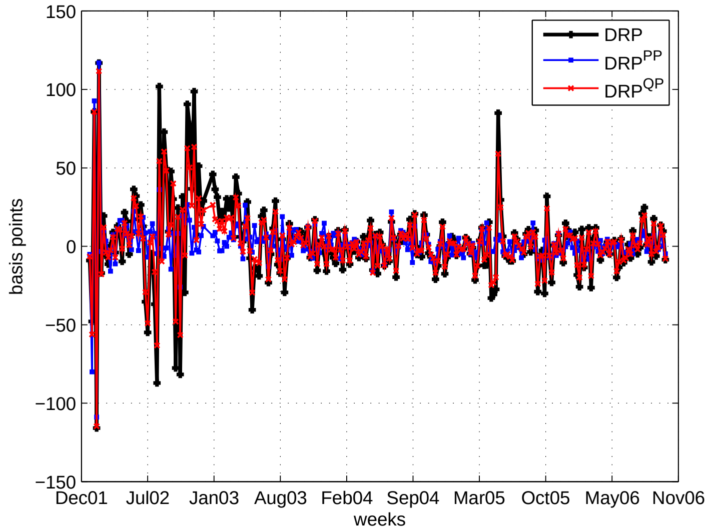

Figure 5: Time series of the DRP factor as extracted from (11) and (12), together with the DRP^{PP} and DRP^{QP} processes.

$R^{QP}_{t,h}(T)$ in (5). Let DRP^{PP} denote the latent common component of risk-adjusted excess returns on defaultable bonds that would have applied in the absence of any risk premia related to default. Likewise, let DRP^{QP} be the latent common component if only the market price of default risk were turned off (but not the jump-to-default risk premia). These two processes can be then extracted using (11) and (12), after replacing $R^i_{t,h}(T)$ by $R^{PP,i}_{t,h}(T)$ and $R^{QP,i}_{t,h}(T)$, respectively. Figure 5 shows the time series of DRP^{PP} and DRP^{QP} in comparison with DRP. We find that DRP^{PP} displays a large amount of time variation only at the beginning of our sample period, and that DRP^{QP} tracks DRP quite closely, especially after the first quarter of 2003. Note that the latter is not surprising given the evidence in Figure 4.

To further scrutinize how much of the time variation in the common component of risk-adjusted excess returns on defaultable debt can be explained without the help of any risk premia related to the default event, we compute the coefficient of determination when regressing DRP on DRP^{PP}, for each quarter in our sample. The results are displayed in Figure 6. They indicate that DRP^{PP} captures almost 95% of the variation in DRP in the first quarter of 2002, with confirms the conclusions drawn based on Figure 5. For the rest of the sample period, however, DRP^{PP} explains a substantially smaller percentage, with a median of 24%. When controlling for DRP^{QP} in addition to DRP^{PP}, we are able to account for most of the time variation in the DRP factor, with R-squares ranging between 87% for the first quarter of 2003 and almost 100% during the first quarter of 2002 and the second quarter of 2005. This

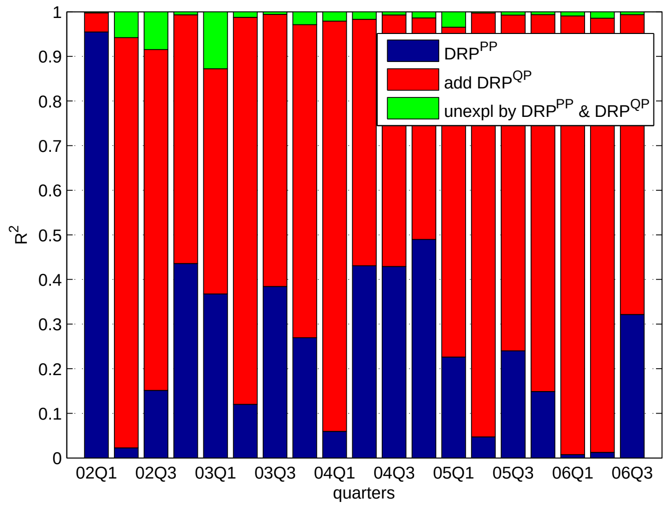

Figure 6: Portion of variation explained by quarter. Blue bars show the coefficient of determination when regressing DRP on DRP^{PP}, whereas the sum of the blue plus the red bar equals the R^2 from regressing DRP on both DRP^{PP} and DRP^{QP}. Green bars equal the amount of variation in DRP that cannot be explained by DRP^{PP} and DRP^{QP}.

implies that, for most of our sample period, jump-to-default risk premia account for the main portion of the time variation in DRP.[15] For the model specification in (10), variation in the market price of default risk only makes a minor marginal contribution towards explaining risk-adjusted excess returns on the 1-year pure default-contingent claims considered here.[16] It accounts for an average 5% of the time variation during the first 15 months of our sample, and for an average of only 1% in the remaining quarters, which is consistent with the observations in Figures 4 and 5.

Having identified both DRP^{PP} and DRP^{QP} in addition to DRP allows us to define $DRP^{JtD} = DRP^{QP} - DRP^{PP}$ and $DRP^{MPR} = DRP - DRP^{QP}$. With DRP^{L} equal to DRP^{PP}, equation (13) follows. Based on the findings in Figure 6, instead of performing asset pricing tests that use all three components in (13) simultaneously, we will focus on the specification

$$DRP_t = DRP_t^L + DRP_t^{-L}, \tag{14}$$

where $DRP^{-L} = DRP - DRP^{PP} = DRP^{JtD} + DRP^{MPR}$ is the common component in risk-adjusted excess returns on defaultable debt after accounting for common

[15]Note that height of the second bar in Figure 6 is not necessarily equal to the amount of variation explained by DRP^{QP} alone. The reason is that DRP^{PP} and DRP^{QP} are likely to exhibit non-zero within-quarter correlations.

[16]For small values of h we have $DRP^{PP} \approx -B^{PP}\lambda^P$, $DRP^{QP} - DRP^{PP} \approx -(B^{QP}\lambda^Q - B^{PP}\lambda^P)$, and $DRP - DRP^{QP} \approx -(B - B^{QP})\lambda^Q$ for some positive constants B^{PP}, B^{QP} and B. Hence, with regard to the time variation in DRP, most of the information is contained in DRP^L and DRP^{JtD}.

changes in expected default losses.

5 Asset Pricing Tests

In this section, we investigate whether the common variation in risk-adjusted excess returns on pure default-contingent claims with a maturity of one year, as captured by our DRP factor in (12), is priced in the cross-section of asset returns. We do so using one of two approaches. The first method, referred to as (M1), is designed for small sets of test assets. It simply inspects the relationship between the time-series loadings on the DRP factor and the average returns on the test assets, in the spirit of Fama and French (1993). The second method, labeled (M2), implements Fama-MacBeth two-pass approaches to estimating beta-pricing models (see Fama and MacBeth (1973)). It relies on large sets of test assets.

In principle, test assets should have two important features. First, they are supposed to be representative of all capital markets, and second they should exhibit a high degree of variation in average returns. The first condition is important in defining the generality of the test, while the second feature ensures that the cross-section of expected returns is sufficiently rich. As a compromise between meeting these conditions and data availability, we focus on a set of test assets that consists of the 100 Fama-French portfolios formed on size and book-to-market equity, the 49 Fama-French equity portfolios sorted on industry, the investment-grade and the high-yield Bloomberg-NASD corporate bond portfolio, plus a total number of 47 Merrill Lynch corporate bond portfolios. The latter include 7 portfolios sorted on S&P credit ratings (AAA to C), 6 portfolios sorted by time to maturity (1-3yrs to more than 15yrs), as well as 30 HY and 4 IG portfolios sorted on industry. We also construct 16 portfolios of put options on the S&P 500 index sorted on time to maturity and moneyness. For a more detailed description of these test portfolios and how they are composed, refer to Section 2.3.

In Section 4, we decompose the systemic behavior of defaultable securities (DRP) into portions associated with common changes in expected default losses (DRP^{L}), common changes in jump-to-default risk premia (DRP^{JtD}), and common variation in the market price of default risk (DRP^{MPR}). The second component explains most of the time variation in DRP (see Figure 6). Test assets which are likely to be exposed to jump-to-default risk, such as corporate bonds and put options that are (far) out of the money, should therefore load significantly on DRP^{JtD}, as well as on DRP, in a time-series regressions. Using sets of corporate bond and put index option portfolios, we will implement (M1) to investigate whether the DRP factor is priced by such assets. In particular, the sets of test assets include the two Bloomberg-NASD corporate bond portfolios, the ML corporate bond portfolios sorted on rating, the ML corporate bond portfolios sorted on time to maturity, the ML corporate bond portfolios sorted on industry (both IG and HY), and the index put option portfolios double-sorted on time to maturity and moneyness. For comparison, we also perform time-series regressions for the Fama-French 100 equity portfolios sorted on size and book-to-market. If we find a set of test assets for which the average returns line up with their DRP-factor loadings, it will be interpreted as evidence in support of the hypothesis that the DRP factor is priced by the assets at hand.

To estimate the loadings on the default risk premia factor, we regress excess returns of the test assets on DRP, after controlling for common factors that proxy for macroeconomic risk. More formally, for each test asset i, we estimate the linear model

$$\begin{aligned} R^i(t) - RF(t) \quad = \quad & \alpha^i + \beta^i_{MKT} MKT(t) + \beta^i_{SMB} SMB(t) + \beta^i_{HML} HML(t) \\ & + \beta^i_{UMD} UMD(t) + \beta^i_{TERM} TERM(t) + \beta^i_{NDEF} NDEF(t) \\ & + \beta^i_{DRP} DRP(t) + \epsilon^i(t). \end{aligned} \tag{15}$$

$R^i(t)$ denotes the return on asset i over the time period $[t-h, t]$, where h in our applications is one week. As defined in Section 4, $RF(t)$ measures the risk-free rate, compounded weekly from the Fama-French T-bill daily returns. MKT, SMB and HML denote the three stock-market factors from Fama and French (1993), UMD is the momentum factor defined in Jagadeesh and Titman (1993), and $TERM$ is the label for the treasury bond market factor. The latter, together with the corporate bond market factor DEF, was introduced in Fama and French (1993) as well.[17] The factor $NDEF$ denotes that component of DEF that is orthogonal to DRP^L, DRP^{JtD} and DRP^{MPR} (and hence, by construction, to DRP). To be precise, we estimate the model

$$\begin{array}{lcllll} DEF_t & = & -0.00002 \; + & 0.1343\, DRP^L_t \; + & 1.8289\, DRP^{JtD}_t \; - & 0.8031\, DRP^{MPR}_t \; + \; \varepsilon^{NDEF}_t, \\ & & (0.00030) & (0.1988) & (0.3290) & (0.5843) \end{array}$$

with standard errors reported in parentheses. The coefficient of determination is 17.8%. We set $NDEF = -0.00002 + \varepsilon^{NDEF}_t$. This factor will absorb the time

[17] We measure $TERM$ as the difference between the weekly returns on the 20-year Treasury bond and on the 3-month T-bill. DEF is set equal to the weekly returns on a market portfolio of corporate bonds with more than 10 years to maturity (Datastream mnemonic MLUCO10(RI)) minus those on 20-year Treasury bonds.

variation in the corporate bond market factor DEF that cannot be explained by any linear combination of default-related components.

To further test the hypothesis that DRP is a priced factor, we make use of method (M2) and implement a variant of the Fama-MacBeth approach to estimating beta-pricing models on larger sets of test assets. Our sample has 250 weeks, from January 2, 2002 to October 11, 2006. We use the first 50 weeks, called the pre-testing period, to compute the time-series factor loadings for each of the test assets. As suggested in Fama and MacBeth (1973), we estimate these loadings directly using the formula $cov(R^i(t), F(t))/var(F(t))$, where $R^i(t)$ and $F(t)$ denote returns on test asset i and on some factor, respectively, rather than running (15) for the first 50 weeks of our sample.[18] Fama and MacBeth (1973) first compute the factor loadings for every stock and then, in a second step, use the estimated loadings to form equity portfolios. A number of reasons prevent us from performing a similar construction of new portfolios that are sorted on betas. On the one hand, our test assets are actual portfolios, meaning we do not necessarily have to form portfolios again. More importantly, even if we wanted to re-sort our portfolios that were grouped *prior* to any estimation, this would not be possible for the corporate bond portfolios since weekly (or, more generally, regularly spaced) pricing data is not available at the individual issue level. Using portfolios that were formed before any estimation of factor loadings is performed differs from the typical econometric approach. Going forward, the asset pricing test results for (M2) should be interpreted with this caveat in mind.

After computing the time-series factor loadings for the first 50 weeks, we compute the returns of our test asset portfolios for the following 50 weeks. We call this later 50-week period the testing period. The cross-sectional regressions are run in this period, using the implementation described next. For each of the first 10 weeks of the testing period, we run cross-sectional regressions of the test assets returns on the time-series factor loadings computed in the 50-week pre-testing period. Specifically, for every week t, we run

$$\begin{aligned} R^i(t) - RF(t) \quad = \quad & \gamma_0(t) + \gamma^{MKT}(t)\beta^i_{MKT}(t-l) + \gamma^{SMB}(t)\beta^i_{SMB}(t-l) \\ & + \gamma^{HML}(t)\beta^i_{HML}(t-l) + \gamma^{UMD}(t)\beta^i_{UMD}(t-l) \\ & + \gamma^{TERM}(t)\beta^i_{TERM}(t-l) + \gamma^{NDEF}(t)\beta^i_{NDEF}(t-l) \\ & + \gamma^{DRP}(t)\beta^i_{DRP}(t-l) + \epsilon^i(t), \end{aligned} \tag{16}$$

where $t-l < t$ implies that the factor loadings are computed l-weeks ago, $1 \leq l < 10$.

[18]The latter might yield different results because factors are not necessarily orthogonal during the first 50 weeks of our sample.

For each of the following 10 weeks of the testing period, we again run cross-sectional regressions as in (16), the only difference being that the time-series factor loadings are re-computed to incorporate additionally the first 10 weeks of the testing period. In other words, the factor loadings are now computed on the sample containing the 50-week pre-testing period plus the first 10 weeks of the testing period. As we advance to the next 10 weeks of the testing period, the factor loadings are re-computed again, and the cross-sectional tests are implemented just as before. This testing procedure continues until we reach the end of the 50-week testing period. At this point, we replace the initial 50-week pre-testing period with the 50-week testing period, and implement the cross-sectional tests just as before. We continue with this procedure until we reach the end of our 250-week sample. To indicate that the factor loadings $\beta^i_\cdot$ are updated every 10-week period, they now carry a time label $(t - l)$ in specification (16).

Inferences about whether the DRP factor is priced will be based on the first and second moments of the series $\gamma^{DRP}(t)$, adjusted for heteroscedasticity. We implement (16) for a number of sets of test assets. The first three sets each contain portfolios from only a single market. To be precise, we form one set of test assets that includes all 52 corporate bond portfolios, a second set that includes the 149 equity portfolios considered in this study, and a third set comprised of the 16 index put option portfolios described in Section 2.3. We also perform cross-sectional tests using sets of test assets that span across multiple markets. In particular, we investigate the set of test assets that includes all corporate bond and equity portfolios, and the set that encompasses all available test assets from all three markets. We now present our asset pricing test results.

5.1 Corporate Bonds

We start by investigating whether the DRP factor is priced in the corporate bond market. Our test assets consist of corporate bond portfolios sorted on characteristics such as credit quality (IG and HY Bloomberg-NASD portfolios, 7 ML portfolios sorted on S&P ratings), time to maturity (6 ML portfolios) and industry (30 HY and 4 IG ML portfolios). Details on the construction of these portfolios were provided in Section 2.3.

Table 5 in Appendix C summarizes the results of time-series regressions related to (15) for the investment-grade and the high-yield Bloomberg-NASD corporate bond portfolios. The table consists of two parts. The first panel shows the estimation results for the case where the explanatory variables include only factors that are known in the existing literature to capture common variation in equity, treasury or corporate bond markets, and are likely to account for macroeconomic risk. To be precise, we estimate (15) after replacing the last two covariates, $NDEF$ and DRP, by the Fama and French (1993) corporate bond market factor DEF. The latter captures an important part of the common time-series variation in the returns on the corporate bond portfolios that were considered in the aforementioned study. We confirm that the same holds true with regard to the Bloomberg-NASD portfolios. We find that the three stock-market factors, momentum and the treasury-market factor combine to explain 43.3% and 69.2% of the time variation in HY and IG portfolio returns, respectively.[19] Adding the DEF factor as a covariate increases these coefficients of determination to 62.3% and 81.6%. The results in Table 5 show that the DEF factor loads positively and significantly on both Bloomberg-NASD corporate bond portfolios, and that the estimated slope coefficient is higher for high-yield bonds, and lower for investment-grade debt.

The second panel in Table 5 shows the results of estimating the model (15) as stated, for both the HY and the IG Bloomberg-NASD portfolios. Using the first panel of results as a benchmark, this allows us to understand whether the explanatory power of the corporate bond market factor stems from a default-risk-premia component (DRP), a non-default-related component ($NDEF$), or both. In the latter scenario, replacing DEF by DRP and $NDEF$ should also yield a sizeable increase in the regression R^2's.[20]

We find that both portfolios load significantly on our DRP factor. The slope coefficient for the HY portfolio is estimated to be more than twice the size of that for the IG portfolio. This difference in exposures to the default risk premia factor helps to explain, at least to some extent, the large difference in average returns for the HY and the IG portfolios. The former earns an average weekly excess return of 24 basis points during our sample period, while the latter earns about 5 basis points. Interestingly, for the non-default-related component of DEF the findings are somewhat different: the estimated slope coefficients for $NDEF$ are comparable for high-credit-quality bonds and high-yield debt. Both are statistically significant. As a result, we find that replacing the DEF factor by DRP and $NDEF$ makes a substantial contribution towards explaining the time-variation in the Bloomberg-NASD portfolios, even after

[19]These results are not reported in Table 5.

[20]Recall from (13) and (16) that DRP and $NDEF$ are orthogonal for our sample period. However, they do not have to add up to DEF.

controlling for known systematic factors. The R^2 increases from 62.3% to 70.2% and from 81.6% to 87.8% for the HY and IG portfolio, respectively. This suggests that bonds are exposed to both the default-risk-premia component and the non-default-related component (likely due to illiquidity risk) of corporate bond returns, although it seems that the latter is relatively more important for IG debt.

Lastly we find that replacing the DEF factor by a default-risk-premia and a non-default-related component makes a significant contribution to reducing the pricing errors of the HY portfolio, lowering them from 6 to 1 basis points per week. Pricing errors are not statistically different from zero, except for the IG portfolio where the size of the error is not trivial relative to the weekly average excess return of about 5 basis points.

The evidence in Table 5 supports the hypothesis that the DRP factor is priced by the Bloomberg-NASD corporate bond portfolios. We now investigate whether this applies more generally to the corporate bond market. Table 6 in Appendix C reports the results of the time-series regression in (15) for 7 Merrill Lynch corporate bond portfolios sorted on S&P credit ratings. We find that the DRP factor loading is estimated to be substantially higher for portfolios below investment-grade status than for portfolios of good and medium credit quality. Given that average returns are higher for high-credit-quality bonds and lower for speculative-grade debt, the cross-sectional relation between the slope coefficient on the DRP factor and the average returns on the rating portfolios is quite striking, both economically and statistically. It suggests that risk exposure to the DRP factor can partially explain the average returns earned by these portfolios, supporting the price behavior already documented in Table 5. The pricing errors of all portfolios are relatively small compared to the corresponding average excess returns, and they are statistically insignificant.

Next, we perform similar time-series regressions for 6 ML corporate bond portfolios sorted on time to maturity. The results are reported in Table 7. Note that average portfolio returns increase monotonically with time to maturity. From a rational-asset-pricing-model point of view this pattern makes perfect sense because longer maturities in bonds are typically associated with a larger exposure to inflation risk. Irrespective of the actual sources of risk impacting these portfolios, if higher average returns represent compensation for bearing more risk, then our goal is to understand whether part of this risk exposure can be attributed to the DRP factor. The DRP coefficient estimates in Table 7 confirm that portfolios with longer maturities tend to be also more exposed to the DRP factor. In addition, all of the pricing errors are small relative to the corresponding average returns, and none are statistically different from zero. The evidence from the maturity portfolios adds to that in Tables 5 and 6 in supporting the hypothesis that the DRP factor is priced in the corporate bond market.

Further evidence is provided in Table 8, where the test assets consist of 30 high-yield and 4 investment-grade ML corporate bond portfolios sorted by sector and broad industry, respectively. Again, both the median high-yield and investment-grade portfolios load significantly on the DRP factor. The median of the average weekly portfolios excess returns earned by HY portfolios is 14 basis points compared to 6 basis points for IG portfolios. This difference in returns can be partially explained by the fact that the estimated median loading for the HY portfolios is more than twice the size of that for the IG portfolios. The median pricing errors for both classes of portfolios are again relatively small in comparison to the corresponding median average returns, and not statistically different from zero.

We conclude this section by implementing the Fama-MacBeth two-pass procedure described as method (M2). The results, shown in Table 11, present more in-depth evidence in support of the hypothesis that the DRP factor is priced in the corporate bond market. The first panel reports the results when the set of test assets consists of the two Bloomberg-NASD portfolios and all 47 Merrill Lynch corporate bond portfolios. We find that the DRP beta alone explains about 13.5% of the cross-section of returns. Adding in the market beta increases the coefficient of determination to 30.3%. In both scenarios, the estimates for the risk premia on the DRP factor, as extracted from this set of test assets, are positive (although not statistically significant for the latter case).[21] For both models presented in the first panel of Table 11, the intercept is statistically insignificant, which is as expected if the underlying asset pricing model is correct.

The second part of Table 12 uses a richer set of test assets, including equity and equity options portfolios. We will postpone a discussion of these results until Section 5.4.

5.2 Equity

We now turn our focus to the equity market. The first panel in Table 9 presents the results of the time-series regression (15) for the Fama-French 100 equity portfolios sorted on size and book-to-market equity. Consistent with the results in Fama and

[21] Given the 52 test assets, we do not have enough power to estimate the model in (16) as stated (that is, with all 7 explanatory variables).

French (1993), we find that the three Fama-French stock-market factors enter with positive coefficient estimates, accompanied by high Newey-West t-statistics (especially for MKT and SMB). The slope coefficients for both the treasury and the corporate bond market factors are estimated to be positive. They contribute little, however, towards explaining the time variation of these equity portfolios, which is also in line with the aforementioned study.

In contrast to what was observed for corporate bond portfolios, replacing the DEF factor by DRP and $NDEF$ does not improve matters. The second panel in Table 9 shows that neither slope coefficient is statistically significant for the median equity portfolio. (The former even enters (15) with the wrong sign.) We also experimented with the 49 Fama-French industry portfolios as well as the Fama-French decile portfolios sorted on book-to-market equity, with similar results.

5.3 Options

Next we test whether our DRP factor is priced in the equity options market. Coval and Shumway (2001) show that something besides market risk is important for pricing the risk associated with option contracts. The authors offer some evidence that systematic stochastic volatility may be an important factor in explaining the time-series variation in option portfolio returns. Jones (2006) argues that a third, so-called "jump" factor accounts for an additional fraction of the option returns, although even such a three-factor model is insufficient to explain the magnitude of expected returns, especially the negative average returns for short-term out-of-the-money put options. The latent jump factor in Jones (2006) is difficult to characterize in terms of any observable series, although it seems to be associated in some way with large one-day returns in the stock market which are usually negative. The fact that the jump factor seems to capture risk associated with rare negative events appears to be helpful in capturing some of the well-documented skew in the returns on index option portfolios.

Unexpected default events with market-wide impact (such as Enron's demise or the Worldcom scandal) are certainly one form of rare events that will lead to large losses in the equity market. Recall that the jump-to-default-risk component of our DRP factor captures the common component in returns on pure default-contingent claims that is due to the risk of such unexpected defaults. DRP^{JtD} is therefore an excellent candidate to be informative about the shape of the return distribution of index options. Compared to Jones' jump factor, it has the advantage that it is intuitive and that it can be measured in a straightforward fashion from credit market data.

According to Figure 6, DRP and DRP^{JtD} are closely linked. It is thus reasonable to examine whether the DRP factor contributes towards explaining the cross-sectional variation in the returns on our put option test portfolios.[22] We conduct asset pricing tests in the spirit of method (M1), using as test assets the 16 portfolios sorted on time to maturity and moneyness that were introduced in Section 2.3. To account for systematic volatility risk premia, we include weekly changes in the logarithm of the stock-market volatility index VIX as an additional covariate in (15).

The results are reported in Table 10. Note that the loadings on the VIX factor line up almost perfectly with the average returns on the portfolios. The price impact of market-wide volatility risk on equity options is well documented in the literature, and our results are consistent with previous findings. With regard to the DRP factor, we discover that both average returns and the estimated slope coefficients for short- and medium-term index put options exhibit an increasing trend in magnitude (decreasing in absolute value) as they move closer to the money. In other words, portfolios that are further away from the money generally have more negative returns and also load more negatively on DRP. Even though we observe the anticipated directional relationship between average returns and beta estimates, the slope coefficients for DRP are not statistically significant during our sample period. For each moneyness bin, both average returns and the beta estimates for our DRP factor increase with increasing time to maturity.

5.4 Cross-Sectional Regressions

Finally, we implement the Fama-MacBeth two-pass procedure using test assets from all three markets, that is, from the corporate bond, equity and option markets. The second panel in Table 12 shows the results, which are based on a total number of 214 test assets. In particular, we include the IG and HY Bloomberg-NASD corporate bond portfolios, all 47 Merrill Lynch corporate bond portfolios described in Section 2.3, the 100 Fama and French equity portfolios sorted on size and book-to-market, the 49 Fama and French industry equity portfolios, and the 16 index put options portfolios sorted on moneyness and time-to-maturity. We find that the DRP beta contributes to the cross-sectional fit of regression (16), even when it is extracted from test assets which span not only the corporate bond market but also the equity and the equity

[22]The results for DRP^{JtD} are described in Section 6.

option markets. Our results show that the weekly risk premia of the DRP factor is about 3 basis points, and that this estimate is statistically significant.

5.5 Test for Firm Characteristics

We conclude this section with a test based on firm characteristics. Following Daniel and Titman (1997), we study the extent to which the common component in firm-specific risk-adjusted excess returns on pure default-contingent claims is due to firm characteristics which may behave very similarly, across firms, over time. To investigate whether the time variation in DRP is solely driven by certain firm characteristics, say $\vartheta(t)$, we estimate the linear model

$$\begin{aligned} R^i_{t,h}(T) - RF_t &= \alpha^i + \beta^i_{MKT}\, MKT(t) + \beta^i_{SMB}\, SMB(t) + \beta^i_{HML}\, HML(t) \\ &+ \beta^i_{UMD}\, UMD(t) + \beta^i_{TERM}\, TERM(t) + \beta^i_{NDEF}\, NDEF(t) \\ &+ \beta^i_{DRP}\, DRP(t) + \beta^i_{Char}\, \vartheta^i(t-h) + \epsilon^i_{\vartheta}(t). \end{aligned}$$

The dependent variables are the firm-specific excess returns on pure default-contingent claims of firm i with a maturity of one year, as defined in (3) in Section 3. On the right-hand side, we have the usual factors, including DRP and $NDEF$, plus a time-varying firm characteristic. Should $\vartheta^i(t-h)$ explain a significant portion of the time variation in $R^i_{t,h}(T) - RF_t$, then DRP will depend on the time-varying characteristic according to (11) and (12). In that case, the common variation in risk-adjusted excess returns on pure default-contingent claims could be due to firm characteristics moving together.

Results are reported in Table 13 in Appendix C, where we consider four different firm characteristics including the firm's 1-year EDF rate, recovery rate, 30-day implied call volatility, and leverage ratio. We find that the common variation in risk-adjusted excess returns on pure default-contingent claims is very unlikely to be due to one of these characteristics. Moreover, for each of the tests, the estimated loading on the DRP factor is always highly significant, both economically and statistically.

6 A Closer Look at the DRP Components

In the previous section, we showed that the DRP factor is priced in corporate bond markets and that for index put options the time-series loadings on the default risk premia factor align with the average returns along the time-to-maturity dimension, for each moneyness bin. According to (13), the DRP factor can be decomposed into three components. These are the portions associated with common changes in expected default losses (DRP^{L}), common changes in jump-to-default risk premia (DRP^{JtD}) and common variation in market prices of default risk (DRP^{MPR}). It is natural to ask to what extent each of these three components contribute to explaining the time variation and the cross-section of asset returns.

To answer this, we reproduce the results in Tables 5 through 12, after replacing the DRP factor in (15) and (16) by each of DRP^{L}, DRP^{JtD} and DRP^{MPR}. The results for corporate bonds are summarized in columns 2 to 4 of Table 14 in Appendix D. We only report the loading estimates for the default-related factor. For corporate bonds, the loadings on both DRP^{JtD} and DRP^{MPR} are statistically significant and line up nicely with average excess returns. For the market-price-of-default-risk component, this is not surprising since given our model specifications it captures much of the same variation as DRP itself (see Footnote 16). The results for DRP^{JtD} indicate that corporate bonds with higher loadings on the jump-to-default risk component have higher average returns, implying that jump to default risk is priced in the corporate bond market in the sense of method (M1). For the equity portfolios, none of the factors by themselves appear to be significant in explaining the time variation of returns. The results for the index put options are more interesting. The DRP^{JtD} factor is estimated consistently to have the right (negative) sign. For each moneyness bin, the beta loading estimates line up with the average excess returns. They are estimated to be lower (more negative) for out-of-money options than for at the money contracts. Also, the loadings for on DRP^{L} line up along the moneyness direction for the short-term put options. The negative coefficient estimate for the deepest OTM puts is significant at the 10% level, showing that common changes in expected default losses are useful in predicting returns for deep-OTM put options. The results for the MPR component are again similar to those for DRP itself, except that the levels of statistical significance are higher and that the loadings have the correct sign also for the long-term options. With regard to the cross-sectional results, Table 16 shows that the risk premia on DRP^{L}, DRP^{JtD} and DRP^{MPR} are 1, 2 and 1 basis points, respectively. The latter two are significant at the 5%-level. It is of interest to note that for the index put options, most of the risk premia is associated with the jump-to-default component of DRP.

Next, we investigate the scenario where we replace DRP by its components, DRP^{L} and DRP^{-L} in (14). The results are summarized in the last two columns of Tables 14 and 16, and the second panel of Table 15. We find that the explanatory power of DRP for returns on corporate debt and on index put options mainly stems from the portion DRP^{-L} of the default risk factor that is not explained by changes in expected default losses. The estimated risk premia on DRP^{-L} amounts to 3 basis points per week, after controlling for all other known systematic risk factors. In the next section, we develop a theoretical framework for a pricing kernel that is in line with our empirical finding that DRP^{-L} is priced for assets with a non-degenerate payoff structure in the default states (such as corporate bonds and index put options).

7 A Model Framework Explaining Our Results

In this section, we propose a theoretical framework for a pricing kernel, M, that is consistent with our empirical findings. We consider an economy with N firms in which the fundamentals are captured by a d-dimensional vector of state variables, X. The dynamics of X are specified as

$$dX_t = \mu(X_t, t)\, dt + \Sigma(X_t, t)\, dW_t,$$

where $\mu(\cdot, t)$ is a d-dimensional column vector of drifts and $\Sigma(\cdot, t)$ denotes the $d \times d$ matrix of state-dependent instantaneous volatilities. W_t is a d-dimensional standard Brownian motion on some probability space (Ω, P), with informational filtration $\{\mathcal{F}_t\}_{t\geq 0}$ generated by this process. The innovations in W_t describe the diffusive systematic risk in our economy.

We extend the doubly-stochastic framework of corporate default in Section 3 by assuming that default of firm i is triggered either by a market-wide credit event $\bar{\tau}^0$ that affects all firms in the economy or by a default event $\bar{\tau}^i$ that is specific to firm i or the sector it belongs to. In other words, we set $\tau^i = \min\{\bar{\tau}^0, \bar{\tau}^i\}$. For each $i = 0, \ldots, N$, $\bar{\tau}^i$ is the first event time of a (non-explosive) counting processes $\bar{N}^i$ with intensity process $\bar{\lambda}^{P,i}$, relative to $(\Omega, \mathcal{F}, P)$. Let us assume that the state process X determines actual default intensities according to $\bar{\lambda}_t^{P,i} = \bar{\lambda}^{P,i}(X_t)$, for all i. For doubly-stochastic models, conditional on X, the various event times are independent Poisson arrivals at time-varying deterministic intensities $\bar{\lambda}^{P,i}(X_t)$. We rule out simultaneous event times and assume $P(\bar{\tau}^i = \bar{\tau}^j) = 0$ for $i \neq j$, which implies that the actual default intensity $\lambda^{P,i}$ for firm i introduced in Section 3 can be interpreted as $\lambda^{P,i} = \bar{\lambda}^{P,0} + \bar{\lambda}^{P,i}$.

Suppose that the pricing kernel M for this economy can be written as

$$\begin{aligned}\frac{dM_t}{M_{t-}} &= -r(X_t)\,dt - \Lambda(X_t)\,dW_t - \sum_{i=0}^{N} \bar{\Gamma}^i(X_{t-})\,(d\bar{N}_t^i - \bar{\lambda}^{P,i}(X_t)\,dt) \\ &= -\left(r_t - \sum_{i=0}^{N} \bar{\Gamma}_t^i\,\bar{\lambda}_t^{P,i}\right) dt - \Lambda_t\,dW_t - \sum_{i=0}^{N} \bar{\Gamma}_{t-}^i\,d\bar{N}_t^i, \qquad (17)\end{aligned}$$

where $r_t = r(X_t)$ is the instantaneous risk-free interest rate, $\Lambda_t = \Lambda(X_t)$ denotes the market price of diffusive risk, $\bar{\Gamma}_t^0 = \bar{\Gamma}^0(X_t)$ is the market price of default risk associated with the market-wide credit event time $\bar{\tau}^0$, and $\bar{\Gamma}_t^i = \bar{\Gamma}^i(X_t)$ is the market price of default risk associated with the credit event for firm i. Risk-neutral event arrival intensities are given by $\bar{\lambda}^{Q,i} = (1-\bar{\Gamma}^i)\bar{\lambda}^{P,i}$. Equation (17) extends the formulation in Dai and Singleton (2003) to a multi-firm setting.

Define $\bar{\lambda}_t^P = \bar{\lambda}_t^{P,1} + \ldots + \bar{\lambda}_t^{P,N}$, and let

$$\bar{\Gamma}_t = \frac{1}{\bar{\lambda}_t^P} \sum_{i=1}^{N} \bar{\lambda}_t^{P,i}\,\bar{\Gamma}_t^i.$$

Under mild technical conditions (see, for example, Protter (2005)), the pricing kernel is given by

$$\begin{aligned}M_t &= \exp\left\{-\int_0^t r_s\,ds + \int_0^t \bar{\Gamma}_s \bar{\lambda}_s^P\,ds - \frac{1}{2}\int_0^t \Lambda_s^2\,ds - \int_0^t \Lambda_s\,dW_s\right\} \\ &\quad \times \exp\left\{\int_0^t \bar{\Gamma}_s^0 \bar{\lambda}_s^{P,0}\,ds\right\} \times \prod_{s\le t}\left[1 - \sum_{i=0}^{N} \bar{\Gamma}_s^i \Delta\bar{N}_s^i\right]. \qquad (18)\end{aligned}$$

Ruling out simultaneous event times implies $1 - \sum_{i=0}^{N} \bar{\Gamma}_s^i \bar{\Delta} N_s^i = \prod_{i=0}^{N}\left[1 - \bar{\Gamma}_s^i \Delta\bar{N}_s^i\right]$. The pricing kernel in (18) can therefore be conveniently expressed as

$$M_t = \mathcal{E}_t \times \exp\left\{\int_0^t \bar{\Gamma}_s \bar{\lambda}_s^P\,ds\right\} \times \exp\left\{\int_0^t \bar{\Gamma}_s^0 \bar{\lambda}_s^{P,0}\,ds\right\} \times \prod_{i=0}^{N}\prod_{s\le t}\left[1 - \bar{\Gamma}_s^i \Delta\bar{N}_s^i\right],$$

where $\mathcal{E}_t = \mathcal{E}(\{X_s\}_{s\le t})$ is the stochastic exponential of $-r(X_t)\,dt - \Lambda(X_t)\,dW_t$ given by

$$\mathcal{E}_t = \exp\left\{-\int_0^t r_s\,ds - \frac{1}{2}\int_0^t \Lambda_s^2\,ds - \int_0^t \Lambda_s\,dW_s\right\}. \qquad (19)$$

Note that $\mathcal{E}_t$ is equal to the pricing kernel that would have applied in the absence of any risk premia associated with default events (that is, for $\bar{\Gamma}^i = 0$ for all i).

For each firm i we have, for small values of h, $R^{QP,i}_{t+h,h} - RF_{t+h} \approx \int_t^{t+h} \left(\bar{\lambda}^{Q,0}_s + \bar{\lambda}^{Q,i}_s\right) ds$ and $R^{PP,i}_{t+h,h} - RF_{t+h} \approx \int_t^{t+h} \left(\bar{\lambda}^{P,0}_s + \bar{\lambda}^{P,i}_s\right) ds$. Hence, the difference between the excess returns associated with (5) and (4) is approximately equal to

$$R^{QP,i}_{t+h,h} - R^{PP,i}_{t+h,h} \approx -\int_t^{t+h} \bar{\Gamma}^0_s \bar{\lambda}^{P,0}_s \, ds - \int_t^{t+h} \bar{\Gamma}^i_s \bar{\lambda}^{P,i}_s \, ds. \tag{20}$$

This suggests that the portion of the excess returns on pure default-contingent claims that is due to common changes in jump to default risk premia DRP^{JtD} is to a large extent driven by the market price of jump-to-default risk associated with the market-wide default event $\bar{\tau}^0$. In what follows we investigate the effect of this market-wide source for jump-to-default risk on the expected returns of a firm's equity and debt claims. Note that for h small, as is the case in our application, $R^{QP,i}$ and $R^{QQ,i}$ are closely related, which suggests that much of the time variation in DRP^{-L} also stems from the jump-to-default risk premia associated with $\bar{\tau}^0$.

Let $\tilde{R}^{E,i}_{t+h}$ and $\tilde{R}^{D,i}_{t+h}$ denote the gross return over the period $[t, t+h]$ on equity and debt of firm i, respectively. If both equity and corporate bond markets are competitive, the pricing equation is the Euler equation, that is,

$$E_t\left[\frac{M_{t+h}}{M_t} \tilde{R}^{\cdot,i}_{t+h}\right] = 1,$$

for $\cdot = E, D$. As long as firm i is solvent, the gross return on equity claims is non-zero. We will assume a zero-recovery value to equity holders in the event of default, which implies $\tilde{R}^{E,i}_{t+h} = \tilde{R}^{E,i}_{t+h} \mathbf{1}_{\{\tau^i > t+h\}}$. With this in mind, we have

$$\begin{aligned} E_t \tilde{R}^{E,i}_{t+h} &= \tilde{RF}_{t+h}\left(1 - cov_t\left[\frac{M_{t+h}}{M_t}, \tilde{R}^{E,i}_{t+h}\right]\right) \\ &= \tilde{RF}_{t+h}\left(1 - cov_t\left[\frac{M^{-i}_{t+h}}{M^{-i}_t}, \tilde{R}^{E,i}_{t+h}\right] + E_t\left[\frac{M_{t+h}}{M_t} - \frac{M^{-i}_{t+h}}{M^{-i}_t}\right] E_t \tilde{R}^{E,i}_{t+h}\right), \end{aligned} \tag{21}$$

where $\tilde{RF}_{t+h}$ is the gross return on risk-less bonds given by

$$\tilde{RF}_{t+h} = \left[E_t\left(\frac{M_{t+h}}{M_t}\right)\right]^{-1}$$

and

$$M^{-i}_t = \mathcal{E}_t \times \exp\left\{\int_0^t \bar{\Gamma}_s \bar{\lambda}^P_s \, ds\right\} \times \exp\left\{\int_0^t \bar{\Gamma}^0_s \bar{\lambda}^{P,0}_s \, ds\right\} \times \prod_{j \neq 0,i} \prod_{s \leq t} \left[1 - \Gamma^j_s \Delta N^j_s\right].$$

To gain intuition as to why the DRP factor does not seem to make a significant contribution to explaining expected returns on equity, let us study (21) after turning off all diffusive risk premia in the economy by setting $\Lambda = 0$. In this simplified scenario, the covariance term in (21) is given by

$$cov_t \left[\exp\left\{A_{t+h}\right\} \times \prod_{j \neq 0,i} \prod_{t<s\leq t+h} \left[1 - \Gamma_s^j \Delta N_s^j\right], \tilde{R}_{t+h}^{E,i} \right], \tag{22}$$

where $A_{t+h} = -\int_t^{t+h} r_s \, ds + \int_t^{t+h} \bar{\Gamma}_s \bar{\lambda}_s^P \, ds + \int_t^{t+h} \bar{\Gamma}_s^0 \bar{\lambda}_s^{P,0} \, ds$. The covariance term in (22) is close to zero as long as r_s and $\{\bar{\Gamma}_s^j \bar{\lambda}_s^{P,j}\}_j$ are relatively stable over the short interval $[t, t+h]$.[23] At the same time, the last term in (21) is small for realistic values of default intensities for firm i. In summary, little or no dependency between expected returns and either DRP^{JtD} or $DRP - DRP^L$ will be detected. A similar observation holds true for DRP by extension.

The fact that corporate bonds have non-zero payoffs in the event of default substantially changes the relation between corporate bond returns and jump-to-default risk premia. According to (21), the gross returns on corporate bonds of firm i, $\tilde{R}_{t+h}^{D,i}$, can be written as

$$E_t \tilde{R}_{t+h}^{D,i} \quad = \quad \tilde{RF}_{t+h} \left(1 - cov_t \left[\frac{M_{t+h}}{M_t}, \tilde{R}_{t+h}^{D,i} \mathbf{1}_{\{\tau^i > t+h\}} \right] - cov_t \left[\frac{M_{t+h}}{M_t}, \tilde{R}_{t+h}^{D,i} \mathbf{1}_{\{t<\tau^i \leq t+h\}} \right] \right).$$

Even though the first covariance term might be negligible as it is for equity, the second covariance term captures the dependency between realized returns and DRP^{JtD} (or, similarly, DRP^{-L}). These results provide intuition as to why for an economy with a unique pricing kernel for valuing both corporate bonds and equity, corporate bonds returns but not equity returns load on the jump-to-default component of DRP, and hence, by extension, on DRP.

8 Discussion and Conclusion

This is the first paper to extract a common risk factor from credit markets and investigate its contribution towards explaining average returns observed in corporate bond, equity and index option markets. Our default risk premia factor, or simply DRP factor, is identified as that portion of the weekly excess returns on an equally-weighted portfolio of pure default-contingent claims that cannot be explained by linear combinations of systematic stock-market and Treasury-market risk factors. Asset

[23] Recall that conditional on default intensities, the realized return on firm i's equity is independent from the credit event times of the other firms in the economy.

pricing tests using returns on Bloomberg-NASD corporate bond indices suggest that the DRP factor is priced in the corporate bond market. A cross-sectional analysis of 47 Merrill Lynch corporate bond portfolios sorted on either industry, maturity or rating supports these findings. We decompose the DRP factor to show that most of its time variation can be explained by the portion DRP^{JtD} that is due to common variation in jump-to-default risk premia. Using 16 portfolios of delta-hedged put options written on the S&P 500 index and sorted on maturity and moneyness, we find that both average returns and the beta estimates for our DRP factor become more negative with decreasing time to maturity. There is little to no evidence of the DRP factor being priced in equity markets. We develop a theoretical framework where DRP^{JtD} is part of the pricing kernel that supports our empirical findings. It shows that DRP^{JtD} captures the jump-to-default risk premia associated with market-wide credit events.

As a final remark we want to address the issue that from a practical perspective, trading strategies based on the DRP factor are difficult to implement because the pure default-contingent claims used to construct the portfolios are not actually traded. To give the reader a sense of how a trading strategy based on the same motivation as for our default risk premia DRP factor can be implemented, we compute an alternative CDS-based DRP factor, named $CDRP$, by replacing the holding returns $R^i_{t,h}(T)$ in (3) with

$$R^{CDS,i}_{t,h} \quad = \quad -\left(\log CDS^i_t - \log CDS^i_{t-h}\right), \tag{23}$$

where CDS^i_t denotes the at-market 5-year default swap rate for firm i at time t. For the median firm in our sample, $CDRP$ explains 20.5% of the risk-adjusted excess returns on default swaps. Note that since each of our CDS observations is considered a new constant-maturity par-coupon credit spread, $R^{CDS,i}_{t,h}$ is no longer a holding period return.[24] Conversations with market participants, however, indicate that for h equal to a week, the effect of different maturity dates associated with CDS^i_t and CDS^i_{t-h} is minimal, and is certainly outweighed by the advantages of having a tradable form of the default risk premia factor available.

The asset pricing test results for $CDRP$ are summarized in Appendix E, showing the estimated loadings for the default-related factors only. For the corporate bond

[24] This is different from the contracts underlying a particular series of the Dow Jones CDX indices, which have a fixed maturity date around either June 20 or December 20 of each year. Data on the HY DJ CDX index is available to us only starting April 2005. In addition, our Moody's KMV EDF data does not completely overlap with the members of the IG or HY index, which would prohibit us from decomposing the $CDRP$ factor.

market, Table 17 indicates that $CDRP$ is priced, and that its explanatory power for returns stems from the portion unexplained by expected losses, in particular the jump-to-default risk component. For equity portfolios, the time-series loadings on $CDRP$ or its components are again not significant. In the case of index put options, for each moneyness bin, the overall trend in the estimated loadings on $CDRP$ is still consistent (although not longer strictly monotone) with that observed for average returns along the time-to-maturity dimension. Interestingly, we now find that for each time-to-maturity bin, the negative factor loadings decrease as the options mover further away from the money, as do average excess returns. (Two exceptions are the third and the first moneyness bin for the first and the second-to-expire options, respectively.) For many option portfolios, the loadings are now statistically significant, especially for longer dated options. Again, similar observations hold true when replacing the CDS-based default risk premia factor by the portion that is associated with jump-to-default risk premia, confirming our findings that most of the explanatory power of $CDRP$ is due to $CDRP^{JtD}$. Finally, we find that the $CDRP$ factor commands a risk premium of 48 basis points per week. Note that this figure is much larger than for DRP due to the fact that $CDRP$ captures returns on par-coupon spreads in the sense of (23).

A Data Coverage

firm	rtg	5yr CDS	1yr CDS	recov	no EDF	no 5yr CDS	no 1yr CDS
				Basic Materials			
Bowater	Ba	289	177	0.41	248	250	250
Cytec Industries	Baa	60	25	0.40	248	231	193
Dow Chemical	A	63	45	0.40	248	250	249
Eastman Chemical	Baa	70	39	0.41	248	250	244
International Paper	Baa	71	45	0.40	248	250	250
Monsanto	Baa	52	23	0.41	248	233	194
PPG Industries	A	34	19	0.41	248	250	250
Praxair	A	26	13	0.41	248	250	243
Rohm and Haas	A	33	15	0.41	248	250	250
				Consumer Goods			
ArvinMeritor	Ba	317	212	0.39	248	250	249
Black & Decker	Baa	42	21	0.41	248	250	249
BorgWarner	Baa	53	27	0.40	248	250	249
Campbell Soup	A	29	14	0.40	248	250	249
Coca-Cola Enterprises	A	29	13	0.40	248	250	250
ConAgra Foods	Baa	46	23	0.39	248	250	250
Dana	Ba	449	421	0.41	248	220	220
Delphi	Baa	308	343	0.41	195	200	200
Eastman Kodak	Baa	172	86	0.39	248	250	250
Ford Motor	Baa	440	284	0.41	248	250	250
General Motors	Baa	456	334	0.41	248	250	250
Georgia-Pacific	Ba	319	265	0.41	206	250	250
Sara Lee	A	36	14	0.40	248	250	246
Tyson Foods	Baa	100	59	0.41	248	250	249
Visteon	Ba	415	317	0.42	248	250	250
				Consumer Services			
Cardinal Health	A	48	21	0.41	248	248	242
Clear Channel Comm	Baa	130	99	0.40	248	250	250
Comcast	Baa	129	104	0.40	244	250	248
Interpublic Group of Cos	Baa	259	192	0.40	248	249	247
Omnicom Group	Baa	71	66	0.40	248	250	249
Royal Caribbean Cruises	Ba	312	305	0.40	248	250	250
Sabre Holdings	Baa	89	50	0.40	248	231	230
Time Warner Cos	Baa	122	103	0.39	248	250	250
Walt Disney	Baa	57	37	0.40	248	250	250
				Health Care			
Baxter International	Baa	40	26	0.40	248	250	250
Boston Scientific	Baa	43	21	0.41	248	250	240
Bristol-Myers Squibb	A	30	17	0.41	248	237	234
Chiron	Baa	43	34	0.40	223	225	222
Genzyme	WR	48	19	0.39	241	156	148
HCA (Oldco)	Ba	174	102	0.41	248	250	246
Health Management Assoc	Baa	67	29	0.39	248	181	149
Humana	Baa	70	44	0.41	248	247	234
Lab of America Holdgs	Baa	47	11	0.40	248	177	108
Merck & Co.	Aaa	18	6	0.41	248	227	183
Quest Diagnostics	Baa	47	14	0.40	248	187	139
Schering-Plough	Baa	35	16	0.41	248	229	187
Universal Health Services	Baa	72	31	0.39	248	166	146
Wyeth	Baa	51	34	0.40	248	250	247
				Industrials			
Boeing	A	40	25	0.40	248	250	250
Caterpillar	A	30	16	0.40	248	250	250
Cummins	Ba	204	165	0.40	248	250	250
Danaher	A	30	23	0.40	248	250	245
Deere	A	37	23	0.40	248	250	250
Eaton	A	31	17	0.40	248	250	247
Goodrich	Baa	98	72	0.40	248	250	250
Honeywell International	A	37	23	0.40	248	250	250
Lockheed Martin	Baa	43	24	0.41	248	250	250
MeadWestvaco	Baa	72	39	0.39	248	244	240
Northrop Grumman	Baa	54	34	0.41	248	250	246
Raytheon	Baa	75	54	0.39	248	250	249
Sealed Air	Baa	164	144	0.38	248	250	240

Table 1 – continued from previous page

firm	rtg	CDS5	CDS1	recov	no EDF	no CDS5	no CDS1
Sherwin-Williams	A	41	20	0.41	248	250	247
Temple-Inland	Baa	100	64	0.40	248	250	235
United Technologies	A	23	12	0.40	248	247	238
Waste Management	Baa	96	74	0.41	248	248	235
				Oil and Gas			
Anadarko Petroleum	Baa	42	21	0.40	248	250	249
Baker Hughes	A	26	15	0.41	248	250	249
Devon Energy	Baa	63	48	0.40	248	250	250
Diamond Offshore Drilling	Baa	43	25	0.40	248	250	248
El Paso	Caa	547	524	0.37	248	250	250
Halliburton	Baa	147	130	0.41	248	247	246
Kerr-McGee	Baa	79	41	0.41	239	249	235
Kinder Morgan Energy P	Baa	56	29	0.41	230	250	231
Kinder Morgan	Baa	71	36	0.40	248	242	215
Marathon Oil	Baa	44	24	0.41	248	239	235
Nabors Industries	A	42	25	0.40	248	250	244
National Oilwell Varco	Baa	49	21	0.39	248	203	157
Pioneer Natural Resources	Ba	87	33	0.40	248	156	124
Pride International	Ba	191	116	0.40	248	205	184
Transocean	Baa	54	41	0.40	248	250	250
Valero Energy	Baa	85	61	0.40	248	250	246
Weatherford International	Baa	34	14	0.40	248	166	150
				Technology			
Computer Sciences	A	60	29	0.39	248	249	244
Electronic Data Systems	Baa	160	120	0.40	248	250	248
Hewlett-Packard	A	47	31	0.39	248	250	250
IBM	A	32	18	0.40	248	250	250
Lucent Technologies	B	684	594	0.38	248	250	250
Pitney Bowes	Aa	22	12	0.41	248	250	240
Sun Microsystems	Baa	126	89	0.40	248	250	249
Xerox	Ba	409	393	0.38	248	250	249
				Telecommunications			
ALLTEL	A	58	26	0.41	248	212	196
AT&T	A	167	132	0.38	248	250	250
BellSouth	A	45	27	0.41	248	250	249
CenturyTel	Baa	98	56	0.41	248	250	237
Citizens Comm	Baa	237	156	0.39	248	250	245
New Cingular Wireless Servs	Baa	261	262	0.38	145	147	147
Nextel Comm	B	511	413	0.37	187	189	167
Sprint Nextel	Baa	210	211	0.38	248	250	250
Verizon Comm	A	73	63	0.42	248	250	243
				Utilities			
American Electric Power	Baa	105	86	0.40	248	250	249
Cinergy	Baa	68	56	0.41	220	250	247
Constellation Energy Group	Baa	80	55	0.41	248	250	239
Dominion Resources	Baa	62	42	0.41	248	250	248
Duke Energy	NaN	62	48	0.40	248	250	249
Exelon	Baa	56	32	0.40	248	246	229
FirstEnergy	Baa	106	74	0.40	248	226	213
ONEOK	Baa	59	39	0.40	248	250	240
Progress Energy	Baa	67	46	0.39	248	250	236
Sempra Energy	Baa	73	46	0.40	248	250	226
TECO Energy	Ba	228	199	0.41	248	230	221
TXU	Ba	186	168	0.39	248	250	249
Williams Cos	B	476	542	0.37	248	250	250
Xcel Energy	Baa	146	140	0.39	248	239	225

Table 1: **Firm Summary Statistics:** For each firm, we report the number of weekly observations of EDF rates, 5- and 1-year CDS rates, the average 5-year CDS rate, the average 1-year CDS rate, and the average recovery rate. The sample period is January 2, 2002 through October 11, 2006.

Moneyness Bin	Maturity Bin			
	1st	2nd	3rd-5th	$\geq$ 6th
	Moneyness			
0.85-0.9	0.88	0.88	0.88	0.88
0.9-0.95	0.93	0.93	0.93	0.93
0.95-1	0.98	0.98	0.98	0.97
> 1	1.07	1.07	1.10	1.13
	Maturity (days)			
0.85-0.9	25	47	100	439
0.9-0.95	24	45	97	415
0.95-1	22	44	90	373
> 1	23	45	98	349
	Number of Valid Return Observations			
0.85-0.9	144	530	980	2509
0.9-0.95	487	1179	1174	2556
0.95-1	1185	1762	1555	2388
> 1	1086	1796	2173	4609

Table 2: **Summary Statistics for the S&P 500 Index Put Option Portfolios:** The first part of the table shows the value-weighted averages of the moneyness for the options in each bin, whereas the second part lists the value-weighted averages of the days until to expiration. The last portion of the table counts the Number of Valid Return Observations for each bin across the time period January 2002 to April 2006. Source: OptionMetrics.

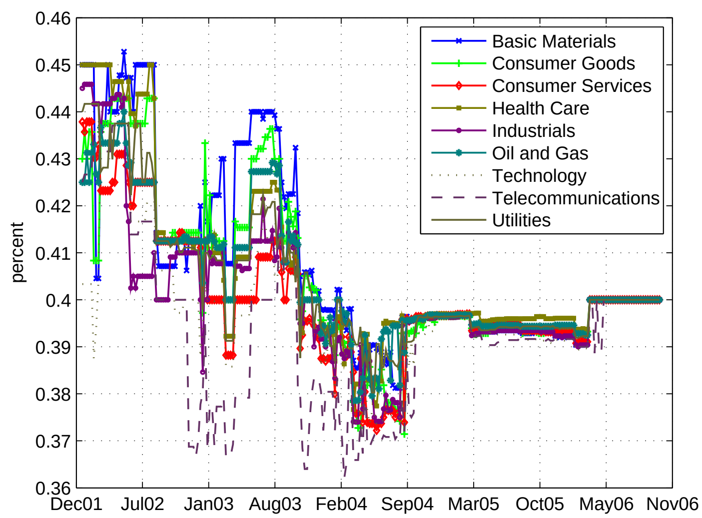

Figure 7: Time series of median recovery rates by sector. Source: Markit.

B Time Series Estimation of Default Intensities

sector	$\hat{\kappa}$	$\hat{\sigma}$	$\hat{\rho}$	avg $\hat{\theta}^i$	log-like	no firms
Basic Materials	0.256	1.041	0.223	2.009	-1.530	9
Consumer Goods	1.196	1.574	0.206	2.993	-2.565	15
Consumer Services	0.236	0.964	0.294	3.147	-2.535	9
Health Care	0.241	1.034	0.172	2.238	-1.774	14
Industrials	0.379	1.067	0.181	2.203	-1.684	17
Oil and Gas	0.109	1.055	0.234	2.584	-2.197	17
Technology	0.667	1.214	0.282	3.621	-3.148	8
Telecommunications	0.225	0.963	0.320	2.949	-2.251	9
Utilities	0.453	1.201	0.335	3.070	-2.628	14

Table 3: Sector-by-sector EDF-implied ML parameter estimates in (6), using weekly Moody's KMV 1-year EDFs from January 2, 2002 to October 11, 2006. The intensities $\lambda^{P,i}$ are measured in basis points per year.

sector	$\hat{\kappa}^{QP}$	$\hat{\sigma}^Q$	$\hat{\rho}^Q$	avg $\hat{\theta}^{QP}$	$\hat{\kappa}^{QQ}$	avg $\hat{\theta}^{QQ}$	log-like
Basic Materials	1.018	1.409	0.298	3.350	0.361	3.567	-2.705
Consumer Goods	0.549	1.255	0.262	4.367	0.250	4.421	-3.585
Consumer Services	0.521	1.836	0.323	3.294	0.393	3.560	-3.332
Health Care	0.963	1.477	0.082	3.294	0.302	2.867	-2.765
Industrials	0.832	1.462	0.207	3.036	0.387	3.489	-2.627
Oil and Gas	0.725	1.306	0.245	3.542	0.339	3.850	-2.827
Technology	0.718	1.692	0.241	3.568	0.315	3.364	-3.414
Telecommunications	0.119	1.576	0.355	3.583	0.276	3.820	-3.489
Utilities	0.681	1.617	0.264	3.101	0.366	3.832	-3.162

Table 4: Sector-by-sector CDS-implied ML parameter estimates in (8), using 1- and 5-year CDS rates with modified restructuring and firm-specific recovery rates from January 2, 2002 to November 11, 2006. The intensities $\lambda^{Q,i}$ are measured in basis points per year.

C Asset Pricing Test Results

α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{TERM}	β_{DEF}	β_{NDEF}	β_{DRP}	R^2	$E[R]-RF$
					Investment-Grade					
-0.0002	0.0240	0.0080	0.0399	-0.0306	0.4339	0.6961	–	–	0.8159	0.0005
(-1.2655)	(1.8139)	(0.3862)	(1.4946)	(-2.1865)	(21.6115)	(7.6490)				
					High-Yield					
0.0006	0.1190	0.1814	0.2060	-0.0965	0.3302	1.6059	–	–	0.6230	0.0024
(1.3935)	(4.2902)	(3.4764)	(3.1014)	(-2.9022)	(6.2063)	(9.6549)				
					Investment-Grade					
-0.0004	0.0371	0.0211	0.0628	-0.0353	0.4025	–	0.4622	0.9947	0.8765	0.0005
(-3.0205)	(3.3388)	(1.0602)	(2.8249)	(-2.5370)	(24.7091)		(5.7547)	(13.3886)		
					High-Yield					
0.0001	0.1916	0.2410	0.3345	-0.1470	0.1877	–	0.4897	2.4944	0.7021	0.0024
(0.3208)	(7.7639)	(4.7794)	(4.9990)	(-4.7951)	(3.3164)		(2.1585)	(8.5218)		

Table 5: **The Bloomberg-NASD IG and HY Corporate Bond Portfolios** This table reports the results of the time-series regressions of weekly realized excess returns of portfolios of IG and HY corporate bonds on MKT, SMB, HML, UMD, $TERM$. The first panel also includes DEF as a covariate. Specifically, for each portfolio we estimate the regression: $R(t) - RF(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \beta_{TERM}TERM(t) + \beta_{DEF}DEF(t) + \epsilon(t)$. The second panel reports the estimation results after replacing DEF by $NDEF$ and DRP. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is October 2, 2002 to October 11, 2006.

Rtg	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{TERM}	β_{NDEF}	β_{DRP}	R^2	$E[R]-RF$
AAA	0.0001	-0.0058	0.0430	0.0138	-0.0115	0.4990	0.0182	0.2180	0.9478	0.0007
	(0.7851)	(-0.8380)	(3.2255)	(1.1406)	(-1.4936)	(44.8414)	(0.5801)	(4.3125)		
AA	0.0000	-0.0041	0.0124	0.0239	-0.0065	0.4476	0.1265	0.2090	0.9323	0.0006
	(0.5004)	(-0.6135)	(1.0264)	(1.7380)	(-0.7927)	(41.6954)	(2.3647)	(4.4938)		
A	0.0000	-0.0037	0.0204	0.0373	-0.0170	0.5299	0.1958	0.2985	0.9562	0.0007
	(0.4978)	(-0.5268)	(1.8189)	(2.7331)	(-2.3496)	(47.2213)	(5.8192)	(5.8592)		
BBB	-0.0002	0.0111	0.0256	0.0663	-0.0342	0.5889	0.6924	0.6698	0.9142	0.0007
	(-1.8701)	(1.2396)	(2.1156)	(2.7409)	(-2.9007)	(39.1004)	(10.4254)	(4.4123)		
BB	-0.0001	0.0754	0.0451	0.1276	-0.0127	0.2748	0.5564	1.3825	0.4854	0.0009
	(-0.3486)	(2.5156)	(0.5308)	(1.9004)	(-0.3513)	(5.3778)	(2.3583)	(5.5121)		
B	0.0003	0.0900	0.1020	0.1563	-0.0630	0.1754	0.7173	1.5643	0.6326	0.0014
	(0.9750)	(4.1913)	(2.8205)	(2.8654)	(-2.4780)	(5.0943)	(5.1561)	(7.7088)		
C	0.0010	0.0765	0.2932	0.1794	-0.0745	0.1578	0.8871	1.5633	0.4536	0.0023
	(1.6140)	(1.7075)	(4.3527)	(2.2191)	(-1.5208)	(2.5674)	(2.7851)	(5.3211)		

Table 6: **The Merrill Lynch Corporate Bond Portfolios Sorted by Ratings** This table reports the results of the time-series regressions of weekly realized excess returns of 7 Merrill Lynch corporate bond portfolios sorted by credit rating on MKT, SMB, HML, UMD, $TERM$, and DRP. Specifically, for each portfolio we estimate the regression: $R(t) - RF(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \beta_{TERM}TERM(t) + \beta_{NDEF}NDEF(t) + \beta_{DRP}DRP(t) + \epsilon(t)$. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is January 2, 2002 to October 11, 2006.

Maturity	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{TERM}	β_{NDEF}	β_{DRP}	R^2	$E[R]-RF$
1-3 yrs	0.0001	0.0011	0.0207	0.0428	-0.0197	0.1323	0.0742	0.2388	0.5996	0.0003
	(0.6133)	(0.1762)	(2.3659)	(3.1078)	(-2.5194)	(12.8200)	(1.6907)	(3.7913)		
3-5 yrs	0.0000	0.0044	0.0348	0.0689	-0.0321	0.3193	0.0919	0.3645	0.7959	0.0005
	(-0.0755)	(0.4338)	(2.3177)	(3.6377)	(-2.8668)	(19.8836)	(1.5915)	(4.4815)		
5-7 yrs	0.0000	0.0017	0.0349	0.0631	-0.0369	0.4801	0.2300	0.4249	0.8670	0.0007
	(0.1187)	(0.1560)	(2.2771)	(2.9231)	(-2.8531)	(27.6637)	(3.0711)	(4.7231)		
7-10 yrs	-0.0001	0.0030	0.0299	0.0642	-0.0350	0.6427	0.4189	0.5057	0.9364	0.0008
	(-0.6701)	(0.3315)	(2.3356)	(3.2810)	(-3.2604)	(45.6782)	(7.2170)	(5.2430)		
10-15 yrs	-0.0002	-0.0074	0.0472	0.0801	-0.0411	0.7803	0.3948	0.5312	0.9420	0.0009
	(-0.9295)	(-0.5390)	(2.5067)	(3.4099)	(-3.5720)	(41.9704)	(4.2720)	(5.7913)		
15+ yrs	-0.0001	0.0004	-0.0067	-0.0147	0.0080	1.0420	1.1099	0.6118	0.9806	0.0010
	(-1.5584)	(0.0670)	(-0.7228)	(-0.7081)	(0.7623)	(86.9993)	(28.7324)	(5.0511)		

Table 7: **The Merrill Lynch Corporate Bond Portfolios Sorted by Time to Maturity** This table reports the results of the time-series regressions of weekly realized excess returns of 6 Merrill Lynch corporate bond portfolios sorted by time to maturity on MKT, SMB, HML, UMD, $TERM$, and DRP. Specifically, for each portfolio we estimate the regression: $R(t) - RF(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \beta_{TERM}TERM(t) + \beta_{NDEF}NDEF(t) + \beta_{DRP}DRP(t) + \epsilon(t)$. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is January 2, 2002 to October 11, 2006.

α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{TERM}	β_{DEF}	β_{NDEF}	β_{DRP}	R^2	$E[R]-RF$
					Investment-Grade Broad Industry Portfolios					
0.0001	-0.0060	0.0299	0.0336	-0.0115	0.4086	0.1782	–	–	0.8747	0.0006
(1.1485)	(-0.8321)	(2.4406)	(1.9285)	(-1.4352)	(29.8452)	(3.8846)				
0.0000	0.0003	0.0320	0.0474	-0.0184	0.3978	–	0.0946	0.2874	0.8837	0.0006
(0.2525)	(0.0565)	(2.6873)	(2.6137)	(-2.2647)	(30.9493)		(1.7544)	(4.4872)		
					High-Yield Sector Portfolios					
0.0010	0.0329	0.1010	0.0935	-0.0054	0.1905	0.5934	–	–	0.3087	0.0014
(2.1865)	(1.0351)	(2.8037)	(1.3260)	(-0.1527)	(4.4024)	(3.7006)				
0.0008	0.0595	0.1059	0.1267	-0.0284	0.1570	–	0.2635	0.7152	0.2937	0.0014
(1.5067)	(2.0321)	(3.0559)	(2.0720)	(-0.8533)	(3.4657)		(1.9368)	(3.0611)		

Table 8: **The Merrill Lynch Industry Investment-Grade and High-Yield Corporate Bond Portfolios** This table reports the results of the time-series regressions of weekly realized excess returns of 4 IG Merrill Lynch corporate bond portfolios sorted by broad industry and of 30 HY Merrill Lynch corporate bond portfolios sorted by sector on MKT, SMB, HML, UMD, $TERM$, and DEF. Specifically, for each portfolio we estimate the regression: $R(t)-RF(t)=\alpha+\beta_{MKT}MKT(t)+\beta_{SMB}SMB(t)+\beta_{HML}HML(t)+\beta_{UMD}UMD(t)+\beta_{TERM}TERM(t)+\beta_{DEF}DEF(t)+\epsilon(t)$. We also report the estimation results after replacing DEF by $NDEF$ and DRP. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. All figures are median values across portfolios. The sample period is October 2, 2002 to October 11, 2006.

α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{TERM}	β_{DEF}	β_{NDEF}	β_{DRP}	R^2
				100 Fama-French Equity Portfolios					
0.0000	1.0581	0.5761	0.2618	-0.0286	-0.0028	-0.0002	–	–	0.8507
(-0.0313)	(25.2910)	(7.3920)	(2.9639)	(-0.4961)	(-0.0481)	(0.0001)			
-0.0001	1.0582	0.5749	0.2552	-0.0293	-0.0026	–	0.0362	-0.0358	0.8504
(-0.2026)	(24.7153)	(7.6078)	(2.9925)	(-0.5681)	(-0.0547)		(0.0909)	(-0.1265)	
				49 Fama-French Industry Portfolios					
0.0004	0.9763	0.2251	0.0867	0.0995	-0.0101	-0.0247	–	–	0.6107
(0.3038)	(13.9128)	(2.1090)	(0.5032)	(0.9198)	(-0.0870)	(-0.0584)			
0.0004	0.9543	0.2400	0.0632	0.0935	0.0151	–	-0.0907	0.1175	0.6114
(0.3456)	(13.9297)	(2.1393)	(0.5122)	(0.7333)	(0.2012)		(-0.1415)	(0.2954)	

Table 9: **The** 100 **Fama-French Equity and the 49 Fama-French Industry Portfolios** This table reports the results of the time-series regressions of weekly realized excess returns of 100 Fama and French equity portfolios sorted on firm size and book-to-market equity and of the 49 Fama-French industry portfolios on MKT, SMB, HML, UMD, $TERM$, and DEF. Specifically, for each portfolio we estimate the regression: $R(t) - RF(t) = \alpha + \beta_{MKT} MKT(t) + \beta_{SMB} SMB(t) + \beta_{HML} HML(t) + \beta_{UMD} UMD(t) + \beta_{TERM} TERM(t) + \beta_{DEF} DEF(t) + \epsilon(t)$. We also report the estimation results after replacing DEF by $NDEF$ and DRP. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. All figures are median values across portfolios. The sample period is October 2, 2002 to October 11, 2006.

Moneyness	Option to expire			
	1st	2nd	3rd-5th	$\geq$ 6th
	Average excess returns			
0.85-0.9	-0.0092	-0.0051	-0.0028	-0.0009
0.9-0.95	-0.0072	-0.0036	-0.0020	-0.0008
0.95-1	-0.0031	-0.0019	-0.0012	-0.0005
>1	-0.0008	-0.0006	-0.0004	-0.0003
	Loadings on DRP factor			
0.85-0.9	-0.4245	-0.1598	-0.0732	0.0991
	(-1.8182)	(-0.6695)	(-0.3841)	(0.6326)
0.9-0.95	-0.4326	-0.2149	-0.0683	0.0596
	(-1.3396)	(-1.1729)	(-0.4605)	(0.4757)
0.95-1	-0.3521	-0.1849	-0.0711	0.0699
	(-1.2295)	(-1.4245)	(-0.6400)	(0.6412)
>1	-0.1439	-0.0680	-0.0246	0.0654
	(-0.9364)	(-0.9373)	(-0.3435)	(1.1035)
	Loadings on $\Delta\log(VIX)$			
0.85-0.9	0.1017	0.0868	0.0755	0.0537
	(6.8200)	(8.1852)	(9.2116)	(8.7100)
0.9-0.95	0.0800	0.0768	0.0652	0.0461
	(7.1673)	(8.2425)	(9.1908)	(9.2257)
0.95-1	0.0706	0.0597	0.0516	0.0400
	(7.1483)	(7.9446)	(8.9274)	(8.5776)
>1	0.0284	0.0282	0.0264	0.0229
	(6.7876)	(7.3996)	(8.1611)	(8.9021)

Table 10: **The Index Put Options Portfolios** This table reports the results of the time-series regressions of weekly realized excess returns of 16 value-weighted delta-hedged index put options portfolios sorted on moneyness and time-to-maturity on MKT, SMB, HML, UMD, $TERM$, and DRP. We also includes changes in $\log VIX$ as a covariate. Specifically, for each portfolio we estimate the regression: $R(t) - RF(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \beta_{TERM}TERM(t) + \beta_{NDEF}NDEF(t) + \beta_{DRP}DRP(t) + \beta_{VIX}\Delta\log VIX(t) + \epsilon(t)$. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is January 2, 2002 to October 11, 2006.

Factors	γ_0	γ_{MKT}	γ_{SMB}	γ_{HML}	γ_{UMD}	γ_{TERM}	γ_{NDEF}	γ_{DRP}	R^2
				Corporate bonds					
DRP	0.0678	–	–	–	–	–	–	0.0634	0.1344
	0.0661							0.0711	
	(0.0478)							(0.0221)	
MKT and DRP	0.0780	0.4908	–	–	–	–	–	0.0291	0.2937
	0.0870	0.4547						0.0115	
	(0.0445)	(0.2215)						(0.0197)	
				Equity					
DRP	0.2642	–	–	–	–	–	–	0.0252	0.0430
	0.3040							0.0124	
	(0.0988)							(0.0224)	
MKT and DRP	0.3692	-0.0274	–	–	–	–	–	0.0090	0.1066
	0.3176	-0.0434						0.0205	
	(0.0842)	(0.1060)						(0.0218)	
all	0.3855	-0.0997	0.1237	0.1643	0.1241	-0.1213	0.0300	0.0199	0.2817
	0.3140	-0.1023	0.0635	0.0716	-0.1022	0.0193	0.0820	0.0110	
	(0.0788)	(0.2088)	(0.0897)	(0.0811)	(0.1584)	(0.1105)	(0.0513)	(0.0180)	
				Options					
DRP	-0.1940	–	–	–	–	–	–	0.1696	0.3501
	-0.1501							0.1507	
	(0.0352)							(0.0501)	
MKT and DRP	-0.1639	-0.7947	–	–	–	–	–	0.1923	0.6504
	-0.1336	-1.0024						0.0561	
	(0.0252)	(0.2656)						(0.0631)	

Table 11: **Cross-Sectional Tests by Market** This table reports the results in percent of weekly cross-sectional regressions by asset class, using either the DRP factor loadings only, or MKT and DRP factor loadings. For each regression, the reported intercepts and slopes are the median (first row) and mean (second row) across time. Newey-West standard errors are shown in parentheses. Refer to Table 12 for details on the estimation.

Factors	γ_0	γ_{MKT}	γ_{SMB}	γ_{HML}	γ_{UMD}	γ_{TERM}	γ_{NDEF}	γ_{DRP}	R^2
				Corporate bonds and equity					
all	0.1375	0.3000	0.0201	0.1360	0.4421	-0.0193	0.0104	0.0094	0.3986
	0.1118	0.2992	0.0222	0.0546	0.1214	-0.0173	0.0777	0.0014	
	(0.0373)	(0.1875)	(0.0884)	(0.0797)	(0.1490)	(0.1111)	(0.0480)	(0.0115)	
				All assets					
all	-0.0349	0.5860	-0.0019	0.1340	0.3997	0.1717	0.0646	0.0408	0.4195
	-0.0110	0.5692	0.0576	0.0611	0.1994	0.1839	0.1174	0.0265	
	(0.0250)	(0.1789)	(0.0888)	(0.0797)	(0.1526)	(0.1097)	(0.0518)	(0.0108)	

Table 12: **Cross-Sectional Tests for Multiple Markets** This table reports the results (in percent) of weekly cross-sectional regressions across markets. Specifically, we estimate the coefficients of the regression: $R^i(t)-RF(t) = \gamma_0(t)+\gamma^{MKT}(t)\beta^i_{MKT}(t-l)+\gamma^{SMB}(t)\beta^i_{SMB}(t-l)+\gamma^{HML}(t)\beta^i_{HML}(t-l)+\gamma^{UMD}(t)\beta^i_{UMD}(t-l)+\gamma^{TERM}(t)\beta^i_{TERM}(t-l)+\gamma^{NDEF}(t)\beta^i_{NDEF}(t-l)+\gamma^{DRP}(t)\beta^i_{DRP}(t-l)+\epsilon^i(t)$, where the loadings $\beta^i_F(t-l)$ are computed directly using the formula $cov_{t-l}(R^i,F)/var(F)$. We report the median (first value) and mean (second value) of the intercepts and slopes of the cross-sectional regressions across weeks. The reported R^2 is the median coefficient of determination of the cross-sectional regressions across weeks. Newey-West standard errors (with 1 lag) are given in parentheses. The sample period is January 2, 2002 to October 11, 2006.

	$\Delta\alpha$	ΔR^2	β_{Char}		β_{DRP}	
Characteristics			Est	tStat	Est	tStat
EDF	-0.0001	0.0029	0.0449	0.6519	0.4313	7.1279
Recovery Rate	-0.0016	0.0028	0.0040	0.4768	0.4473	7.5960
Implied Vol	-0.0002	0.0020	0.0009	0.4557	0.4278	7.0517
Leverage	-0.0004	0.0020	0.0012	0.3334	0.4068	6.7819

Table 13: **The Impact of Firm Characteristics** This table reports the results of the regressions of the excess returns of pure default-contingent claims with 1 year to maturity of 112 firms on MKT, SMB, HML, UMD, $TERM$, DRP, and a firm characteristic ϑ. Specifically, for each firm we estimate the regression: $R^i_{t,h}(T) - RF_t = \alpha^i + \beta^i_{MKT}\, MKT(t) + \beta^i_{SMB}\, SMB(t) + \beta^i_{HML}\, HML(t) + \beta^i_{UMD}\, UMD(t) + \beta^i_{TERM}\, TERM(t) + \beta^i_{NDEF}\, NDEF(t) + \beta^i_{DRP}\, DRP(t) + \beta^i_{Char}\, \vartheta^i(t-h) + \epsilon^i_{\vartheta}(t)$. We report the median across firms of the change in the intercept and the R^2 due to the characteristic, as well as summary statistics of the loadings on the characteristic and the default risk premia factor. The sample period is January 2, 2002 to October 11, 2006.

D The DRP Components

Name	one default-related component β_{DRP}	β_{DRP^L}	$\beta_{DRP^{JtD}}$	$\beta_{DRP^{MPR}}$	two default-related compts β_{DRP^L}	$\beta_{DRP^{-L}}$
			Bloomberg-NASD Portfolios			
IG	0.9947	2.3244	1.3918	2.5093	1.9374	0.7984
	(13.3886)	(8.6889)	(8.4300)	(9.8090)	(9.6777)	(10.5035)
HY	2.4944	2.5198	4.5389	6.6943	1.1782	2.7685
	(8.5218)	(2.9758)	(10.2952)	(5.6553)	(2.4165)	(8.0216)
			ML Rating Portfolios			
AAA	0.2180	0.2943	0.2759	0.4294	0.2852	0.1816
	(4.3125)	(2.4419)	(3.0769)	(2.0514)	(2.6434)	(2.9071)
AA	0.2090	0.2566	0.2940	0.4119	0.2472	0.1883
	(4.4938)	(2.1662)	(3.7941)	(2.6725)	(2.3616)	(3.3231)
A	0.2985	0.2374	0.5370	0.6889	0.2204	0.3408
	(5.8592)	(2.3049)	(7.3027)	(3.9867)	(2.6910)	(6.4185)
BAA	0.6698	0.1546	1.5358	1.8781	0.1060	0.9749
	(4.4123)	(0.8341)	(18.8489)	(5.9564)	(0.9317)	(14.5689)
BA	1.3825	0.5822	2.6308	2.9412	0.0069	1.6296
	(5.5121)	(1.2422)	(4.9563)	(5.0229)	(0.0126)	(4.8297)
B	1.5643	0.9644	2.8333	3.4812	0.3341	1.7854
	(7.7088)	(2.4412)	(9.5794)	(5.8354)	(0.7608)	(8.5783)
C	1.5633	1.1344	2.7203	3.6593	0.5161	1.7514
	(5.3211)	(1.3414)	(4.2146)	(4.2890)	(0.6027)	(4.5795)
			ML Maturity Portfolios			
1-3yrs	0.2388	0.2226	0.3829	0.5788	0.2099	0.2545
	(3.7913)	(1.4210)	(4.6226)	(3.2789)	(1.5038)	(4.6263)
3-5yrs	0.3645	0.2989	0.6318	0.8833	0.2784	0.4111
	(4.4815)	(1.5227)	(6.1370)	(3.9102)	(1.6701)	(5.7381)
5-7yrs	0.4249	0.2654	0.8248	1.0544	0.2391	0.5255
	(4.7231)	(1.5487)	(8.3258)	(4.7893)	(1.7459)	(7.3197)
7-10yrs	0.5057	0.2517	1.0458	1.2866	0.2187	0.6611
	(5.2430)	(1.6420)	(10.9020)	(4.6506)	(2.0718)	(9.3790)
10-15yrs	0.5312	0.3183	1.0473	1.3155	0.2851	0.6643
	(5.7913)	(2.4928)	(6.8088)	(5.3341)	(3.4522)	(6.1017)
15+yrs	0.6118	0.0059	1.5487	1.7493	-0.0423	0.9658
	(5.0511)	(0.0837)	(30.3014)	(6.4455)	(-0.4940)	(14.6657)
			ML IG Broad Industry Portfolios			
	0.2874	0.3647	0.4534	0.6265	0.3575	0.2919
	(4.4872)	(2.1380)	(3.5166)	(3.4160)	(2.5097)	(3.7765)
			ML HY Sector Portfolios			
	0.7152	0.1902	1.6650	1.9520	0.1263	1.0519
	(3.0611)	(0.9485)	(4.2014)	(2.7291)	(0.8381)	(3.9328)

Table 14: **Corporate Bond Portfolios** This table reports the results of the time-series regressions of weekly realized excess returns of various corporate bond portfolios on MKT, SMB, HML, UMD, $TERM$, and DRP. The first column summarizes the results for the DRP factor reported in Tables 5 through 8. The next three columns report these estimates after replacing DRP with DRP^L, DRP^{JtD} and DRP^{MPR}, respectively. The last two columns show the estimation results after replacing DRP by DRP^L and DRP^{-L}. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is January 2, 2002 to October 11, 2006, except for the Bloomberg-NASD portfolios which where initiated in October 2002.

Loading	Moneyness	Option to expire			
		1st	2nd	3rd-5th	$\geq$ 6th
β_{DRP^L}	0.85-0.9	-0.4161	0.0838	0.2806	0.4842
		(-1.8391)	(0.3535)	(1.4139)	(2.6901)
	0.9-0.95	-0.3341	0.0827	0.2290	0.4162
		(-1.0375)	(0.5052)	(1.4462)	(2.8161)
	0.95-1	-0.0091	0.1079	0.2305	0.4116
		(-0.0330)	(0.8897)	(1.7927)	(2.8185)
	1-1.05	0.0478	0.0791	0.1747	0.3085
		(0.2717)	(0.8436)	(2.0271)	(2.8194)
$\beta_{DRP^{JtD}}$	0.85-0.9	-0.4873	-0.3982	-0.3859	-0.1965
		(-0.6045)	(-0.7929)	(-0.9314)	(-0.7231)
	0.9-0.95	-0.5276	-0.5091	-0.3444	-0.2145
		(-0.6141)	(-1.1994)	(-1.0520)	(-0.9292)
	0.95-1	-0.8086	-0.4950	-0.3493	-0.1958
		(-1.4546)	(-1.5835)	(-1.3990)	(-1.0054)
	1-1.05	-0.3782	-0.2151	-0.1979	-0.1129
		(-1.3189)	(-1.2600)	(-1.3526)	(-0.9742)
$\beta_{DRP^{MPR}}$	0.85-0.9	-1.9833	-0.8011	-0.6071	-0.0673
		(-2.3205)	(-0.9233)	(-0.8575)	(-0.1027)
	0.9-0.95	-2.2344	-1.0411	-0.4968	-0.1932
		(-2.1656)	(-1.5995)	(-0.8769)	(-0.3861)
	0.95-1	-1.9270	-0.8524	-0.5172	-0.1228
		(-2.3433)	(-1.8773)	(-1.2992)	(-0.2600)
	1-1.05	-0.8822	-0.3528	-0.2827	-0.0606
		(-2.5888)	(-1.7760)	(-1.6232)	(-0.3336)
β_{DRP^L}	0.85-0.9	-0.3105	0.1006	0.2961	0.4906
		(-1.5144)	(0.4503)	(1.4928)	(2.7052)
	0.9-0.95	-0.2294	0.1046	0.2423	0.4240
		(-0.9099)	(0.6547)	(1.4887)	(2.8197)
	0.95-1	0.1061	0.1279	0.2441	0.4183
		(0.5446)	(0.9457)	(1.7387)	(2.7738)
	1-1.05	0.1025	0.0876	0.1824	0.3124
		(0.7360)	(0.8441)	(1.9180)	(2.7135)
$\beta_{DRP^{-L}}$	0.85-0.9	-0.5250	-0.3032	-0.2742	-0.1140
		(-1.2391)	(-0.9578)	(-1.1220)	(-0.6374)
	0.9-0.95	-0.5835	-0.3888	-0.2374	-0.1388
		(-1.1800)	(-1.5220)	(-1.2319)	(-0.9961)
	0.95-1	-0.6892	-0.3552	-0.2427	-0.1197
		(-2.0216)	(-1.8997)	(-1.7052)	(-1.0060)
	1-1.05	-0.3254	-0.1527	-0.1373	-0.0695
		(-1.9219)	(-1.5130)	(-1.5978)	(-1.1055)

Table 15: **Index Put Options Portfolios** This table reports the results of the time-series regressions of weekly realized excess returns of 16 value-weighted delta-hedged index put option bond portfolios on MKT, SMB, HML, UMD, $TERM$, and $\Delta \log VIX$. We also include either DRP^L, DRP^{JtD} or DRP^{MPR} as a covariate. The last two columns show the estimation results when DRP^L and DRP^{-L} are included in the regression. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is January 2, 2002 to October 11, 2006, except for the Bloomberg-NASD portfolios which where initiated in October 2002.

Factors	single dflt-rltd component				two default-rltd components	
	γ_{DRP}	γ_{DRP^L}	$\gamma_{DRP^{JtD}}$	$\gamma_{DRP^{MPR}}$	γ_{DRP^L}	$\gamma_{DRP^{-L}}$
				Corporate bonds		
dflt-rltd	0.0634	-0.0105	0.0338	0.0166	-0.0060	0.0586
	0.0711	-0.0046	0.0267	0.0241	-0.0068	0.0493
	(0.0221)	(0.0141)	(0.0149)	(0.0082)	(0.0134)	(0.0177)
plus MKT	0.0291	-0.0075	0.0123	0.0048	-0.0098	0.0220
	0.0115	-0.0118	0.0038	0.0037	-0.0121	0.0044
	(0.0197)	(0.0084)	(0.0144)	(0.0084)	(0.0092)	(0.0231)
				Equity		
dflt-rltd	0.0252	0.0124	-0.0005	0.0011	0.0124	0.0021
	0.0124	0.0083	0.0030	0.0042	0.0019	0.0047
	(0.0224)	(0.0102)	(0.0121)	(0.0074)	(0.0105)	(0.0188)
plus MKT	0.0090	0.0200	-0.0039	-0.0059	0.0165	-0.0044
	0.0205	0.0101	0.0066	0.0030	0.0020	0.0102
	(0.0218)	(0.0105)	(0.0112)	(0.0071)	(0.0106)	(0.0176)
				Options		
dflt-rltd	0.1696	0.0031	0.0855	0.0471	0.0285	0.1928
	0.1507	-0.0343	0.1020	0.0355	-0.0144	0.1378
	(0.0501)	(0.0528)	(0.0323)	(0.0138)	(0.0666)	(0.0563)
plus MKT	0.1923	-0.0345	0.0773	0.0328	0.0306	0.2149
	0.0561	-0.0960	0.0453	0.0117	-0.0797	0.1611
	(0.0631)	(0.0538)	(0.0303)	(0.0162)	(0.0612)	(0.0463)
				All assets		
all	0.0408	0.0112	0.0244	0.0132	0.0106	0.0396
	0.0265	0.0081	0.0190	0.0090	0.0060	0.0258
	(0.0108)	(0.0075)	(0.0064)	(0.0040)	(0.0077)	(0.0097)

Table 16: **Cross-sectional Tests** This table reports the results (in percent) of weekly cross-sectional regressions in (16). The first column summarizes the results for the DRP factor reported in Tables 11 and 12. The next three columns report these estimates after replacing DRP with DRP^L, DRP^{JtD} and DRP^{MPR}, respectively. The last two columns show the estimation results after replacing DRP by DRP^L and DRP^{-L}. We report the median (first value) and mean (second value) of the intercepts and slopes of the cross-sectional regressions across weeks. The reported R^2 is the median coefficient of determination of the cross-sectional regressions across weeks. Newey-West standard errors (with 1 lag) are given in parentheses. The sample period is January 2, 2002 to October 11, 2006.

E Asset Pricing Test Results using CDS Returns

Name	one default-related component β_{CDRP}	β_{CDRP^L}	$\beta_{CDRP^{JtD}}$	$\beta_{CDRP^{MPR}}$	two default-related compts β_{CDRP^L}	$\beta_{CDRP^{-L}}$
			Bloomberg-NASD Portfolios			
IG	0.0332	0.0081	0.0337	0.0603	0.0449	0.0334
	(5.5044)	(0.8317)	(5.0476)	(4.0012)	(3.6170)	(5.5230)
HY	0.1294	-0.0108	0.1340	0.3112	0.1316	0.1295
	(8.3823)	(-0.4238)	(7.1915)	(6.6907)	(4.8094)	(8.3939)
			ML Rating Portfolios			
AAA	0.0085	-0.0090	0.0117	0.0149	-0.0001	0.0084
	(2.7310)	(-1.5730)	(3.3237)	(1.8127)	(-0.0118)	(2.6794)
AA	0.0081	-0.0110	0.0121	0.0112	-0.0026	0.0079
	(2.8542)	(-2.0732)	(4.1233)	(1.3373)	(-0.4195)	(2.7809)
A	0.0178	-0.0106	0.0216	0.0337	0.0083	0.0177
	(5.4611)	(-1.7637)	(6.5782)	(4.2842)	(1.4017)	(5.3876)
BAA	0.0516	-0.0057	0.0554	0.0956	0.0493	0.0516
	(8.6212)	(-0.6131)	(9.4859)	(6.8012)	(5.4626)	(8.6127)
BA	0.0979	0.0025	0.0991	0.2137	0.1061	0.0980
	(5.3950)	(0.1604)	(4.9643)	(7.2775)	(4.3413)	(5.4014)
B	0.1062	0.0070	0.1054	0.2390	0.1194	0.1064
	(8.6621)	(0.4068)	(7.7914)	(7.2813)	(5.3594)	(8.6648)
C	0.1504	0.0148	0.1443	0.3685	0.1741	0.1507
	(9.4498)	(0.4116)	(5.8680)	(8.8809)	(4.7927)	(9.5727)
			ML Maturity Portfolios			
1-3yrs	0.0096	-0.0073	0.0133	0.0075	0.0028	0.0095
	(3.1519)	(-1.3526)	(4.1679)	(0.9752)	(0.4647)	(3.0900)
3-5yrs	0.0163	-0.0127	0.0218	0.0205	0.0045	0.0162
	(3.7297)	(-1.6524)	(4.8707)	(1.8128)	(0.5356)	(3.6711)
5-7yrs	0.0267	-0.0126	0.0316	0.0478	0.0157	0.0265
	(5.5620)	(-1.4113)	(6.4411)	(3.9455)	(1.7459)	(5.5174)
7-10yrs	0.0333	-0.0079	0.0375	0.0572	0.0275	0.0332
	(5.8066)	(-0.9066)	(6.7051)	(4.2745)	(3.1907)	(5.7941)
10-15yrs	0.0287	-0.0001	0.0315	0.0393	0.0305	0.0287
	(4.6295)	(-0.0128)	(5.1591)	(3.0672)	(2.7024)	(4.6253)
15+yrs	0.0619	-0.0038	0.0631	0.1369	0.0622	0.0619
	(13.9868)	(-0.4385)	(12.4390)	(11.9418)	(8.9966)	(13.9795)
			ML IG Broad Industry Portfolios			
	0.0155	-0.0100	0.0188	0.0157	0.0063	0.0153
	(2.6375)	(-1.5034)	(3.1334)	(1.1628)	(0.8531)	(2.6238)
			ML HY Sector Portfolios			
	0.0816	-0.0044	0.0800	0.2258	0.0881	0.0812
	(7.0487)	(-0.2258)	(5.1234)	(6.1938)	(2.9496)	(7.0955)

Table 17: **Corporate Bond Portfolios** This table reports the results of the time-series regressions in (15) for various corporate bond portfolios when using the return definition in (23). The first column summarizes the results for the $CDRP$ factor. The next three columns report these estimates after replacing $CDRP$ with $CDRP^L$, $CDRP^{JtD}$ and $CDRP^{MPR}$, respectively. The last two columns show the estimation results after replacing $CDRP$ by $CDRP^L$ and $CDRP^{-L}$. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is January 2, 2002 to October 11, 2006, except for the Bloomberg-NASD portfolios which where initiated in October 2002.

Loading	Moneyness	Time to Expiration			
		1st	2nd	3rd-5th	$\geq$ 6th
β_{CDRP}	0.85-0.9	-0.0295	-0.0260	-0.0260	-0.0304
		(-1.0590)	(-1.4775)	(-2.0116)	(-3.6708)
	0.9-0.95	-0.0250	-0.0292	-0.0215	-0.0243
		(-1.3949)	(-1.8833)	(-2.0624)	(-3.4661)
	0.95-1	-0.0350	-0.0215	-0.0160	-0.0194
		(-2.4247)	(-2.0591)	(-2.1137)	(-3.1144)
	1-1.05	-0.0234	-0.0092	-0.0085	-0.0081
		(-2.4675)	(-1.7661)	(-1.6991)	(-1.9060)
β_{CDRP^L}	0.85-0.9	-0.1578	-0.0316	-0.0079	0.0015
		(-1.5999)	(-0.9592)	(-0.3619)	(0.0841)
	0.9-0.95	-0.0911	-0.0174	-0.0065	0.0001
		(-1.2096)	(-0.7530)	(-0.3538)	(0.0068)
	0.95-1	-0.1214	0.0029	0.0037	0.0033
		(-2.0936)	(0.1647)	(0.2556)	(0.2482)
	1-1.05	-0.0912	0.0152	0.0124	0.0091
		(-2.2350)	(1.3488)	(1.2985)	(0.9956)
$\beta_{CDRP^{JtD}}$	0.85-0.9	-0.0224	-0.0222	-0.0253	-0.0280
		(-0.6018)	(-1.2501)	(-2.0545)	(-3.0654)
	0.9-0.95	-0.0295	-0.0259	-0.0212	-0.0230
		(-1.2350)	(-1.6676)	(-2.0535)	(-2.9700)
	0.95-1	-0.0421	-0.0246	-0.0191	-0.0199
		(-2.2355)	(-2.2648)	(-2.3977)	(-3.0001)
	1-1.05	-0.0245	-0.0143	-0.0128	-0.0109
		(-2.2383)	(-2.3638)	(-2.3755)	(-2.3064)
$\beta_{CDRP^{MPR}}$	0.85-0.9	0.0410	-0.0282	-0.0438	-0.0920
		(0.4184)	(-0.5103)	(-1.1080)	(-3.1587)
	0.9-0.95	-0.0241	-0.0488	-0.0341	-0.0656
		(-0.5395)	(-1.0358)	(-1.1434)	(-2.7692)
	0.95-1	-0.0348	-0.0277	-0.0180	-0.0478
		(-0.9644)	(-0.9805)	(-0.9159)	(-2.3469)
	1-1.05	-0.0370	-0.0144	-0.0119	-0.0165
		(-1.3589)	(-1.0013)	(-0.8540)	(-1.2042)

Table 18: **Index Put Options Portfolios** This table reports the results of the time-series regressions in (15) for 16 value-weighted delta-hedged index put option portfolios when using the return definition in (23). The first column summarizes the results for the $CDRP$ factor. The next three columns report these estimates after replacing $CDRP$ with $CDRP^L$, $CDRP^{JtD}$ and $CDRP^{MPR}$, respectively. The last two columns show the estimation results after replacing $CDRP$ by $CDRP^L$ and $CDRP^{-L}$. Newey-West t-statistics adjusted for heteroscedasticity (with 3 lags) are reported in parentheses. The sample period is January 2, 2002 to October 11, 2006.

Factors	single dflt-rltd component				two default-rltd components	
	γ_{CDRP}	γ_{CDRP^L}	$\gamma_{CDRP^{JtD}}$	$\gamma_{CDRP^{MPR}}$	γ_{CDRP^L}	$\gamma_{CDRP^{-L}}$
				Corporate bonds		
dflt-rltd	0.8155	-0.0249	1.0672	0.2442	0.5153	1.1946
	0.6594	-0.0692	0.6515	0.1865	0.1710	0.7355
	(0.4133)	(0.4473)	(0.4760)	(0.1373)	(0.3682)	(0.5427)
plus MKT	0.2677	0.4007	0.1205	0.0611	0.5061	0.3872
	0.1919	0.0658	0.2454	0.0416	0.1000	0.3068
	(0.4235)	(0.3243)	(0.4552)	(0.1397)	(0.3448)	(0.5617)
				Equity		
dflt-rltd	0.1088	0.3317	0.0013	0.0304	0.2143	0.3602
	-0.0675	0.1707	-0.2524	0.0115	0.1743	-0.0165
	(0.3229)	(0.1808)	(0.3517)	(0.0947)	(0.1862)	(0.3569)
plus MKT	-0.0292	0.2180	0.0787	-0.0081	0.1963	-0.0522
	0.0256	0.1555	-0.2364	0.0267	0.1431	0.0377
	(0.2780)	(0.1493)	(0.2583)	(0.0777)	(0.1622)	(0.3348)
				Options		
dflt-rltd	3.6058	-0.5178	1.8229	0.2807	-0.2287	3.3980
	2.8957	-1.4498	1.4023	0.2038	-1.1121	1.6852
	(0.7640)	(0.7069)	(0.7797)	(0.2216)	(0.5713)	(0.8537)
plus MKT	2.9164	-0.3291	1.8907	0.7536	0.0547	3.2913
	2.8698	-0.4261	1.6274	0.8302	0.5882	2.2043
	(0.6304)	(0.6383)	(0.6954)	(0.1877)	(0.5194)	(0.8195)
				All assets		
all	0.7344	0.0458	0.4003	0.1668	0.2544	0.7558
	0.4812	0.1450	0.2590	0.1515	0.2380	0.5827
	(0.1556)	(0.1244)	(0.1707)	(0.0492)	(0.1321)	(0.2136)

Table 19: **Cross-sectional Tests** his table reports the results (in percent) of weekly cross-sectional regressions in (16). The first column summarizes the results for the $CDRP$ factor. The next three columns report these estimates after replacing $CDRP$ with $CDRP^L$, $CDRP^{JtD}$ and $CDRP^{MPR}$, respectively. The last two columns show the estimation results after replacing $CDRP$ by $CDRP^L$ and $CDRP^{-L}$. We report the median (first value) and mean (second value) of the intercepts and slopes of the cross-sectional regressions across weeks. The reported R^2 is the median coefficient of determination of the cross-sectional regressions across weeks. Newey-West standard errors (with 1 lag) are given in parentheses. The sample period is January 2, 2002 to October 11, 2006.

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