Cross-Market and Cross-Firm Effects in Implied Default Probabilities and Recovery Values*

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Abstract

We propose a novel method of estimating default probabilities for firms using equity option data. The resulting default probabilities are significantly correlated with estimates of default probabilities extracted from CDS spreads, which assume constant recovery rates. They are significantly related to firm characteristics and ratings categories. In regressions of (log) CDS spreads on (log) option-implied default probabilities, we cannot reject the hypothesis that, in aggregate, the coefficient on the default probability estimate is one. An inferred recovery rate, after controlling for liquidity effects, also varies through time and is related to underlying business conditions.

1 Introduction

One of the most notable financial innovations of the past two decades is the advent of the credit default swap (CDS), which provide investors with the ability to transfer credit risk. First engineered by J.P. Morgan in 1994 (Augustin, Subrahmanyam, Tang, and Wang (2016)), the market for CDS reached its peak in late 2007, with the Bank for International Settlements reporting in excess of $58 trillion in notional principal outstanding. However, since 2007, the market for CDS has substantially decreased in size. Bank for International Settlements data suggest that notional CDS outstanding in mid-2016 had declined to $11.777 trillion, or roughly one-fifth of the notional principal outstanding at the 2007 peak. The decline followed criticism of the CDS market as being partially responsible for the financial crisis of 2007-2009; Stulz (2010) discusses how CDS may have contributed to the crisis. Since the crisis, significant additional regulation on CDS trading has been implemented, including central clearinghouses and contract standardization. As noted in Augustin, Subrahmanyam, Tang, and Wang (2016), Deutsche Bank shuttered its single-name corporate CDS operations in 2014, and the market for single-name CDS contracts has declined further since then.

From the perspective of academics, market professionals, and regulators, one of the attractive features of a CDS contract is its window into market perceptions of credit risk. Based on no-arbitrage pricing formulations, one can use the quoted spread on a CDS contract to infer the market's implied risk neutral probability of default. This measure stands as a nonparametric alternative to agency credit ratings and structural models of default. Thus, the decline in the single-name CDS market represents a loss for those interested in market-driven beliefs about the credit risk of a corporate entity.

In this paper, we propose an alternative measure of the risk neutral probability of default based on option prices. It is well-known that option prices are informative about the risk neutral distribution of equity payoffs; Breeden and Litzenberger (1978) show the relation between the second derivative of the option price with respect to the strike price and the risk neutral distribution. The equity payoff depends on default risk; in principle, if absolute priority holds, the value of equity will be zero in the case of a default as in Merton (1974). As a result, we can define a default region of the equity payoff distribution, and use the cumulative probability of that region inferred from option prices to identify a probability of default.

Our results indicate that, for the entire sample, estimates of the levels of implied default probabilities extracted from equity options are strongly, but not perfectly, correlated with default probabilities estimated using CDS. If we assume constant recovery rates (as is typically done in the CDS market), median correlations between estimates of default probabilities for the cross-section of firms extracted from these two markets vary between 0.54 and 0.70 for different values of default thresholds. Aggregated across firms, the default probabilities are very highly correlated through time, with the correlation varying between 0.79 and 0.91 for various values of the default threshold. The default probabilities estimated from equity options prices increase monotonically with lower credit ratings; in addition, the relations between default probabilities estimated from equity options and firm characteristics are quite similar to the relations estimated between CDS default probabilities and firm characteristics. Overall, the evidence suggests that equity options can provide important information concerning the probability of default for the underlying firm.

An imperfect correlation between option- and CDS-implied default probabilities implies that there may be information about default in one set of derivatives that is not common to the other. We investigate the possibility that the imperfect correlation reflects the fact that CDS contain information about losses in the case of default in addition to probability of default, while options do not. In typical no-arbitrage models of credit risk, such as Duffie and Singleton (1999), loss given default cannot be identified separately from the probability of default. Therefore, it is common practice to assume a loss rate when using CDS to infer risk neutral probabilities of default. This loss rate is often assumed to be 60%, corresponding to historical averages of losses on bonds in the case of default. Under the assumption that equity has zero recovery, cross-sectional and time-series variation in the CDS-implied default probability that is unrelated to that of the option-implied default probability may reflect market participants' beliefs about cross-sectional and time-series variation in loss given default (or, equivalently, recovery rates).

There is good reason to suspect that perceptions of losses given default may vary aross firms and across time. Duffie and Singleton (1999) report that Moody's recovery rates vary substantially across bonds. Similarly, in a study of the term structure of sovereign CDS spreads, Pan and Singleton (2008) find that recovery rates vary across countries. Doshi, Elkamhi, and Ornthanalai (2014) use the term structure of CDS to estimate recovery rates, and show that they exhibit substantial cross-sectional variation, with the average recovery rate significantly higher than the constant 40% that is typically assumed in CDS pricing. Scheurmann (2004) provides evidence that the distribution of recovery rates varies not only cross-sectionally, but also with the business cycle. Similar evidence is provided in Altman, Bradi, Resti, and Sironi (2005). While the evidence supports time variation in recovery rates, identifying implicit *ex ante* recovery rates separately from probability of default has posed a significant challenge, as discussed in Duffie and Singleton (1999) and Houweling and Vorst (2005).

We begin by measuring information about loss given default simply as the log difference between the option-implied default probability and the CDS spread. We find that this quantity varies in aggregate with the frequency of default; the difference is high during the early 2000s and the financial crisis, and declines in the mid-2000s and after the financial crisis. While some of this difference in the option-implied default probability and CDS spread is related to measures of illiquidity, the time-series patterns in this variable remain after removing variation due to illiquidity. Additionally, we find that innovations in the aggregate recovery rate estimates have predictive power for an index of stock returns.

Our paper is related to a literature investigating the information in option prices for inferring probabilities of default. Most closely related to our paper are Capuano (2008) and Carr and Wu (2011). Capuano (2008) uses a cross-entropy functional to infer default probabilities. Our approach is computationally simpler; additionally, Vilsmeier (2011) notes that the entropy approach has issues with accuracy and numerical stability (and provides some technical fixes for those problems). Carr and Wu (2011) show that deep out-of-the-money options can be used to synthesize a default insurance contract, and, as a consequence, infer the probability of default. Their approach is simple and intuitive, but necessitates the existence of options that are very deep out of the money, limiting the number of firms for which these probabilities can be calculated.

This paper is also related to others that have inferred recovery rates from the market prices of securities. Duffie and Singleton (1999) and Das and Sundaram (2003) provide examples of how recovery rates might be inferred from securities with the same probability of default but different payout structure or priority. Doshi, Elkamhi, and Ornthanalai (2014), as noted above, uses the term structure of CDS to estimate recovery rates. Additionally, Madan and Unal (1998) empirically investigate separation of probability of default and recovery rates in junior and senior debt prices. Bakshi, Madan, and Zhang (2006) use a risky debt model with stochastic recovery rates to infer measures of recovery rates from risky bond prices. Madan, Unal, and Güntay (2003) exploit differences in priority of debt to infer losses given default. Most closely related to our work, Le (2007) develops a model of CDS and option prices and uses the model to recover information about loss given default from data on these two securities' prices. A distinction of our paper is its investigation of the dynamics of loss given default.

The remainder of the paper is organized as follows. In Section 2, we discuss the methodology we employ for extracting risk neutral default probabilities from options and from CDS spreads and their implications for recovery rates. We describe the data that we employ in this paper in section 3, and present estimates of default probabilities and recovery rates. In Section 4, we present results for the time-series relation between risk neutral default probabilities and recovery rates in individual firms, and across sectors. We conclude in Section 5.

2 Risk Neutral Probabilities Implied by CDS and Option Prices

2.1 Pricing Credit Default Swaps

In order to infer risk neutral default probabilities from the prices of credit default swaps (CDS), we follow a model widely used in practice for their valuation, detailed in O'Kane and Turnbull

(2003). In the discussion that follows, we assume that the swap being valued is a one-year CDS with quarterly premium payments, and that there is no information on CDS with maturities of less than one year. Under these assumptions, the practice is to assume a flat default probability term structure from zero to one year, as there is no information from which to infer risk neutral default probabilities for horizons of less than one year.

When a CDS contract is struck, the swap premium is set such that the value of the premium leg, received by the writer of the swap, is equal to the value of the protection leg, received by the swap purchaser. Assuming that premiums are accrued in case of default during a quarter, the value of the premium leg is given by

$$\frac{1}{2}s_t \sum_{j=1}^{4} 0.25 e^{-r(0.25\times j)j}\left(e^{-\lambda_t(0.25\times(j-1))} + e^{-\lambda_t \times 0.25\times j}\right), \tag{1}$$

where $r(\tau)$ is the continuously compounded zero coupon Treasury yield with maturity τ and λ_t is the default intensity. Because of the assumption of a flat term structure of default probability over one year, this intensity is invariant to maturity for a horizon of one year, but is indexed by t to indicate that default intensity may change over time. The quantity $e^{-\lambda_t \tau}$ represents the risk neutral probability that the entity survives to time τ. Intuitively, expression (1) simply calculates the present value of the swap payments received by the swap writer, conditional on survival of the entity.

The value of the protection leg is the risk neutral expected loss on the CDS,

$$(1-R)\sum_{j=1}^{12} e^{-r(\frac{j}{12})\frac{j}{12}}\left(e^{-\lambda_t \frac{j-1}{12}} - e^{-\lambda_t \frac{j}{12}}\right), \tag{2}$$

where R designates the rate of recovery as a fraction of the amount owed. Expression (2) is a discrete approximation to an integral that represents the expected risk neutral loss on the underlying entity. O'Kane and Turnbull (2003) conduct an analysis of the approximation error to the true integral given by the approximation above. They show that for a constant default intensity, the approximation error is given by $\frac{r(\tau)}{2M}$, where $r(\tau)$ is the continuously compounded risk free rate over the constant default intensity horizon and M is the number of summation periods. The authors suggest that for $M = 12$ as above and a risk free rate of 3%, the absolute value of the error is 1 basis point on a spread of 800 basis points.

The above expressions indicate how to determine the break-even CDS spread given recovery rates and risk neutral survival probabilities. The expressions can also be used to infer risk neutral default probabilities given rates of recovery and constant maturity CDS spreads. For example, using the expressions above, the break-even CDS spread is given by

$$s_t = \frac{(1-R)\sum_{j=1}^{12} e^{-r(\frac{j}{12})\frac{j}{12}}\left(e^{-\lambda_t \frac{j-1}{12}} - e^{-\lambda_t \frac{j}{12}}\right)}{\frac{1}{2}\sum_{j=1}^{4} 0.25 e^{-r(0.25\times j)j}\left(e^{-\lambda_t(0.25\times(j-1))} + e^{-\lambda_t \times 0.25\times j}\right)}. \tag{3}$$

Equation(3) is a nonlinear equation in the default intensity, λ_t.

For our initial calculations, we assume a constant recovery rate, $R = 0.40$, consistent with common practice. Then, given data on the risk-free term structure and one year credit default swaps, we solve equation (3) for λ_t for each reference entity and date in our sample. Given this default intensity, the probability of default is given by

$$Q_t^C = 1 - e^{-\lambda_t}, \tag{4}$$

where the superscript C indicates that CDS data are used to infer default probabilities.

2.2 Measuring Default Probabilities from Option Prices

An alternative approach to extracting default probabilities is based on the work of Breeden and Litzenberger (1978), who show that one can recover the risk neutral density of equity returns from option prices. Given this risk neutral density, the risk neutral probability of default can be thought of as the mass under the density up to the return that corresponds to a default event.

We construct the risk-neutral density using estimates of the risk neutral moments as in Bakshi, Kapadia, and Madan (2003) and the Normal Inverse Gaussian (NIG) method developed in Eriksson, Ghysels, and Wang (2009). Specifically, Bakshi, Kapadia, and Madan (2003) show that one can use traded option prices to compute estimates of the variance, skewness, and kurtosis of the risk neutral distribution. These moments in turn serve as the inputs to the NIG distribution, which is defined by four parameters. Eriksson, et al show that the NIG has several advantages to alternatives such as Gram-Charlier series expansions in pricing options. In particular, the distribution prevents negative probabilities, which the expansions can generate for the levels of skewness and kurtosis implied by option prices. Further, the density is known in closed form, avoiding the computational intensity of expansion approaches.

We first estimate the moments of the distribution using the prices of quadratic, cubic, and quartic contracts on the underlying security. Designating these contracts as $V_{i,t}(\tau)$, $W_{i,t}(\tau)$, and $X_{i,t}(\tau)$, respectively, Bakshi, Kapadia, and Madan (2003) show that the moments are given by

$$\mathcal{V}_{i,t}(\tau) = e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2 \tag{5}$$

$$\mathcal{S}_{i,t}(\tau) = e^{r\tau}W_{i,t}(\tau) - 3\mu_{i,t}(\tau)e^{r\tau}V_{i,t}(\tau) + 2\mu_{i,t}(\tau)^3 \tag{6}$$

$$\mathcal{K}_{i,t}(\tau) = e^{r\tau}X_{i,t}(\tau) - 4\mu_{i,t}(\tau)W_{i,t}(\tau) + 6e^{r\tau}\mu_{i,t}(\tau)^2V_{i,t}(\tau) - \mu_{i,t}(\tau)^4 \tag{7}$$

where

$$\mu_{i,t}(\tau) = e^{r\tau} - 1 - e^{r\tau}V_{i,t}(\tau)/2 - e^{r\tau}W_{i,t}(\tau)/6 - e^{r\tau}X_{i,t}(\tau)/24 \tag{8}$$

and r represents the risk-free rate. The prices of the contracts $V_{i,t}(\tau)$, $W_{i,t}(\tau)$, and $X_{i,t}(\tau)$ are provided in the appendix.

Given the moments calculated above, we measure the probability of default as the cumulative density of the NIG distribution at a critical threshold α,

$$Q^{O}_{it}(\tau) = \int_{-\infty}^{\alpha} f_{NIG}\left(x, \mathcal{E}_{i,t}(\tau), \mathcal{V}_{it}(\tau), \mathcal{S}_{it}(\tau), \mathcal{K}_{it}(\tau)\right) dx \tag{9}$$

where f_{NIG} is the NIG density function evaluated at a log return of x with parameters given by the risk neutral expectation, $E_{i,t}(\tau)$, volatility, $\mathcal{V}_{i,t}(\tau)$, skewness, $\mathcal{S}_{it}(\tau)$, and kurtosis, $\mathcal{K}_{it}(\tau)$.[1] The superscript O in equation (9) indicates that the risk neutral probability has been recovered from options data. The exact functional form of the density is provided in the Appendix.

A critical detail in this procedure is the definition of the default threshold, α. In the Merton (1974) model, equity has zero value in the case of default. The density at $x = \ln(0)$ cannot be calculated. Carr and Wu (2011) deal with this problem by assuming that there is a range of values of the stock price, $[A, B]$, in which default occurs. Prior to default, the equity value is assumed to be greater than B, and upon default the value is assumed to drop below the value $A \in [0, B)$. In their empirical implementation, the authors set $A = 0$, and choose the lowest priced put with positive bid price and positive open interest with strike price less than \$5 and option delta of less than or equal to 15% in absolute value.

We assume a range of threshold values at which the firm defaults. To gain insight into this value, we utilize an updated version of the data on bankruptcy filing dates from Chava and Jarrow (2004).[2]. We merge these data with CRSP, and calculate the decline in price from 12 months prior to the bankruptcy filing to either the delisting date or the CRSP price observed in the bankruptcy month. There are 1560 bankruptcy events in which the price declined over the previous twelve months, with an average decline in price of 79.40%.[3] Of these events, there are 383 in which we have S&P long-term credit ratings for the borrowers 12 months prior to bankruptcy.

Mean declines in price are depicted by credit rating in Table 1, where we group together all firms of a particular letter grade (i.e., 'A', 'A+', and 'A-'). The table suggests that there is a clear relation between credit rating and price decline in the 12 months leading up to bankruptcy. Between 'BBB'-rated and 'CC'-rated firms, there is a near monotonic decline in losses. The prices of 'BBB'-rated firms are on average 8% of their 12-month prior levels and the prices of 'CC'-rated firms are 45% of their 12-month prior levels on average. The magnitude of losses does not increase

[1]In a few cases, our estimates of the kurtosis are too small given the calculated skewness. In order to calculate the cumulative density, it is necessary that $K_{it} > 3 + \frac{5}{3}S_{it}^2$. In cases in which this restriction is violated, we set the kurtosis to $K_{it} = 3 + \frac{5}{3}S_{it}^2 + 1e - 14$.

[2]Thanks to Sudheer Chava and Claus Schmitt for making these data available.

[3]There are an additional 86 cases in which returns are positive over the 12 month period.

perfectly with credit rating; the average loss of 'A'-rated firms is higher than that of 'BBB'-rated firms and the loss of 'BB'-rated firms is higher than that of 'B'-rated firms.[4]. However, the overall pattern suggests that average losses in the 12 months leading up to bankruptcy filing decrease with credit rating.

With this evidence in mind, we let α, the default threshold, vary across credit ratings. According to Standard and Poor's, from 1981-2015, no AAA-rated credit has defaulted, and AA-rated defaults have been extremely rare.[5]. As a consequence, we assign an initial threshold of $\alpha = 0.01$ to these firms. We assign $\alpha = 0.05$ to 'A'-rated firms, to match the median price decline of the 'A'-rated firms in the Chava and Jarrow (2004) data, at approximately 94%. 'BBB'-rated firms are assigned $\alpha = 0.10$. As there is little apparent distinction between 'BB'- and 'B'-rated firms in terms of price decline, we assign $\alpha = 0.15$. Finally, firms with ratings of 'CCC' and below are assigned $\alpha = 0.25$. In robustness checks, we also compute default probabilities for each firm assuming a constant critical value across firms, ranging from $\alpha = 0.01$ to $\alpha = 0.40$. In the interest of brevity, these results are not included in the paper, but are available from the authors upon request.

3 Risk Neutral Probabilities Implied by CDS and Option Prices

3.1 Data Description

Data on CDS are obtained from Markit. The initial sample consists of daily representative CDS quotes on all entities covered by Markit over the period January, 2001 through December, 2012. The initial sample includes CDS from 6 months to 30 years to maturity. While the five-year contract is generally thought to be the most liquid, our proposed measure of default probability relies on options data, of which few are struck for maturities in excess of one year. Since there are

[4]The average losses of 'A'-rated firms are driven by the relatively small sample size; there are only 3 cases in the data in which 'A'-rated firms file for bankruptcy. These firms are PG&E, with a stock price drop of 63.6% prior to filing in April, 2001, Armstrong Cork, with a stock price drop of 93.8% prior to filing in December, 2000, and Lehman Brothers, with a drop of 99.9% prior to delisting in September, 2008.

[5]These data are sourced from Standard and Poor's Annual Global Corporate Default Study and Ratings Transitions 2015.

relatively few observations on six month CDS, we restrict attention to entities with one year CDS data quotes. We use these quoted prices, together with zero coupon discount rates to solve for the default intensity, λ_t in equation (3) assuming a constant recovery rate of 40%. Discount rates are obtained by fitting the extended Nelson and Siegel (1987) model in Svensson (1994) using all non-callable Treasury securities from CRSP. Our initial sample consists of 984 entities for which we have at least one default intensity observation.

Options data are from OptionMetrics. The calculation of the risk neutral moments requires the computation of integrals over a continuum of strikes. However, options are struck at discrete intervals. In addition, while the CDS in our sample have a constant one-year maturity, the maturity of options available in our sample varies and there are relatively few contracts available that are close to one year to maturity. We follow Hansis, Schlag, and Vilkov (2010) and Chang, Christoffersen, and Jacobs (2013) in constructing the volatility surface for options at 365 days to maturity using a cubic spline. We interpolate implied volatilities over the support of option deltas ranging from -99 to 99 at one-delta intervals, setting implied volatilities constant for deltas outside the span of observed option prices. We then convert implied volatilities to option prices and integrate over out-of-the-money calls and puts using the rectangular approximation in Dennis and Mayhew (2002). In order to be included in the sample, we require that options have positive open interest, positive bid and offer prices, at least two out of the money puts and out of the money calls, offer prices greater than bid prices and offer prices greater than \$0.05. We also eliminate options where the offer price is greater than five times the bid price. Our sample of option-implied default probabilities yields 680 firms for which we have at least one observation for the estimated default probability.

A last detail of our sample construction involves merging Markit data with data from OptionMetrics. This task is challenging as multiple Markit entities correspond to a single security identifier on OptionMetrics. Markit's unique identifier is the "ticker," which is sometimes the exchange traded ticker and sometimes an abbreviation used by Markit for the entry. We first merge OptionMetrics data with CRSP data to obtain the permno as a unique identifier for each firm. We then hand-match Markit tickers with OptionMetrics security id's on the basis of the ticker and name from both OptionMetrics and Markit. When multiple Markit tickers match a single permno, we take the average across the Markit tickers and assign the resulting default probability to the permno on that date. Merging the Market and OptionMetrics data yields 616 firms with at least one observation of both option-implied and CDS-implied default probabilities.

Finally, we merge the matched sample of option- and CDS-implied default probabilities with credit ratings data from Compustat. We retain observations for which Compustat has a Standard and Poor's ratings grade for the month of the observation. The final sample of firms, which have at least one time series observation with an option-implied default probability, a CDS-implied default probability, and a Standard and Poor's credit rating, consists of 540 firms over the period January, 2001 through December, 2012.

3.2 Descriptive Statistics

Summary statistics for default probabilities implied by options and credit default swaps are presented in Table 2. For each firm, we calculate the mean default probability implied by both CDS spreads and option prices. We report the mean, standard deviation, fifth, fiftieth, and ninety-fifth percentiles of the distribution of these average probabilities in Panel A. Additionally, we report the fifth, fiftieth, and ninety-fifth percentile of the distribution of the correlation between CDS- and option-implied probabilities in Panel B.

The summary statistics indicate that across the distribution of firms, option-implied probabilities are on average lower than, and exhibit less cross-sectional variation than CDS-implied default probabilities. The average option-implied default probability is 1.37%, vs. 2.17% for CDS, with standard deviations of 1.37% and 3.21% respectively. The relative flatness of the distribution of option-implied probabilities is also apparent in the extreme percentiles of the distribution; while the fifth percentile of the distribution of both default probabilities is similar, the ninety-fifth percentile of the distribution of mean CDS-implied default probabilities is roughly twice as large as that of option-implied probabilities. However, median probabilities across both markets are similar; the median average default probability implied by options is 0.93%, compared to 1.14% by CDS. These results suggest a strong skew in the average CDS-implied default probability.

We observe a substantial but imperfect correlation between CDS-implied and option-implied probabilities. At the median, the default probabilities have a correlation coefficient of 0.59, suggesting that there is some information that is not common between the securities. Even at the 95th percentile, the correlation is less than 1.0. /footnoteAt the fifth percentile, note that the correlation between the two default probabilities is negative. However, we find that this result is driven by the large gaps in the time series for some firms, with virtually all of the negative correlations concentrated in firms with relatively few time series observations.

In Figure 1, we plot the time series of cross-sectionally averaged default probabilities implied by CDS and options, using the default thresholds across credit ratings described earlier. The plot shows that both measures of default probability exhibit common features; default probabilities are uniformly low during the economic expansion of the mid-2000s and spike during times of economic turbulence. In particular, the default probabilities rise sharply during the recession in the early 2000s and the financial crisis of 2007-2009. Default probabilities also spike in late 2011, corresponding to the uncertainty surrounding the United States Congress' willingness to raise the federal debt ceiling and the subsequent downgrade of U.S. sovereign debt by Standard and Poor's. Through time, the correlation between the option-implied and CDS implied default probabilities is xxx.

The greater variability in CDS-implied default probabilities observed in Figure 2, with higher default probabilities compared to option-implied probabilities during market downturns and lower default probabilities compared to option-implied probabilities during market upturns, may reflect variation in recovery rates. This would be the case if recovery rates (or asset values) covaried negatively with true default probabilities. We investigate these possibilities later in the paper.

3.3 Default Probabilities and Credit Ratings

To investigate cross-sectional variation in implied default probabilities, we first examine summary statistics for default probabilities by credit rating. Some of the cross-sectional variation is induced, as we use the historical returns on firms of different credit ratings to guide the level of default thresholds for option-implied default probabilities. Therefore, we also examine option-implied default probabilities holding the default threshold fixed.

In Table 3, we present mean default probabilities and the number of firms conditional on ratings class. Since firms may migrate across ratings, the total N reported in the table differs from the total number of firms reported in the sample. Thus, the $N = 14$ for 'AAA'-rated firms indicates that there are 14 firms that at some point in this time series have been rated 'AAA.' As above, we group together firms with a '+,' '-,' or no modifier.

The summary statistics indicate that for both CDS- and option-implied default probabilities, the average risk neutral probability of default increases across ratings classes. Using options data, default probabilities increase from 0.09% for 'AAA'-rated firms to 16.73% for firms rated 'CCC+' and below. CDS-implied probabilities exhibit more extreme probabilities at the risky end of the credit rating spectrum, ranging from 0.28% for 'AAA'-rated firms to 22.12% for 'CCC+' and below-rated firms. Across all ratings groups, the average option-implied probability is lower than that of the CDS-implied probability, consistent with the aggregate evidence reported earlier.

In untabulated results, we examine default probabilities across ratings classes, while keeping the default threshold constant across firms. Our results indicate that, as credit ratings deteriorate, the default probabilities implied by options for firms with poor credit ratings and relatively high default thresholds (high α) are more similar to those implied by CDS than those implied by relatively low thresholds (low α). Similarly, the default probabilities implied by options for firms with strong credit ratings are more similar to those implied by CDS when the threshold is low. This evidence suggests that default thresholds may vary both cross-sectionally (as in Chava and Jarrow (2004)) and over time as credit ratings migrate.

3.4 Firm Characteristics and Probability of Default

As shown in the previous section, option-implied risk neutral probabilities of default are strongly and positively correlated with CDS-implied risk neutral probabilities of default, and are cross-sectionally correlated with Standard and Poor's credit ratings. We analyze cross-sectional variation in default probabilities in more detail in this section, by examining the relation between both estimates of default probability and firm characteristics. In particular, we use a variant of Campbell, Hilscher, and Szilagyi (2008), who specify a pooled logit model for prediction of default, yielding estimates of the physical probability of default. Instead of using a limited dependent variable based on an observation of default, we regress estimates of default probabilities on firm-specific variables:

$$Q_{it}^{k} = a_{it} + \mathbf{b}_{it}'\mathbf{x}_{it} + u_{it},$$

where Q_{it}^{k} is the final observation in month t of the risk neutral probability, $k = \{C, O\}$ indexes CDS- and option-implied default probabilities and $\mathbf{x}_{it}$ is a vector of firm-specific characteristics. As in Davydenko and Strebulaev (2007), we follow the Fama and MacBeth (1973) procedure and report the means of the coefficient estimates on firm characteristics, with Newey-West standard errors.

The independent variables that we use comprise the fundamental variables examined in Campbell, Hilscher, and Szilagyi (2008):

- *Profitability.* More profitable firms are hypothesized to have a higher cash flow buffer to weather financial distress and meet debt service payments. Profitability is measured as the ratio of net income to the market value of total assets, $NIMTA_{j,t}$. Market value of total assets is assumed to be the sum of the book value of liabilities and the market value of equity. Since profitable firms are expected to be more resilient to distress, we hypothesize that the relation between profitability and probability of default will be negative.

- *Leverage.* Leverage is viewed as a catch-all measure of the debt capacity of a firm and potential financial distress. We measure a firm's leverage as the ratio of total liabilities to the market value of total assets, as defined above. We expect this variable, $TLMTA_{j,t}$ to be positively related to probability of default.

- *Cash.* Campbell, Hilscher, and Szilagyi (2008) hypothesize that cash provides a buffer in the case of financial distress, as a firm can use its cash reserves to service debt. The variable, $CASHMTA_{j,t}$ is measured as the ratio of cash and short-term investments to the market value of total assets. Since cash represents a buffer, we anticipate that the variable will be negatively related to probability of default. However, it should be noted that the relation between this variable and default probability is not unambiguous. Acharya, Davydenko, and Strebulaev (2012) show that credit spreads and cash holdings are positively correlated. The authors provide evidence to support the notion that riskier firms hold more cash due to a precautionary savings motive.

- *Book-to-Market.* Book-to-market is a measure of the growth prospects of the firm, and also reflects the equity market's outlook for the future of the company. If equityholders anticipate bankruptcy, market value of equity is likely to fall, increasing this ratio. We measure the book-to-market ratio, $BM_{j,t}$, as the ratio of book value of equity to market value of equity, where book value of equity is the difference in the book value of assets and book value of liabilities. If high book-to-market firms are more distressed, we expect the ratio to be positively associated with probability of default.

- *Volatility.* A central idea in the Merton (1974) model is that distance to default of firms with more volatile asset returns, which are in turn reflected in more volatile equity returns, is smaller. We measure volatility as the annualized standard deviation of the firm's daily stock return over the past three months, $SIGMA_{j,t}$. We expect that firms with more volatile equity will have a higher probability of default.

- *Excess return.* The excess return, $EXRET_{j,t}$, is the quarterly log return on the firm's equity in excess of the log return on the S&P 500 index. This variable is expected to be negatively related to the probability of default, as we expect that firms with high probabilities of default will experience declines in share price in anticipation of default.

- *Price.* Distressed firms tend to trade at low prices per share. This measure, $PRICE_{j,t}$ is the minimum of the natural log of the firm's share price, or the log of \$15. Since distressed firms tend to have low stock prices, we expect a negative relation to default probability.

- *Relative size.* $RSIZE_{j,t}$ is the log ratio of the capitalization of firm j to that of the CRSP value-weighted index. Both size and book-to-market are hypothesized to be related to distress by Fama and French (1992) and we expect a negative relation between this variable and default probability.

Market data are obtained from CRSP and quarterly firm financial information is obtained from Compustat. Since we are interested in correlations rather than prediction, we measure firm financial information concurrently with Compustat data, rather than allowing for a lag as in Campbell, Hilscher, and Szilagyi (2008). Quarterly information for a firm's first quarter ending in March is matched to month-end default probabilities measured from January 1 through March 31 of the same year.

Summary statistics for the firm-specific variables are shown in Table 4. We present means and medians for firms in our sample, as well as for firms in the CRSP/Compustat universe not in our sample. The table shows that on average, our sample firms are more profitable, more levered, have lower volatility and book-to-market ratios, have larger relative market capitalizations and lower cash holdings, and are less likely to be low-priced firms. These results are expected, as the requirement that firms in our sample have CDS written on them tilts us toward larger, more established firms.

The results of the Fama and MacBeth (1973) regressions of default probabilities on the explanatory variables are presented in Table **??**. We split the sample into financial and non-financial firms, defined by the firm's GICS sector from Compustat. Campbell, Hilscher, and Szilagyi (2008) consider only non-financial firms, and ratios such as leverage and book-to-market ratio are likely to be very different for financial firms than non-financial firms.

The results for non-financial firms suggest a number of similarities in the correlations between CDS-implied and option-implied default probabilities. First, implied default probabilities for non-financial firms are statistically significantly decreasing in profitability, relative size, and price when default probabilities are measured using either options or CDS. The default probabilities are statistically significantly increasing in leverage and return volatility. All of these relations are consistent with the predictions above and the results in Campbell, Hilscher, and Szilagyi (2008). The book-to-market ratio is negatively associated default probabilities, counter to the arguments in Campbell, Hilscher, and Szilagyi (2008). As we will discuss later, this result may be due to book-to-market ratios proxying for differences in recovery rates, rather than distress.

We observe one puzzling result: when default probabilities are measured using option prices, a high excess return is associated with a high default probability.

Results for financial firms are broadly similar to those for non-financial firms, but fewer coefficients are statistically significantly different than zero. The results indicate that for both sets of security measures, volatility is positively associated with the probability of default, and size and price are associated with lower probability of default. Book-to-market ratios are positively, but only marginally significantly associated with default probabilities in the case of CDS. For financial firms, the option-implied probabilities are negatively and statistically significantly associated with cash holdings. Finally, in the option-implied measures, excess returns are again positively associated with probability of default.

In general, the results of this analysis suggest that the relation of firm characteristics to both CDS and option-implied default probabilities are consistent with the underlying fundamentals of the firm.

4 Sources of Differences Between Option- and CDS-Implied Default Probabilities

In a previous section, we compared the probabilities of default implied by CDS (and a constant recovery rate) to those obtained from equity options. For the median firm in the cross-section, the default probabilities are strongly correlated and, when we aggregate default probabilities across firms, option-implied and CDS-implied default probabilities are very highly correlated. This evidence suggests that the probabilities contain broadly similar information about time series innovations in probabilities of default. Additionally, the evidence suggests that credit ratings and firm characteristics that are hypothesized to be related to the probability of default are related to both option- and CDS-implied default probabilities. This evidence suggests that both estimates of default probabilities are capturing cross-sectional information.

However, as noted above, default probabilities estimated from the CDS and equity options market are not perfectly correlated. In particular, CDS-implied default probabilities have higher cross-sectional variation and higher skew. It is possible that these differences may simply arise from estimation error; in particular, the option-implied default probabilities are based on estimation of risk neutral moments and the imposition of the NIG distributional assumption. In this section, we consider some systematic, rather than measurement-related reasons that the probabilities from the two markets might differ.

One possibility mentioned above is that differences in option and CDS prices are due to variation in rates of recovery. Studies of recovery rates, including Altman and Kishore (1996) and Altman (2011) suggest that recovery rates vary cross-sectionally and over time. Cross-sectional variation associated with recovery rates may also drive some differences in the Fama and MacBeth (1973) regressions of CDS- and option-implied default probabilities on firm characteristics above.

A second possibility is that aggregate and security-level liquidity may impact option and CDS prices, and therefore the imputed default probabilities derived from these markets. For example, our option-based probabilities begin by calculating implied volatility surfaces using out-of-the-money puts and calls. These contracts, especially deep out-of-the-money contracts, are likely to have less liquidity than near-the-money puts and calls. Further, we are interpolating the volatility surface at a maturity of 365 days, where there are likely to be fewer available contracts with lower liquidity. CDS are also likely to suffer from liquidity issues. We are using one-year CDS contracts, which have lower liquidity than five-year contracts. Finally, CDS are relatively sparsely traded at the beginning of our sample period and also suffered from liquidity issues during the financial crisis.

A third possibility involves the default threshold, α, that is used when estimating default probabilities from the options market. That is, higher α's may result in option-implied default probabilities that better match CDS-implied default probabilities in times when CDS-implied probabilities are high and for firms with poorer credit ratings. Thus, it may be that the market perceives the default threshold for equity as being different during times of financial market stress or when a firm is closer to its default boundary. There may be other economic rationales for a varying default threshold, such as strategic bankruptcies; that is, in some circumstances, firms may find it beneficial to default even if they are solvent and able to make debt payments.

To analyze the differences in the information about default probability in the two markets, we begin with the relation between the CDS spread, the default probability, and the recovery rate (or loss given default). If we consider a simple one-period CDS contract:

$$S_t = Q_t^C \left(1 - R_t\right),$$

the CDS spread is the product of the default probability and the loss given default, or one minus the recovery rate. In logs, the log spread is the sum of the log of default probability and log of one minus the recovery rate. While the relationship between spreads, default probabilities, and recovery rates is not strictly log-linear as shown in equation (3), this approximation is useful for understanding the intuitive relation between spreads, default probabilities and recovery rates.

Under standard practice of assuming a constant recovery rate of 40%, the log spread and the log CDS implied default probability in this simple model are perfectly correlated by construction, both cross-sectionally and in the time series. However, if the option-implied default probability is a valid estimate of the true default probability, then subtracting the log option-implied default probability from the log CDS spread should provide an (approximate) estimate of log loss given default, that is allowed to vary across firms and through time. Of course, this difference will also capture effects related to liquidity, mis-specification of the default threshold, and other estimation errors. We calculate this difference, D, and consider its properties below.

4.1 Cross-market inferences

In Table 6, we report the average difference in the log spread and the log option-implied default probability, denoted as D, in the first column, for three constant threshold values of α and for a threshold value that varies across firms according to credit rating. In the remaining columns, we mirror our results for default probabilities and also present the standard deviation, fifth percentile, fiftieth percentile, and 95th percentile of the cross-sectional distribution of D. In Panel B, we compute correlations in the log difference D for each firm when the critical threshold is 0.05, 0.10, and 0.15 and when the critical threshold varies across credit rating as described earlier in the paper. Again, we present fifth, fiftieth, and ninety-fifth percentiles of the cross-sectional distribution of these correlations.

In Panel A of Table 6, the results show that with $\alpha = 0.05$, the mean and median of D are positive. Without controlling for liquidity effects, estimation error, etc., this would imply negative recovery rates, or losses given default in excess of 100%. Intuitively, these negative recovery rates are related to the low default probabilities obtained when using a default threshold of 0.05 for all firms. As can be seen in the equation above, holding the CDS value constant, as the default probability declines, the recovery rate must also decline. The option-implied default probabilities at a default threshold of 0.05 are sufficiently low that using them to impute recovery rates calculated from observed CDS spreads forces those rates below zero. This result is more likely to hold for firms with low credit ratings.

This result is also consistent with our interpretation of the evidence in Table 1 and Figure

1. At higher default thresholds, option-implied default probabilities increase and so average and median values of D decline. At $\alpha = 0.10$, the mean (median) D is equal to -0.65 (-0.71). Without controlling for other effects, this value of D implies a recovery rate of 48 (51%)

When the threshold is set by credit ratings, xxx

The results in Panel B of Table 6 indicate that log differences in spreads and option-implied default probabilities across critical thresholds are also highly correlated. The fifth percentile correlation in estimates of D between default thresholds of 0.05 and 0.15 is 0.94, which is the lowest correlation observed. The median correlation observed when $\alpha = 0.05$ and $\alpha = 0.15$ is close to perfect, with a coefficient of 99%; the ninety-fifth percentile correlation of estimates of D across firms is perfect. Our interpretation is that, although the level of the log differences varies across default thresholds, estimates across critical values contain very similar information about *relative values* of D in the cross-section.

In Figure 2, we present the time series of average estimates of D across firms for different default thresholds. It is apparent that the time series are highly correlated. The behavior of D through time is consistent with the interpretation that it is inversely related to loss given default, or one minus the recovery rate; that is, note that regardless of the default threshold the average D varies strongly with business conditions, consistent with the relation between recovery rates and market fundamentals documented in Jankowitsch, Nagler, and Subrahmanyam (2014). In particular, the variation in D implies that recovery rates are low in the early 2000s and recover with the economy in the mid-2000s. The rates plunge during the financial crisis of 2007-2009, and then gradually rise. The secondary decrease in recovery rates in 2011 is contemporaneous with the downgrade of U.S. debt in 2011.

Although the time-series variation in D is quite similar across default thresholds, and the variation through time for all thresholds seems sensible given market fundamentals, it is clear from Figure 2 that any inference about the level of implied recovery rate is sensitive to the level of the default threshold that one chooses. That is, average values of D in the sample are largely positive for $\alpha = 0.05$, and frequently positive for $\alpha = 0.10$. For the default threshold of 0.15, average values of D are almost invariably negative, consistent with average recovery rates that are positive. When default thresholds vary by firm across credit ratings, xxx

The evidence in Figure 2 that D varies with economic conditions is consistent with an inference that D contains information about recovery rates, and indicates that the assumption that recovery rates are constant through time is a poor fit to the data. In the next sections, we examine the variation in D across sectors, and analyze the relation between spreads and option-implied default probability estimates, while controlling for other factors such as liquidity.

Recovery Rates and Industry Sectors

Altman and Kishore (1996) report considerable variation in realized recovery rates by three-digit SIC code. In this section, we analyze variation in D across sectors. Since the results in Figure 2 indicate that setting a constant $\alpha = 0.15$ results in estimates of D that are consistent with positive recovery rates, and the time-series information in D across different values of α is very similar, we report results using only 2 values of D: one that uses a constant default threshold $\alpha = 0.15$ across all firms, and a second that uses a firm-specific default threshold based on credit rating. We utilize the GICS sector definitions, which separate firms into 10 sectors; Energy, (EN) Materials (MA), Industrials (IN), Consumer Discretionary (CD), Consumer Staples (CS), Healthcare (HC), Financial (FI), Information Technology (IT), Telecommunications (TC), and Utilities (UT). Sector classifications are obtained from Compustat.

We present summary statistics for D in Table **??**. Specifically, each week we calculate the average difference (by sector) of the implied one-year CDS spreads and option-implied default probabilities. The average number of firms in each sector varies from 5 (Telecommunications) to 51 (Discretionary). Grouped into sectors, inferences about D are much more precise. With a default threshold of $\alpha = 0.15$, the average D is negative for each of the ten sectors, and varies from -1.14 to -1.79. For nine out of the ten sectors, the maximum value of D is also negative. In addition, the standard deviation of D is smaller by a factor of 2 than the dispersion in D across individual firms reported in Table 4. When default thresholds are allowed to vary across firms based on credit ratings, xxx

We observe considerable variation in D across sectors. At the constant threshold of $/alpha = 0.15$, the lowest values of D (of -1.79 in both cases) are observed in Staples and Healthcare, corresponding to higher implied recovery rates; the highest values of D (-1.14 and -1.19) are observed in Consumer Discretionary and Utilities, respectively. The result that average values of D are higher, and thus recovery rates are lower, for Utilities is surprising, particularly given the evidence in Altman and Kishore (1996), who find that the highest average recovery rates in their sample is observed in public utilities. Note, however, that we also observe the second highest time-series variability in D in Utilities (and the highest variability in D is observed in the financial sector). This suggests that inferences about recovery values in the Utilities sector may be sensitive to the sample period that one uses. In general, the values of D reported in Table 5 are consistent with positive recovery rates. Ignoring liquidity effects, biases and estimation error, the recovery rates implied by the average values of D in Table 5 vary from 68% (in Consumer Discretionary) to 83% (in Healthcare and Staples).

We examine time-series variation in sector averages of D, in Figure 4, where we show the weekly cross-sectional average value of D in each sector. We observe significant time-series variation in D in every sector, and the values of D in each sector generally share features in common with the aggregate time series plot in Figure 3. That is, implied recovery rates are generally low during the economic contraction of the early 2000s, rise in the mid-2000s, and fall sharply with the financial crisis of 2007-2009. Values of D are negative through the entire sample period for every sector except Utilities, where we observe positive values of D in 2003 and again in the fall of 2008 and early 2009.

Although there are similarities in the time-series, there do appear to be differences in the sensitivity of sectors to fundamentals. For example, Healthcare, Telecommunications and Information Technology, while clearly affected by economic conditions, show relatively small declines in D (and so relatively small implied increases in recovery rates) during the mid-2000s expansion and relatively smaller decreases in implied recovery rates during the crisis. Financial firms experience very sharp changes in D through the sample period; the large decline in D in the mid-2000s implies a large increase in recovery rates at that time, followed by a very large reversal in D, and so implied recovery rates, at the time of the financial crisis. Energy, Materials, Consumer Discretionary, and Utilities also seem to be severely impacted by economic conditions.

Broadly, this variation across sectors seems sensible. When economic conditions weaken, the value of factors to production, such as energy and materials falls, and with it the values of these assets. Similarly, the value of consumer discretionary assets is likely to be significantly affected by economic conditions. In contrast, the value of healthcare and technology firm assets may be less subject to variation in the economy. The biggest surprise for us is utilities; we would expect the value of these assets to be less sensitive to economic conditions, but the sector shows surprising weakness in 2003 and again during the financial crisis.

Firm Characteristics and Implied Recovery

We undertake a more detailed examination of the cross-sectional variation in D by repeating the Fama and MacBeth (1973) analysis undertaken in Section 3.4 above, with D replacing the implied default probability as the dependent variable. Results of these regressions are presented in Table 7.

The regression results for the "non-strategic variables" are quite similar to those in the CDS-implied default probability regressions in Table 5. D is negatively related to profitability, relative size, cash holdings and, in some specifications, to price. The difference is positively related to leverage and equity volatility. Generally, these results are consistent with the idea that the higher the value of assets available to debtholders in case of a bankruptcy, the higher the rate of recovery that investors can expect on their debt. Thus, these variables broadly support the interpretation of D as potential loss given default.

Variables that Davydenko and Strebulaev (2007) relate to costs of liquidation are generally statistically significantly related to the difference in spread and option-implied probability, D, with the exception of the book-to-market ratio, which is only marginally significant. The three statistically significant measures are all negatively related to D. In the case of non-fixed assets and

R&D expenditures, this sign is the opposite of that found in the Alderson and Betker (1996) study of liquidation costs in Chapter 7. However, these results may not be as applicable in a Chapter 11 context, and the negative sign on $TANG$, and its likely correlation with $NONFIXED$ suggests that firms with more tangible assets are more likely to have higher differences in log credit default spreads and option-implied default probabilities. This evidence appears consistent with the idea that firms with a greater fraction of tangible assets are expected to have greater rates of recovery in case of a debt default.

Finally, the strategic variables $INST$ and $NSHARE$ also exhibit behavior similar to the results reported in Table 5 for option-implied default probabilities. $INST$ is not statistically significantly associated with differences across firms in D, suggesting that although it is positively associated with option-implied default probabilities, institutional ownership does not statistically significantly affect ex ante beliefs about recovery. This result is again consistent with the idea that $INST$ captures the likelihood of strategic default. The number of shareholders, $NSHARE$, is statistically significantly negatively associated with loss given default. Again, Davydenko and Strebulaev (2007) use this variable to capture renegotiation frictions, specifically the degree of difficulty in coordination across shareholders in bankruptcy negotiation. The results suggest that the more difficult this coordination, the lower D imply that, if D measures loss given default, the expectation of loss given default is lower the more difficult it is for shareholders to coordinate.

We view these results as broadly supporting the interpretation of D as a measure of the loss given default. It is particularly interesting to us to note areas in which the results from Table 7 differ from those for option-implied probabilities in Table **??**. Cash holdings and stock price appear to be at least marginally significantly related to D, but not to the option-implied default probability. These results suggest to us that these variables are more potentially relevant to recovery in default than the probability that a firm will default. This idea is reinforced by the opposing signs for $NONFIXED$ and $TANG$ in the regressions of D on firm characteristics compared to option-implied default probabilities. The results indicate that firms with more cash, more tangible assets, and more non-fixed assets may be more likely to default but, to the extent that D measures loss given default, will have a greater surplus of assets to satisfy bondholders claims.

4.2 Liquidity and Default Probabilities

While variation in recovery rates is an appealing explanation for differences in risk neutral default probabilities across options and CDS, an additional possibility is that these probabilities differ as a result of frictions. In particular, the out-of-the-money options used to construct the moments that are used as inputs into the option-implied default probabilities may be thinly traded. Further, the liquidity of CDS contracts is low in the early part of our sample period, and, for some firms in our sample, is low again during the financial crisis. Since the data suggest a marked decline in implied recovery associated with the crisis, it is possible that this reflects not variation in *ex ante* recovery, but rather a decline in market liquidity. [6] As a consequence, we estimate the relation between changes in the (log) spread and changes in the log of option-implied default probabilities, while controlling for liquidity effects.

Illiquidity in the CDS and options markets may reflect both security-specific and market-wide variation in liquidity.[7] We are somewhat limited in measuring security-specific liquidity by the fact that we have information only on quotes, and not on trades, for both sets of securities. In the case of options, we have information on bid-ask spreads, open interest, and volume. Since the default probabilities recovered from options are likely to depend most on the prices of out-of-the-money options close to 365 days to maturity, we construct $SPREAD_t^O$, the average percentage bid-ask spread for the out-of-the-money options used in constructing our volatility surface. We also compute VOL_t^O and $OPEN_t^O$, the sum of volume and open interest for these contracts. In the case of CDS, we have a measure of the depth for five-year CDS contracts. We assume that depth for the one-year contracts is correlated with the depth of the five-year contracts, and use $DEPTH_t^C$, the depth of the five-year contract, as another measure of liquidity.

[6]It is possible that precipitous declines in market liquidity are associated with declines in asset values and thus recovery rates (see, e.g., Brunnermeier and Pedersen (2009). If that is the case, our controls for market liquidity will cause the decline in recovery rates during periods of market illiquidity to be estimated conservatively.

[7]Note that by examining Fama and MacBeth (1973) regressions we are in effect including a time fixed effect in the regression. Thus, the results reported earlier supporting the interpretation of D as a loss given default are unlikely to be due to aggregate liquidity effects.

To capture aggregate liquidity, we use two measures that may be of particular importance in the fixed income security markets. First, we use the Treasury-Eurodollar spread, TED_t, measured as the difference in 90-day LIBOR and 90-day Treasury Bill yields. An increase in the TED spread potentially indicates an increase in interbank counterparty credit risk, and a consequent drop in financial liquidity. The second measure is the root mean squared error of the difference in market Treasury security yields from those implied by a Nelson-Siegel-Svensson model. This measure, $NOISE_t$, is investigated in Hu, Pan, and Wang (2013). The authors suggest that $NOISE_t$ is high when there is less arbitrage capital available in the Treasury market, a condition associated with lower liquidity. Finally, we include a proxy for liquidity in the equity markets; Nagel (2012) suggests that a high level of the VIX index, VIX_t is associated with a high risk premium, and a consequent large reduction in liquidity provision, in equity markets. The TED spread is constructed using data from the Federal Reserve and $NOISE_t$ is obtained from Jun Pan's webpage.[8] Data on the VIX are also obtained from the Federal Reserve.

We plot natural logs of these liquidity series in Figure **??**. Given their construction, note that, with the exceptions of volume, open interest and depth measures, an increase in these measures represents a decrease in liquidity. The aggregate series exhibit a familiar pattern, dominated by a sharp decrease in liquidity associated with the financial crisis of 2007-2009. This decline in measures of aggregate liquidity is associated with an increase in counterparty credit risk and a decrease in the arbitrage capital available in the fixed income and equity markets. The trend in these series is strongly related to the trend in the implied recovery rates in Figure 3. In particular, the log recovery rate is -83% correlated with log $NOISE_t$ and -80% correlated with the log of the VIX. These trends also induce in-sample nonstationarity of the series.

The option-specific liquidity measures exhibit different patterns. These series are the cross-sectional averages each week of the individual firm data used in our analysis. Volume and open interest are generally increasing over the sample period. There is some periodicity in these series associated with option writing dates; open interest and volume decline as options approach maturity.

[8]We thank Jun Pan for making these data available at `http://www.mit.edu/~junpan/`.

There is a sharp downward spike in open interest in option markets associated with the financial crisis, and a less striking downward spike in volume. Additionally, the spread shows a sharp upward spike during the crisis. There is some relation of these measures with the aggregate series; however, none of the option-specific series exhibit more than 40% correlation with the aggregate liquidity measures.

Finally, the depth of the five-year CDS contract does exhibit a strong time trend. Contract depth steadily increases from 2001 to 2005, before slackening slightly in 2006 through 2007. CDS contract depth plummets in early 2008 until mid-2009, clearly associated with the financial crisis. Depth remains low in 2010 and 2011, before picking up somewhat in 2012.

Given the strong trends in these data, we estimate the relation between first differences in the CDS spread and differences in the liquidity variables and differences in the option-implied default probability, beginning at the aggregate level. That is, we estimate the parameters of a regression,

$$\begin{aligned} \Delta s_{a,t} &= a_a + b_{a,1}/DeltaQ^o_{a,t} + b_{a,2}\Delta ted_t + b_{a,3}\Delta noise_t + b_{a,4}\Delta vix_t + b_{a,5}\Delta spread^O_{a,t} \\ &\quad + b_{a,6}\Delta vol^O_{a,t} + b_{a,}7\Delta open^O_{a,t} + b_{a,8}\Delta depth^C_{a,t} + e_{a,t}, \end{aligned} \tag{10}$$

where a indicates that we are measuring the quantity at the aggregate level, where aggregate variables are calculated as the cross-sectional average of individual time series observations. Lowercase variables are natural logs of their uppercase counterparts.

Results of this regression are reported in Table 8. The results suggest that innovations in fixed income market liquidity variables are not statistically significantly associated with innovations in CDS spreads. An increase in counterparty credit risk as measured by the TED spread is positively, but not significantly associated with increases in spreads, while a decrease in arbitrage capital in fixed income markets, measured by a positive innovation in $NOISE_t$, is negatively, but insignificantly associated with innovations in CDS spreads. In contrast, an innovation in the VIX is associated with a significant increase in CDS spreads, suggesting that some of the marked decline in recovery rates exhibited over the course of the financial crisis may be associated with an increase in market-wide volatility. This result may be consistent with the evidence in Nagel (2012), who shows that an increase in the VIX is associated with a reduction of equity arbitrage capital; alternatively, rather than a liquidity narrative, the increase in market-wide volatility may be associated with an increase in aggregate risk which then causes a decline in asset values and so an increase in CDS spreads.

There is weak evidence that security-specific liquidity is related to CDS spreads. Specifically, innovations in the open interest of options are statistically significantly positively associated with innovations in CDS spreads. Thus, as options become less liquid, reflected in lower open interest, this is associated with increases in CDS spreads. This may reflect an aggregate decline in liquidity in derivatives markets. Again, this result suggests that at least part of the sharp decline in implied recovery rates during the financial crisis of 2007-2009 may be associated with a decline in liquidity.

Even after controlling for liquidity variables, however, note that the coefficient on differences in the option-implied default probability is significantly positive and, at 0.961, is not significantly different from 1. In addition, the R-squared of this regression is relatively large, at 38%. This evidence suggests that there are significant linkages between the CDS and equity options market; in particular, changes in the default probabilities inferred from equity options have significant explanatory power for variation in the prices of CDS.

We also report the results of this regression across sectors in Table 9. The results are generally consistent with the results observed in the aggregate: we continue to find evidence that changes in the VIX are positively associated with changes in the average log CDS spread in the sector, and the coefficient on log changes in the option-implied default probability are very significantly related to changes in the log CDS spread. In only two sectors, Industrials and Consumer Staples, is the coefficient on changes in the option-implied default probability significantly different from 1; for Industrials, the coefficient is significantly larger than 1, at 1.543, and for Consumer Staples, the coefficient is significantly smaller, at 0.434.

Overall, these results suggest that variation in default probabilities inferred from the option market is related to variation in the CDS spread; however, there is also evidence that variables such as the VIX and option open interest may influence the relation between CDS spreads and option-implied default probabilities. As a result, the simple difference between the CDS spread and option-implied default probability will contain confounding information about liquidity, in addition to information about recovery rates. In the next section, we examine variation in CDS spreads after removing information about default probabilities (taken from options markets) and liquidity effects.

4.3 Inferred recovery rates

In our last analysis, we use the regression above to generate an inferred recovery rate from the CDS spread, which controls for variation in default probabilities and liquidity effects. Specifically, we compute an estimate of the residual change in the CDS spread, after removing the effects of changes in option-implied default probabilities as well as liquidity effects.

$$\hat{r}_t = \hat{a}_a + \sum_{j=0}^{t} \hat{e}_{a,t-j},$$

Since the regression equation is in differences, note that we are calculating cumulated values of the changes in CDS spreads that are unrelated to changes in option-implied default probabilities and liquidity variables.

In Figure **??**, we plot this variable, which is an estimate of the cumulative percentage increase or decrease in recovery rates relative to $\hat{a}$. The figure shows that, even after controlling for liquidity, the pattern in implied recovery rates is strikingly similar to the variation in D in Figure 2. Implied recovery rates drop by 20% in the early 2000s recession, before a large increase in the mid-2000s. Recovery rates plunge during the financial crisis, before slowly recovering to pre-crisis levels by the end of the sample period.

Overall, these results indicate that, after controlling for liquidity effects and changes in default probabilities, the recovery rates inferred from CDS exhibit significant time-series variation. Specifically, implied recovery rates exhibit substantial increases prior to the financial crisis, decline sharply during the crisis, and then recover by the end of 2013.

5 Conclusion

In this paper, we propose a new method of estimating default probabilities for firms. Using option prices, we construct an estimate of the risk-neutral density; the default probability for the firm is the mass under the density up to the return that corresponds to a default event. We estimate default probabilities for three different default thresholds; we find that, although the level of estimated default probabilities is sensitive to the choice of default threshold, they are very highly correlated with one another and behave very similarly over time.

We examine the relationship of the option-implied default probabilities to default probabilities estimated from CDS prices, as well as their relation to firm characteristics, and ratings categories. We find that option-implied are strongly, but not perfectly, related to CDS default probabilities that assume constant recovery rates, with the latter exhibiting higher variation and higher skewness. With respect to firm characteristics and ratings categories, the option-implied default probabilities behave one would expect. Specifically, the default probabilities increase as ratings decline; in addition, default probabilities are significantly and positively related to leverage, volatility and book-to-market equity ratio; they are negatively and significantly related to profitability, past quarterly excess returns, size and price. The one surprising result is that we find that estimated default probabilities increase with cash holdings.

If option-implied default probabilities are valid, then an examination of the relation between these probabilities and CDS prices should provide information about recovery rates. We examine the log difference in spreads and option-implied default probabilities, and find significant time-series variation in this difference, which is related to economic conditions. While the difference is highly correlated across default thresholds, the evidence indicates that default thresholds as low as 5% are too low, in that they appear to be consistent with negative recovery rates. We also find evidence of significant cross-sectional variation in this difference.

When we estimate the relation between CDS spreads and option-implied default probabilities, while controlling for liquidity effects, we find evidence that the VIX and option open interest are significantly and positively related to CDS spreads. In addition, in aggregate, and for eight out of the ten sectors that we analyze, we cannot reject the hypothesis that the coefficient on the option-implied default probability is equal to one. Finally, after controlling for changes in the default probability (taken from the options market) and liquidity effects, the recovery rate inferred from CDS prices again shows a strong relation to underlying business conditions. Overall, the equity option market may provide useful information with which to infer default probabilities, as well as the recovery values of underlying assets.

Appendix

The scale-invariant NIG distribution is characterized by the density function

$$f\left(x;\alpha,\beta,\mu,\delta\right)=\frac{\alpha}{\pi\delta}\exp\left(\sqrt{\alpha^2-\beta^2}-\frac{\beta\mu}{\delta}\right)\frac{K_1\left(\alpha\sqrt{1+\left(\frac{x-\mu}{\delta}\right)^2}\right)}{\sqrt{1+\left(\frac{x-\mu}{\delta}\right)^2}}\exp\left(\frac{\beta}{\delta}x\right). \tag{11}$$

In this expression, $x\in\Re$, $\alpha>0$, $\delta>0$, $\mu\in\Re$, $0<|\beta|<\alpha$, and $K_1(\cdot)$ is the modified Bessel function of the third kind with index 1. The formal properties of the distribution are discussed in greater detail in Eriksson, Forsberg, and Ghysels (2004). As shown, the density is characterized by the four parameters α, β, μ, and δ.

As discussed above, a principal advantage of this density function is that it is completely characterized by its first four moments. More specifically, let the mean, variance, skewness, and excess kurtosis be denoted as $\mathcal{M}$, $\mathcal{V}$, $\mathcal{S}$, and $\mathcal{K}$. The parameters are nonlinearly related to the moments by

$$\alpha = \frac{3\left(4\rho^{-1}+1\right)}{\mathcal{K}\sqrt{\left(1-\rho^{-1}\right)}} \tag{12}$$

$$\beta = sign\left(\mathcal{S}\right)\frac{3\left(4\rho^{-1}+1\right)}{\mathcal{K}^{-1}\sqrt{\rho-1}} \tag{13}$$

$$\mu = \mathcal{M}-sign\left(\mathcal{S}\right)\sqrt{\frac{3\left(4\rho^{-1}+1\right)\mathcal{V}}{\mathcal{K}\rho}} \tag{14}$$

$$\delta = \sqrt{\frac{3\left(4\rho^{-1}+1\right)\left(1-\rho^{-1}\right)\mathcal{V}}{\mathcal{K}}} \tag{15}$$

where $\rho=3\mathcal{K}\mathcal{S}^{-2}-4>1$ and $sign(\cdot)$ is the sign function. Thus, given risk neutral moments, one can compute the risk neutral density.

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Table 1: Drop in Equity Prices Over 12 Months Prior to Bankruptcy

This table presents the magnitude of the drop in equity prices for firms that file bankruptcy over the 12 months. B ankruptcy filing dates are from the updated version of the data in Chava and Jarrow (2004) and are merged with CRSP data on equity prices and returns. We include only those firms that have CRSP data 12 months prior to the bankruptcy and in the month of bankruptcy filing and whose price declined over the 12 months prior to filing. The table presents summary statistics by credit rating for the decline in price by Standard and Poors credit rating for those firms for which ratings data are available. We present means, standard deviations, minima, and maxima of the ratio of the value of the stock price in the month of bankruptcy filing or delisting price to the price 12 months prior.

Rating	N	Mean	Std.	Min.	Max.
A	3	0.14	0.18	0.00	0.35
BBB	26	0.08	0.11	0.00	0.47
BB	67	0.13	0.20	0.00	0.98
B	197	0.12	0.16	0.00	0.95
CCC	59	0.20	0.22	0.00	0.84
CC	9	0.45	0.23	0.18	0.86
D	22	0.38	0.30	0.02	1.00

Table 2: Summary Statistics for Probabilities of Default

Table 2 presents summary statistics for risk neutral probabilities of default implied by credit default swap (CDS) spreads and prices of options on the equity of the same firm. CDS-implied default probabilities are calculated using a Nelson-Siegel-Svensson zero coupon term structure and constant one-year maturity CDS, assuming a recovery rate of 40% on the underlying bond. Option-implied default probabilities are measured using the Bakshi, Kapadia, and Madan (2003) (BKM) procedure for computing risk neutral moments, then computing risk neutral probabilities of the Normal Inverse Gaussian distribution (NIG) on the basis of these moments. Risk neutral moments are computed using the implied volatility surface of options with 365 days to maturity. In Panel A, we present means, standard deviations, fifth, fiftieth, and ninety-fifth percentiles of the distribution of averages of probabilities implied by each security. In Panel B we present the fifth, fiftieth, and ninety-fifth percentile of the distribution of correlations of a firm's option-implied and CDS-implied default probability. CDS data are from Markit and options data are from OptionMetrics. Data are sampled at the weekly frequency for 539 firms over the period January, 2001 through December, 2012.

Panel A: Distribution

	Mean	Std	p5	p50	p95
Option	1.37	1.37	0.24	0.93	4.28
CDS	2.17	3.21	0.24	1.14	8.19

Panel B: Correlations

p5	p50	p95
-0.30	0.59	0.91

Table 3: Summary Statistics for Probabilities of Default by Credit Rating

Table 3 presents summary statistics for risk neutral probabilities of default implied by credit default swap (CDS) spreads and prices of options on the equity of the same firm, grouped by credit rating. Firms with credit ratings augmented by '+' or '-' are grouped together; for example, rating 'BBB' refers to firms with a credit rating of 'BBB+', 'BBB', or 'BBB-'. CDS-implied default probabilities, q^C, are calculated using a Nelson-Siegel-Svensson zero coupon term structure and constant one-year maturity CDS, assuming a recovery rate of 40% on the underlying bond. Option-implied default probabilities are measured using the Bakshi, Kapadia, and Madan (2003) (BKM) procedure for computing risk neutral moments, then computing risk neutral probabilities of the Normal Inverse Gaussian distribution (NIG) on the basis of these moments. Risk neutral moments are computed using the implied volatility surface of options with 365 days to maturity. We calculate the average default probability for each firm, conditional on its ratings group, and report the mean of these averages by ratings group. CDS data are from Markit, options data are from OptionMetrics, and ratings data are from Compustat. Options and CDS data are sampled at the weekly frequency, and ratings at the monthly frequency for 539 firms over the period January, 2001 through December, 2012.

	N	Option	CDS
AAA	14	0.09	0.28
AA	50	0.10	0.65
A	192	0.44	0.89
BBB	291	1.03	2.01
BB	189	2.06	3.53
B	106	4.19	6.51
CCC+ and below	24	16.73	22.12

Table 4: Summary Statistics for Firm Characteristics

Table 4 presents summary statistics for firm characteristics used in regressions of risk neutral default probabilities on firm-specific variables: $NIMTA$, the ratio of net income to market value of total assets, $TLMTA$, the ratio of total liabilities to market value of assets, $EXRET$, the monthly log return on the firm's equity in excess of that of the S&P 500, $SIGMA$, the volatility of the firm's equity return over the past three months, $RSIZE$, the log ratio of the market capitalization of the firm's equity to that of the S&P 500, $CASHMTA$, the ratio of cash and to market value of assets, $PRICE$, a variable that is the maximum of the log of $15 or the log price per share of the the firm's equity, and BM, the book-to-market ratio. Financial statement information is obtained from Compustat and stock market information is obtained from CRSP. We present means and medians of each variable for the firms in our sample, as well as the set of firms not included in our sample. Differences in means are presented in the final column. The sample consists of 502 firms over the period January, 2001 through December, 2012.

	Sample		Non-Sample		Difference
	Mean	Median	Mean	Median	in Mean
NIMTA	0.487	0.727	−0.352	0.396	0.838***
TLMTA	0.477	0.456	0.452	0.403	0.024***
SIGMA	0.221	0.196	0.287	0.244	−0.066***
RSIZE	−7.556	−7.567	−11.059	−11.076	3.503***
CASHMTA	6.524	4.069	12.039	6.337	6.404***
PRICE	14.134	15.000	10.545	13.500	3.590***
BM	0.559	0.452	2.894	0.622	−2.335***

*,**,*** denotes significance at the 10%, 5%, and 1% critical level, respectively.

Table 5: Relation between Firm Characteristics and Default Probabilities

Table 5 examines the relationship between default probabilities implied by either CDS spreads using a 40% recovery rate assumption or options with a critical threshold that varies with credit rating, and firm-specific characteristics. Default probabilities at the end of each month are regressed on a set of nine firm-specific variables: $NIMTA$, the ratio of net income to market value of total assets, $TLMTA$, the ratio of total liabilities to market value of assets, $EXRET$, the monthly log return on the firm's equity in excess of that of the S&P 500, $SIGMA$, the volatility of the firm's equity return over the past three months, $RSIZE$, the log ratio of the market capitalization of the firm's equity to that of the S&P 500, $CASHMTA$, $PRICE$, and BM, the firm's ratio of book value of equity to market value of equity. Point estimates are the average of monthly regression coefficients, and standard errors in parentheses are corrected using the Newey-West procedure. We present results for financial firms and for firms excluding financial firms, defined as those in GICS sector 40. Data for CDS are obtained from Markit, data for options is obtained from Option Metrics, return information is obtained from CRSP, financial statement and ownership information is obtained from Compustat.

	CDS		Option	
	Financial	Non-Financial	Financial	Non-Financial
$NIMTA$	21.417	-11.494^{***}	16.062	-3.734^{***}
	(1.208)	(2.603)	(11.244)	(11.469)
$TLMTA$	0.478	3.768^{***}	0.140	1.265^{***}
	(0.767)	(0.408)	(0.166)	(0.130)
$EXRET$	0.336	-0.060	0.588^{*}	0.388^{***}
	(0.609)	(0.228)	(0.290)	(0.361)
$SIGMA$	1.375^{***}	0.898^{***}	0.528^{***}	0.685^{***}
	(0.332)	(0.152)	(0.064)	(0.073)
$RSIZE$	-0.658^{***}	-0.221^{***}	-0.272^{***}	-0.138^{***}
	(0.143)	(0.026)	(0.053)	(0.052)
$CASHMTA$	-0.187	1.717^{*}	-0.896^{***}	0.583
	(0.923)	(0.997)	(0.032)	(0.349)
$PRICE$	-0.209^{***}	-0.597^{***}	-0.174^{***}	-0.214^{***}
	(0.059)	(0.071)	(0.032)	(0.029)
BM	0.423^{*}	-0.767^{**}	-0.058	-0.315^{***}
	(0.223)	(0.105)	(0.091)	(0.081)
R^2	0.704	0.603	0.664	0.687

*,**,*** denotes significance at the 10%, 5%, and 1% critical level, respectively.

Table 6: Summary Statistics for Differences in CDS Spreads and Option Probabilities

Table 6 presents summary statistics for the difference in log one year CDS spreads and log default probabilities implied by risk neutral probabilities of default as measured by options. Option-implied default probabilities are measured using the Bakshi, Kapadia, and Madan (2003) (BKM) procedure for computing risk neutral moments, then computing risk neutral probabilities of the Normal Inverse Gaussian distribution (NIG) on the basis of these moments. Risk neutral moments are computed using the implied volatility surface of options with 365 days to maturity. CDS data are from Markit and options data are from OptionMetrics. The table presents the number of firms, mean, standard deviation, fifth, fiftieth, and ninety-fifth percentiles of the cross-sectional distribution of average differences in log one year CDS spreads and log default probabilities. Results are presented for all firms in the sample and with GICS sectors. The final column, labeled 'D' presents the mean of the exponentiated difference, with median in parentheses. Data are sampled at the weekly frequency for 539 firms over the period January, 2001 through December, 2012.

Sector	N	Mean	Std	p5	p50	p95	D
All	539	-0.54	0.62	-1.47	-0.60	0.49	1.02 (0.74)
Energy	52	-0.65	0.49	-1.55	-0.69	0.28	0.70 (0.62)
Materials	44	-0.62	0.48	-1.10	-0.71	0.20	1.00 (0.71)
Industrials	60	-0.61	0.61	-1.55	-0.59	0.51	0.92 (0.73)
Discretionary	104	-0.55	0.62	-1.38	-0.60	0.49	0.96 (0.70)
Staples	41	-0.66	0.53	-1.42	-0.77	0.19	0.75 (0.60)
Healthcare	53	-0.50	0.56	-1.28	-0.49	0.45	1.00 (0.82)
Financials	86	-0.35	0.76	-1.64	-0.47	0.87	1.58 (1.03)
Technology	54	-0.64	0.67	-1.48	-0.69	0.61	0.81 (0.64)
Telecommunications	18	-0.44	0.52	-1.26	-0.51	0.91	1.06 (0.78)
Utilities	27	-0.39	0.67	-1.43	-0.33	0.89	1.09 (0.97)

Table 7: Differences in CDS Spreads and Option-Implied Probabilities and Firm Characteristics

Table 7 examines the relationship between the difference in log one-year CDS spreads and log option-implied default probabilities and firm-specific characteristics. Differences are regressed on a set of nine firm-specific variables: $NIMTA$, the ratio of net income to market value of total assets, $TLMTA$, the ratio of total liabilities to market value of assets, $EXRET$, the monthly log return on the firm's equity in excess of that of the S&P 500, $SIGMA$, the volatility of the firm's equity return over the past three months, $RSIZE$, the log ratio of the market capitalization of the firm's equity to that of the S&P 500, $CASHMTA$, $PRICE$, a variable that is the maximum of the log of $15 or the log price per share of the the firm's equity, $INST$, the fraction of shares owned by insititutions, and $NSHARE$, the number of shareholders divided by market value of equity. Additionally, one of four measures of liquidation costs are included: $NONFIXED$, one minus the ratio of net property, plant, and equipment to total assets, BM, the firm's ratio of book value of equity to market value of equity, $TANG$, the measure of asset tangibility from Almeida and Campello (2007), and $R\&D$, the ratio of research and development expenses to investment. Standard errors are presented in parentheses below point estimates. Data for CDS are obtained from Markit, data on options from OptionMetrics, return information is obtained from CRSP, financial statement and ownership information is obtained from COMPUSTAT.

	(1)	(2)	(3)	(1)
$NIMTA$	-4.625^{***}	-3.869^{***}	-3.937^{***}	-4.142^{***}
	(0.963)	(0.787)	(0.845)	(0.851)
$TLMTA$	1.128^{***}	1.023^{***}	1.062^{***}	1.023^{***}
	(0.084)	(0.089)	(0.081)	(0.077)
$EXRET$	0.009	0.011	0.004	-0.023
	(0.081)	(0.081)	(0.085)	(0.082)
$SIGMA$	0.260^{***}	0.272^{***}	0.279^{***}	0.271^{***}
	(0.036)	(0.034)	(0.035)	(0.034)
$RSIZE$	-0.309^{***}	-0.317^{***}	-0.320^{***}	-0.321^{***}
	(0.021)	(0.020)	(0.021)	(0.022)
$CASHMTA$	-0.743^{**}	-1.151^{***}	-0.909^{***}	-1.142^{***}
	(0.360)	(0.353)	(0.346)	(0.386)
$PRICE$	-0.206^{*}	-0.137^{**}	-0.178^{*}	-0.186^{*}
	(0.124)	(0.055)	(0.095)	(0.100)
$NONFIXED$	-0.368^{***}			
	(0.053)			
BM		0.080^{*}		
		(0.047)		
$TANG$			-0.347^{***}	
			(0.099)	
$R\&D$				-0.033^{***}
				(0.009)
$INST$	0.024	-0.043	-0.027	-0.041
	(0.133)	(0.138)	(0.137)	(0.146)
$NSHARE$	-3.632^{***}	-3.485^{***}	-3.684^{***}	-3.893^{***}
	(0.857)	(0.928)	(0.897)	(0.854)
R^2	0.589	0.582	0.584	0.582

Table 8: Liquidity, CDS Spreads and Option-Implied Default Probabilities

Table 8 presents the results of regressions of innovations in log one-year CDS spreads on innovations in log option-implied default probabilities and aggregate and firm-specific measures of liquidity. The regressions are specified as

$$\begin{aligned}\Delta s_{i,t+1} &= a_i + b_{1i}\Delta ted_{t+1} + b_{2i}\Delta noise_{t+1} + b_{3i}\Delta vix_{t+1} + b_{4i}\Delta vol^O_{i,t+1} \\ &\quad + b_{5i}\Delta open^O_{i,t+1} + b_{6i}\Delta spread^O_{i,t+1} + b_{7i}\Delta depth^C_{i,t+1} + b_{8i}\Delta q^O_{i,t+1} + e_{i,t+1},\end{aligned}$$

where $s_{i,t+1}$ is the log of the one-year CDS spread, ted_{t+1} is the log TED spread, the difference between the yield on 90-day LIBOR and 90-day Treasury Bills, $noise_{t+1}$ is the log of the noise measure from Hu, Pan, and Wang (2013), vix_{t+1} is the log VIX index, $vol^O_{i,t+1}$ is the log of the sum of volume for out-of-the-money (OTM) options on firm i, $open^O_{i,t+1}$ is the log sum of open interest on firm i's OTM options, $spread^O_{i,t+1}$ is the log of the average percentage bid-ask spread for firm i's OTM options, $depth^C_{i,t+1}$ is the depth of 5-year CDS contracts for firm i, and $q^O_{i,t+1}$ is firm i's option-implied default probability. Options data is from OptionMetrics, CDS data from Markit, financial market data from the Federal Reserve, and the noise measure from Jun Pan's website. The table first reports results of regressions of the change in log aggregate CDS spreads on the explanatory variables, where the aggregate is constructed as the cross-sectional average of each week's observations. The table also reports results for the fifth, twenty-fifth, median, seventy-fifth, and ninety-fifth percentile coefficient estimates and their associated standard errors for firm-specific regressions. Finally, the table reports the number of observations that are statistically less than zero and statistically greater than zero at the 2.5% significance level. We eliminate firms with insufficient variation in the independent variables to estimate standard errors, resulting in 481 firms over the period January, 2001 through December, 2012.

	Δted	$\Delta noise$	Δvix	Δvol^O	$\Delta open^O$	$\Delta spread^O$	$\Delta depth^C$	Δq	$\bar{R}^2$
Aggregate	-0.010	0.007	0.209	-0.020	-0.060	-0.031	0.031	1.098	0.451
SE	(0.021)	(0.022)	(0.025)	(0.015)	(0.057)	(0.082)	(0.049)	(0.055)	
p5	-0.209	-0.142	-0.126	-0.028	-0.176	-0.266	-0.112	-0.176	0.019
SE	(0.144)	(0.193)	(0.105)	(0.020)	(0.077)	(0.422)	(0.049)	(0.171)	
p25	-0.053	-0.016	0.065	-0.006	-0.065	-0.080	-0.026	-0.011	0.046
SE	(0.060)	(0.061)	(0.120)	(0.007)	(0.083)	(0.152)	(0.025)	(0.077)	
p50	0.008	0.048	0.227	0.003	-0.001	-0.004	0.007	0.061	0.080
SE	(0.062)	(0.085)	(0.050)	(0.022)	(0.059)	(1.350)	(0.032)	(0.041)	
p75	0.073	0.122	0.328	0.014	0.062	0.079	0.045	0.175	0.139
SE	(0.086)	(0.070)	(0.151)	(0.014)	(0.084)	(0.066)	(0.049)	(0.071)	
p95	0.186	0.299	0.502	0.037	0.180	0.287	0.172	0.434	0.408
SE	(0.317)	(0.189)	(0.061)	(0.017)	(0.170)	(0.140)	(0.087)	(0.088)	
< 0	11	4	2	9	19	28	17	10	
> 0	17	43	263	28	16	35	49	77	

Table 9: Liquidity, CDS Spreads and Option-Implied Default Probabilities by Sector

Table 9 presents the results of regressions of innovations in log one-year CDS spreads on innovations in log option-implied default probabilities and aggregate and firm-specific measures of liquidity. The regressions are specified as

$$\begin{aligned}\Delta s_{i,t+1} &= a_i + b_{1i}\Delta ted_{t+1} + b_{2i}\Delta noise_{t+1} + b_{3i}\Delta vix_{t+1} + b_{4i}\Delta vol^O_{i,t+1} \\ &\quad + b_{5i}\Delta open^O_{i,t+1} + b_{6i}\Delta spread^O_{i,t+1} + b_{7i}\Delta depth^C_{i,t+1} + b_{8i}\Delta q^O_{i,t+1} + e_{i,t+1},\end{aligned}$$

where $s_{i,t+1}$ is the log of the one-year CDS spread, ted_{t+1} is the log TED spread, the difference between the yield on 90-day LIBOR and 90-day Treasury Bills, $noise_{t+1}$ is the log of the noise measure from Hu, Pan, and Wang (2013), vix_{t+1} is the log VIX index, $vol^O_{i,t+1}$ is the log of the sum of volume for out-of-the-money (OTM) options on firm i, $open^O_{i,t+1}$ is the log sum of open interest on firm i's OTM options, $spread^O_{i,t+1}$ is the log of the average percentage bid-ask spread for firm i's OTM options, $depth^C_{i,t+1}$ is the depth of 5-year CDS contracts for firm i, and $q^O_{i,t+1}$ is firm i's option-implied default probability. Options data is from OptionMetrics, CDS data from Markit, financial market data from the Federal Reserve, and the noise measure from Jun Pan's website. The table reports results for series aggregated across two-digit GICS codes, Energy (EN), Materials (MA), Industrials (IN), Consumer Discretionary (CD), Consumer Staples (CS), Healthcare (HC), Financials (FI), Information Technology (IT), Telecommunications (TC), and Utilities (UT). Data are sampled at the weekly frequency from January, 2001 through December, 2012.

	Δted	$\Delta noise$	Δvix	Δvol^O	$\Delta open^O$	$\Delta spread^O$	$\Delta depth^C$	Δq	$\bar{R}^2$
EN	0.009	0.028	0.175***	0.021	0.340***	0.218**	0.065	0.993***	0.444
	(0.042)	(0.047)	(0.050)	(0.020)	(0.049)	(0.104)	(0.066)	(0.053)	
MA	−0.001	0.023	0.199***	0.010	−0.176***	0.079	−0.111**	1.143***	0.471
	(0.035)	(0.038)	(0.043)	(0.015)	(0.060)	(0.093)	(0.048)	(0.053)	
IN	−0.013	0.094**	0.126**	−0.014	0.077	0.277**	0.068	1.122***	0.562
	(0.041)	(0.044)	(0.049)	(0.021)	(0.081)	(0.127)	(0.068)	(0.042)	
CD	−0.034	−0.015	0.223***	0.008	−0.089	0.050	0.035	1.191***	0.418
	(0.027)	(0.029)	(0.033)	(0.014)	(0.060)	(0.091)	(0.050)	(0.063)	
CS	−0.002	0.028	0.190***	0.021	0.035	−0.103	0.045	0.964***	0.345
	(0.032)	(0.034)	(0.038)	(0.013)	(0.054)	(0.105)	(0.055)	(0.059)	
HC	0.004	0.001	0.071*	0.001	−0.048	0.604***	0.068	0.408***	0.280
	(0.035)	(0.038)	(0.418)	(0.177)	(0.060)	(0.097)	(0.057)	(0.033)	
FI	−0.024	0.086**	0.279***	−0.002	−0.067	0.320***	−0.008	0.716***	0.455
	(0.034)	(0.036)	(0.041)	(0.016)	(0.059)	(0.105)	(0.051)	(0.036)	
IT	0.015	−0.009	0.143***	0.026	−0.141***	−0.006	−0.128***	0.970***	0.425
	(0.035)	(0.037)	(0.042)	(0.017)	(0.048)	(0.099)	(0.051)	(0.050)	
TC	0.029	−0.022	0.201***	0.020	−0.270***	0.552***	−0.038	0.905***	0.511
	(0.058)	(0.062)	(0.069)	(0.017)	(0.054)	(0.101)	(0.045)	(0.040)	
UT	0.011	0.067	0.236***	0.028*	0.074*	0.377***	−0.040	0.796***	0.484
	(0.060)	(0.061)	(0.067)	(0.016)	(0.041)	(0.115)	(0.058)	(0.052)	

*,**,*** represent statistical significance at the 10%, 5%, and 1% critical threshold, respectively.

Table 10: Predictability of Returns by CDS- and Option-Implied Probabilities and their Difference

The table presents the results of regressions,

$$r_{p,t+1} = a + b\Delta x_{p,t} + e_{p,t},$$

where $r_{p,t+1}$ is the log return on an index, $x_{p,t} = \{q^C_{p,t}, q^O_{p,t}, q^C_{p,t} - q^O_{p,t}\}$ is, depending on specification, the log CDS-implied risk neutral probability of default, the log option-implied risk neutral probability of default, or the difference in the log probabilities of default. Predictive regressions are performed for the CRSP value-weighted index and indices of 10 sectors; Energy (EN), Materials (MA), Industrials (IN), Consumer Discretionary (CD), Consumer Staples (CS), Healthcare (HC), Financials (FI), Information Technology (IT), Telecommunications (TC), and Utilities (UT). The table presents slope coefficients, associated standard errors, and R^2 for univariate regressions of returns on the variables. Data are sampled at the weekly frequency from January, 2001 through December, 2012.

	q^C	SE	R^2	q^O	SE	R^2	$q^C - q^O$	SE	R^2
Aggregate	1.826	(1.220)	0.358	0.170	(3.273)	0.000	3.690^{**}	(1.776)	0.689
EN	0.151	(0.979)	0.004	−2.436	(1.533)	0.411	3.465^{**}	(1.604)	0.758
MA	2.291^{**}	(0.997)	0.841	1.377	(1.734)	0.101	3.386^{**}	(1.438)	0.883
IN	0.717	(0.750)	0.147	0.181	(0.986)	0.005	3.762^{**}	(1.474)	1.036
CD	2.733^{*}	(1.481)	0.545	1.944	(2.568)	0.092	2.111	(2.068)	0.167
CS	0.424	(0.620)	0.075	−0.912	(1.057)	0.119	1.666^{*}	(0.892)	0.559
HC	−0.863	(0.816)	0.181	−0.778	(0.717)	0.190	−0.049	(0.911)	0.000
FI	3.497^{***}	(1.197)	1.353	0.384	(1.350)	0.013	5.491^{***}	(1.839)	1.413
IT	−0.928	(1.024)	0.132	0.533	(1.574)	0.018	-2.818^{**}	(1.423)	0.626
TC	−0.545	(0.462)	0.223	−0.539	(0.635)	0.116	−0.311	(0.733)	0.029
UT	-1.745^{*}	(1.005)	0.493	-2.807^{**}	(1.385)	0.670	−1.204	(1.549)	0.099

Figure 1: Implied Default Probabilities

Figure 1 plots the time series of aggregate default probabilities. Default probabilities are measured using one year CDS spreads with an assumed recovery rate of 40% and using the risk neutral distribution implied by option prices with a ratings-dependent critical threshold and a constant threshold $\alpha = 0.05$. CDS data are obtained from Markit and options data from OptionMetrics. Data are sampled at the weekly frequency and aggregated by taking the average across the firms in the sample. The data cover the period January, 2001 through December, 2012, and cover 539 firms.

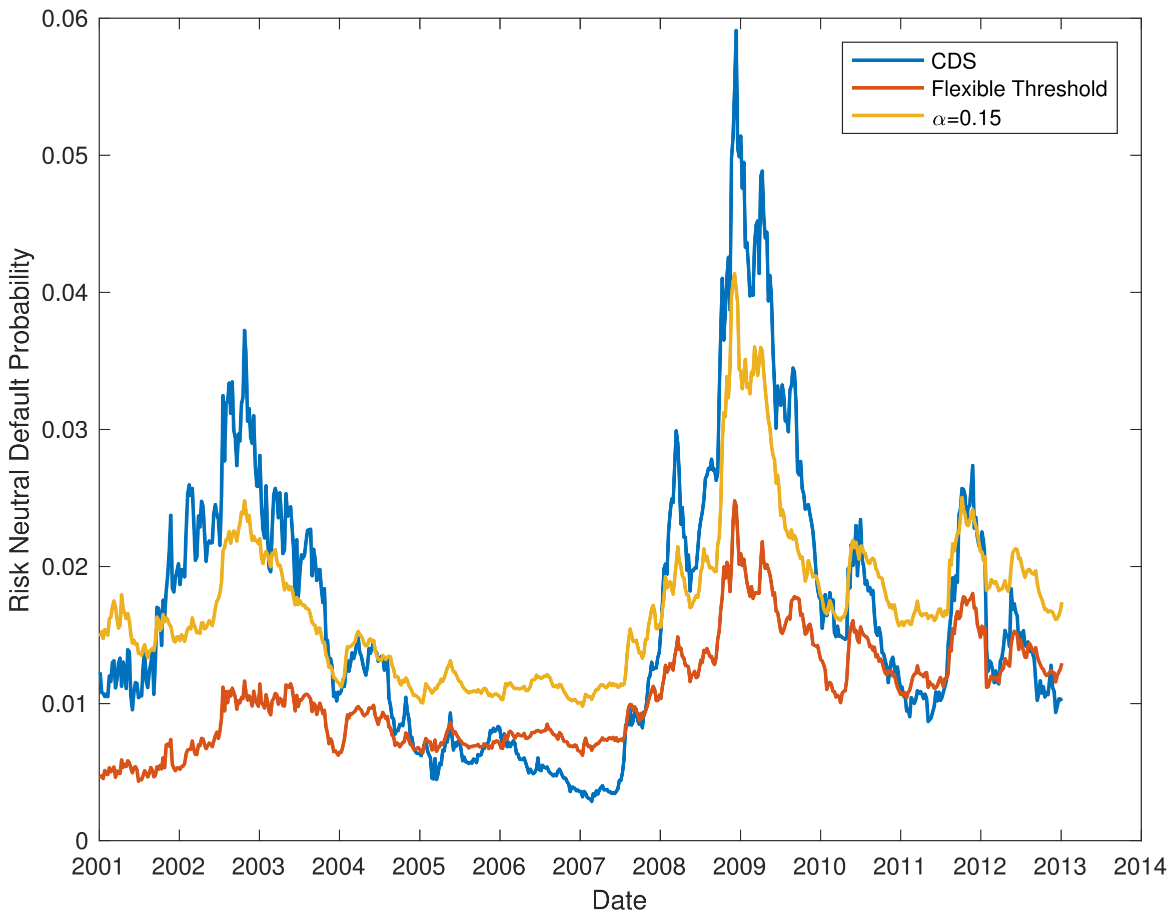
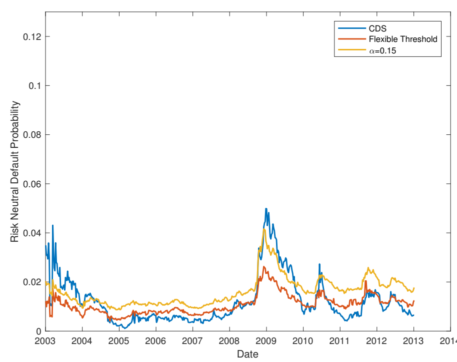
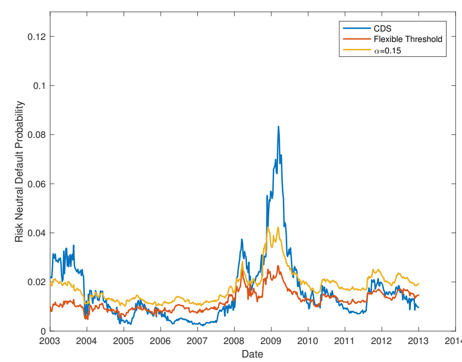


Figure 2: Implied Default Probabilities by Sector

Figure 2 plots the time series of aggregate default probabilities by GICS sector. Default probabilities are measured using one year CDS spreads with an assumed recovery rate of 40% and using the risk neutral distribution implied by option prices with a ratings-dependent critical threshold and a constant threshold $\alpha = 0.05$. Option-implied default probabilities are calculated with a ratings-dependent critical threshold and a constant threshold $\alpha = 0.15$. Options data are from OptionMetrics and CDS data are from Markit. Option-implied default probabilities are calculated at the firm level, and probabilities and spreads are aggregated by sector by averaging within each sector cross-sectionally each week. Sector definitions are obtained from Compustat and cover the sectors Energy (EN), Materials (MA), Industrials (IN), Consumer Discretionary (CD), Consumer Staples (CS), Healthcare (HC), Financials (FI), Information Technology (IT), Telecommunications (TC), and Utilities (UT). Data cover 539 firms over the period January, 2003 through December, 2012.



(a) EN



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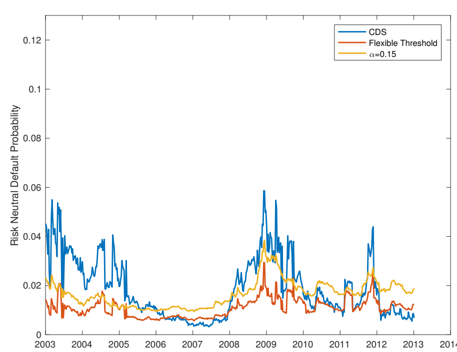
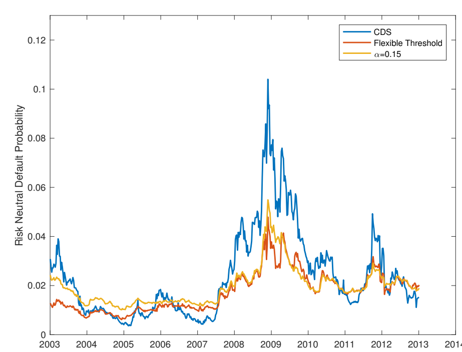


(c) IN



(d) CD

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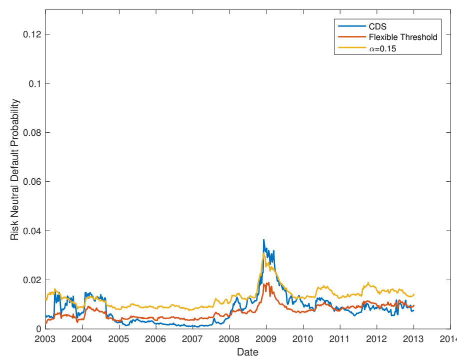

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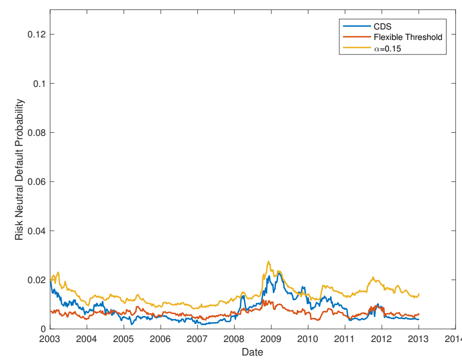

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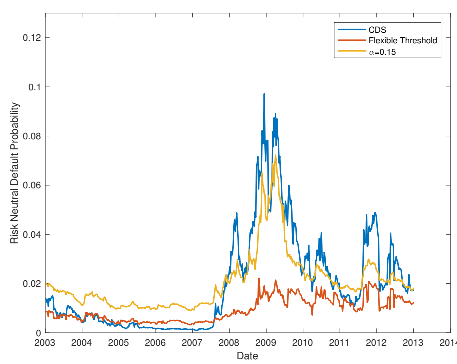
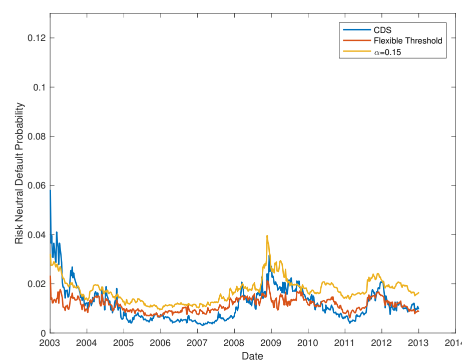


(g) FI



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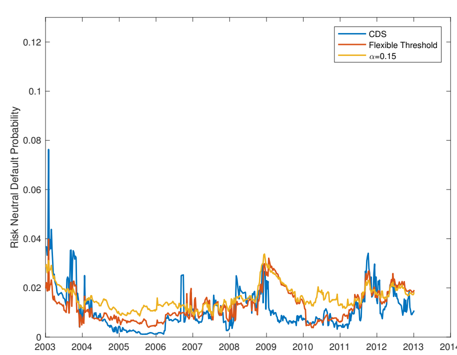
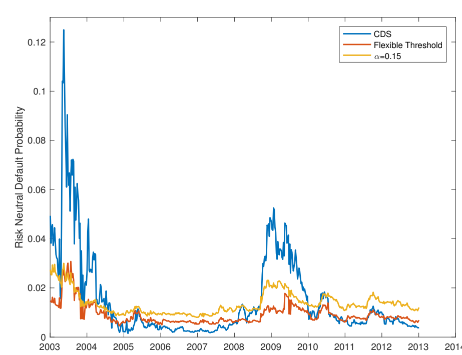


(i) TC



(j) UT

Figure 3: Differences in log CDS Spreads and Option-Implied Default Probabilities

Figure 3 plots the time series of of the difference in log one-year CDS spreads and log option-implied default probabilities aggregated over firms. The difference is calculated by first averaging the spread and default probability across firms and then taking logs of the average. Option-implied default probabilities are calculated with a ratings-dependent critical threshold and a constant threshold $\alpha = 0.15$. Options data are from OptionMetrics and CDS data are from Markit. Data cover 539 firms over the period January, 2001 through December, 2012.

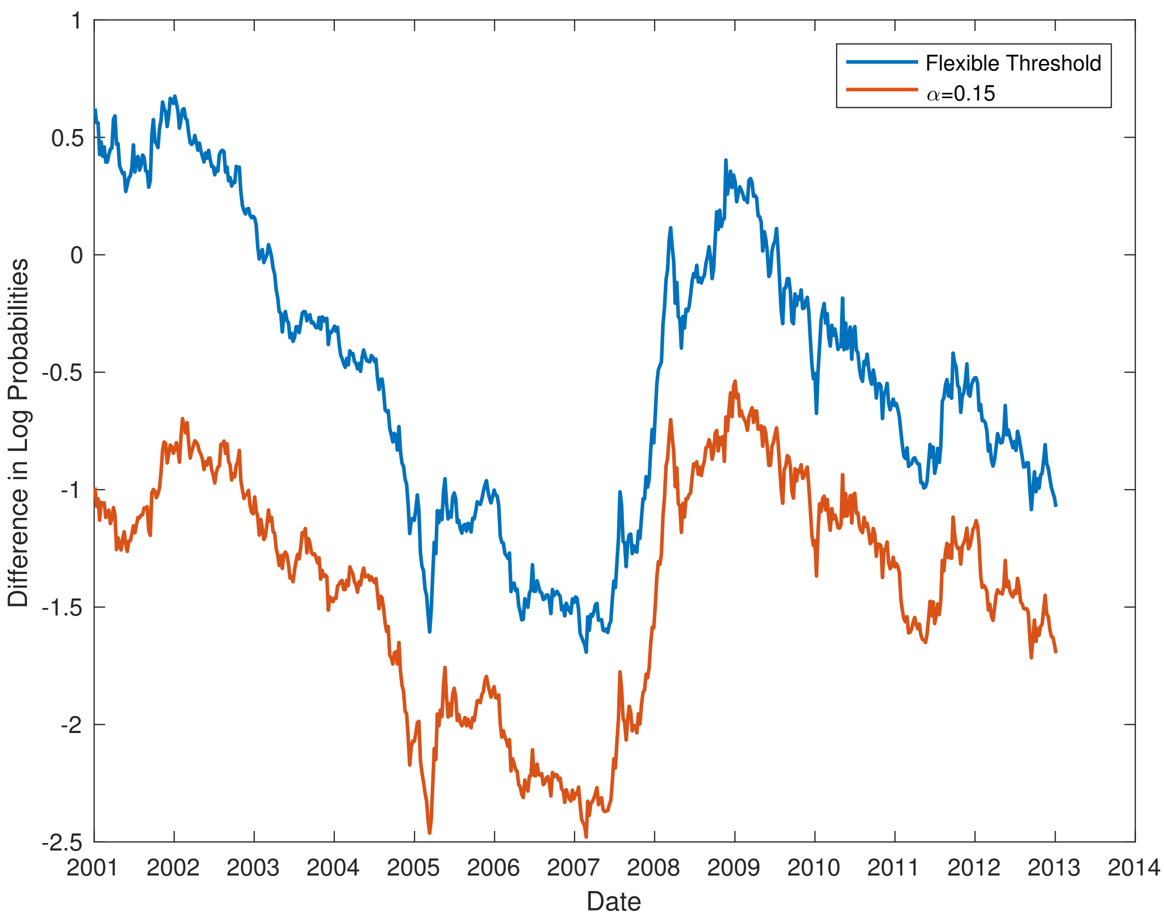
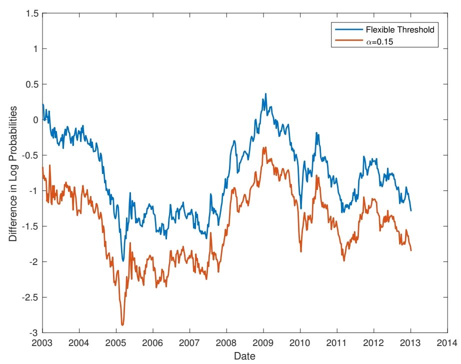


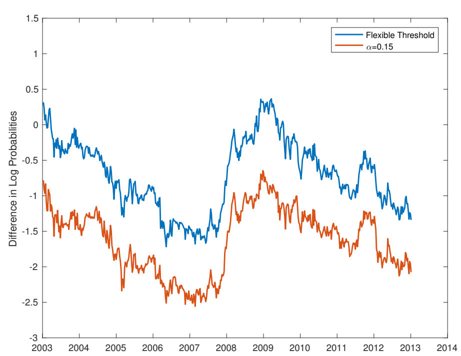
Figure 4: Differences in log CDS Spreads and Option-Implied Default Probabilities by Sector

Figure 4 presents the difference in the log of one-year CDS spreads and the log of option-implied default probabilities aggregated by GICS sector. Option-implied default probabilities are calculated with a ratings-dependent critical threshold and a constant threshold $\alpha = 0.15$. Options data are from OptionMetrics and CDS data are from Markit. Option-implied default probabilities are calculated at the firm level, and probabilities and spreads are aggregated by sector by averaging within each sector cross-sectionally each week. Sector definitions are obtained from Compustat and cover the sectors Energy (EN), Materials (MA), Industrials (IN), Consumer Discretionary (CD), Consumer Staples (CS), Healthcare (HC), Financials (FI), Information Technology (IT), Telecommunications (TC), and Utilities (UT). Data cover 539 firms over the period January, 2003 through December, 2012.

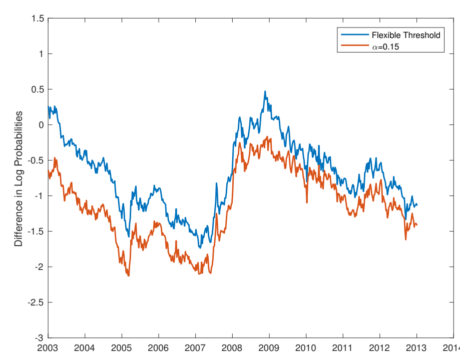


(a) EN

(b) MA



(c) IN



(d) CD

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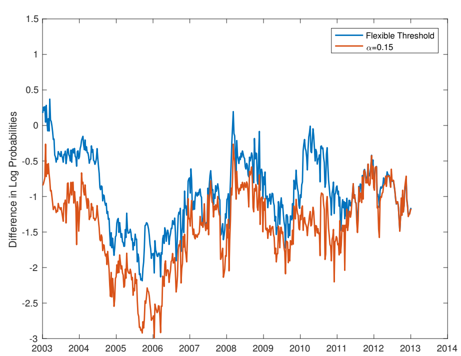
(e) CS

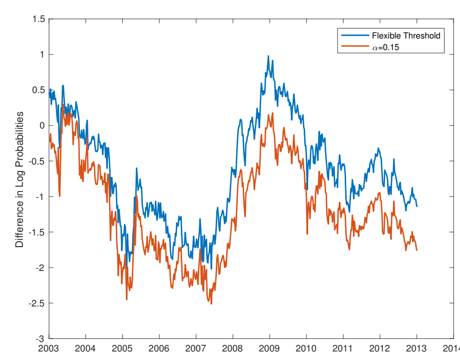
(f) HC

(g) FI

(h) IT



(i) TC



(j) UT