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Accounting-based versus market-based cross-sectional models of CDS spreads

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ABSTRACT

Models of financial distress rely primarily on accounting-based information (e.g. [Altman, E., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 23, 589–609; Ohlson, J., 1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research 19, 109–131]) or market-based information (e.g. [Merton, R.C., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29, 449–470]). In this paper, we provide evidence on the relative performance of these two classes of models. Using a sample of 2860 quarterly CDS spreads we find that a model of distress using accounting metrics performs comparably to market-based structural models of default. Moreover, a model using both sources of information performs better than either of the two models. Overall, our results suggest that both sources of information (accounting- and market-based) are complementary in pricing distress.

1. Introduction

Recent studies have put in question the value-relevance of accounting information to providers of capital. Although the brunt of the assault has focused on the relevance to providers of equity capital with a vast body of literature finding temporal declines in the power of accounting data to explain equity prices (e.g. Lev and Zarowin, 1999; Francis and Schipper, 1999; Brown et al., 1999), relevance to the credit markets has not remained unscathed. In particular, the class of models using accounting variables in the modeling of default (notably, Altman, 1968; Ohlson, 1980) have been challenged by two new classes of models, so-called structural and reduced-form, that rely exclusively on market data. Specifically, structural models (Merton, 1974) use option pricing methods to compute a probability of default from the level and volatility of market value of assets and reduced-form models (Jarrow and Turnbull, 1995; Duffie and Singleton, 1999) allow the default intensity to be extracted from debt/credit market securities. Market-based approaches to pricing distress have been embraced by academics and practitioners. Indeed, many purists believe that these approaches yield a superior probability of default statistic (e.g. Crosbie, 1999). For example, Hillegeist et al. (2004), using a large sample of bankruptcies, find that structural models of default are better at forecasting distress than either Altman's *Z*-score or Ohlson's *O*-score. Furthermore, default probabilities of public companies using structural models of credit risk are now popular among investors since their commercial introduction by firms such as KMV and CreditMetrics in the 1990's. Likewise, default probabilities calculated using reduced-form approaches have been growing rapidly in popularity since the early 2000s (offered commercially as well, for example, by firms such as Kamakura Inc.).

Despite the popularity of market-based default metrics, anecdotal evidence suggests that accounting information has a potentially important role to play in predicting distress. For example, the case of Enron underscores the possible pitfalls of relying exclusively on market information. In their promotional material, KMV point out that when Enron's stock price began to fall, the KMV probability of default immediately increased whereas agency ratings took several days to downgrade the company's debt. However, when Enron's stock price was artificially high the KMV probability of default was actually lower than that assigned by traditional agency ratings. This observation led Bharath and Shumway (2008) to state: "If markets are not perfectly efficient, then conditioning on information not captured by the KMV probability of default probably makes sense". Moreover, regardless of the quality of market-based information, many companies are privately held and thus by necessity accounting information must be used to estimate the probability of default on their (sometimes public) debt. Estimating the relevance of accounting information in the pricing of default risk is therefore an important exercise in its own right.

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We examine how accounting-based and market-based variables compare in pricing the risks of default by examining a sample of 2860 firm-quarters of Credit Default Swap spreads (CDS).[1] Using CDS spreads to test the relevance of distress models provides a viable alternative to using samples of observed bankruptcies (e.g. Altman, 1968; Ohlson, 1980; Altman, 2000; Sobehart et al., 2000; Hillegeist et al., 2004; Duffie et al., 2005; Chava and Jarrow, 2004; Agarwal and Taffler, 2008), credit ratings (e.g. Ang and Patel, 1975; Kaplan and Urwitz, 1979; Blume et al., 1998), or bond spreads (e.g. Wu and Zhang, 2004; Huang and Kong, 2005; Collin-Dufresne et al., 2001; Longstaff and Rajan, 2006). First, CDS spreads offer cross-sectional and time-series credit quality information. This continuous variable contrasts with studying binary data samples of bankruptcies where a company is identified as healthy until default occurs. Second, CDS spreads reflect market perceptions of default as opposed to those of a rating agency. Third, spreads capture both the default and recovery risk aspects of firm distress. And fourth, CDS spreads are less susceptible to liquidity and tax effects than corporate bond spreads (see Elton et al. (2001) for a look at factors other than default risk that determine bond spreads).

We find that accounting-based variables are able to explain roughly two-thirds of CDS spreads and have comparable explanatory power to market-based variables. Furthermore, a hybrid model using accounting-based variables in conjunction with market-based variables is able to explain three-quarters of the variation in CDS spreads.

Since the relative ranking of credit derivative spreads is an important decision variable for a variety of market participants including corporate bond fund managers (especially for high-yield portfolios), rating agencies, credit market data vendors, hedge funds, and regulators, we explore how three models fare in this ordinal ranking task. We test the performance of all three models in ranking spreads by examining their cumulative accuracy profiles (CAP curves) and their corresponding accuracy ratios. We find that the accounting-based model performs comparably to the market-based one and that the comprehensive model performs substantially better.

These results present evidence that (i) accounting information is relevant in spread prediction even without the inclusion of market-based information; and (ii) that accounting- and market-based variables possess complementary information in the prediction of credit spreads. Moreover, if one is to believe that distress information is important to equity markets (see Dichev, 1998; Vassalou and Xing, 2004, for differing viewpoints) our results, albeit indirectly, also support the value-relevance of accounting information for equity prices.

The rest of the paper proceeds as follows. In Section 2, we provide a description of CDS and derive our empirical specifications. In Section 3, we present the data and methodology. Section 4 reports the results, and Section 5 concludes.

2. Credit default swaps

CDS are contingent claims with payoffs that are linked to the credit risk of a given entity. In practice, buying a CDS contract is tantamount to buying insurance against default where the premium payments are determined from the CDS spreads (see Das and Hanouna (2006) for more detail on CDS contracts).[2]

We motivate our empirical specification through a generic model of CDS prices. If the rate of default arrival of an issuer depends on a (usually stochastic) intensity process λ_t, then the survival probability for the issuer from time zero to time τ is given by $s_\tau = \exp\left(-\int_0^\tau \lambda_t dt\right)$. In a fairly priced CDS contract, the expected present value of premium payments by the buyer to the seller will equal the expected present value of default loss payments from the seller to the buyer (under the risk-neutral probability measure).[3] The expected present value of payments by the seller of the CDS to the buyer will be, for a notional value of \$1, given various default times τ:

$$E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau \lambda_\tau (1-\phi_\tau) d\tau\right], \tag{1}$$

where r_t is the instantaneous interest rate at time t, and ϕ_τ is the recovery rate at default time τ. The expectation $E[\cdot]$ is taken over all interest rate, intensity and recovery paths, and all default times.

The expected present value of premium payments at rate CS (credit spread) per annum from the buyer to the seller are as follows:

$$E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau CS d\tau\right]. \tag{2}$$

Since the payments in expected present value terms between buyer and seller should be equal for the CDS to be fairly priced, equating (1) and (2) and re-arranging, results in the formula for the CDS spread:

$$CS = \frac{E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau \lambda_\tau (1-\phi_\tau) d\tau\right]}{E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau d\tau\right]}. \tag{3}$$

For details on the valuation of CDS contracts, see the article by Duffie (1999). Jankowitsch et al. (2008) discuss the delivery option on CDS.

It is clear that the spread CS must depend on factors that determine interest rates (r_t), default intensities (λ_t) and recovery rates (ϕ_t), comprising both firm variables as well as economy-wide factors. Firm-level variables can be either market-based (market prices of debt and/or equity) and/or accounting-based, whereas economy-wide variables can be obtained from equity and interest rate markets. We now heuristically motivate how the structure of the function for CDS spreads leads to an empirical specification in the logarithm of spreads when the default intensity is of exponential affine form. Assume the following functional form for the default intensity (suppressing the time subscript on these forward intensities):

$$\lambda = \exp[\mathbf{B}'\mathbf{X}], \tag{4}$$

where $\mathbf{B} = [\beta_0, \ldots, \beta_k]'$ is a vector of coefficients in the non-linear specification above, and $\mathbf{X} = [1, X_1, \ldots, X_k]'$ is a vector of explanatory variables, which may include both market variables and firm financials. (Both vectors are dimension $(k+1)$, where k depends on the specifics of the model.) Given that the default intensity lies in the range $[0, \infty)$, this specification maintains the required bounds as well. We substitute this specification into a discrete form of Eq. (3), presented below, and estimate this non-linear model for all three of the models described earlier, the accounting-based, market-based, and comprehensive one.

[1] Campbell et al. (2008) use accounting and market data to examine the role of default risk in asset returns. Alexander and Kaeck (2008) show that CDS spreads are regime dependent.

[2] CDS securities have resulted in a number of innovative structures in the credit markets thereby making it easy to trade the credit risk of debt. These securities are popular among hedge funds wishing to hedge current credit risk exposures or wishing to take a credit view.

[3] We note that since CDS contracts are derivatives, pricing will be undertaken using the risk-neutral probability measure, which is then consistent with obtaining the no-arbitrage price of the security.

We assume that the discrete periods in the model are based on a fixed time interval h, and that defaults and premium payments occur at the end of the period. Given the CDS maturity, the number of periods n is determined. The periods are indexed by $j = 1, 2, \ldots n$. The discrete-time equivalent of Eq. (3) is as follows:

$$CS[\lambda(\mathbf{B})] = \frac{E\left[\sum_{j=1}^{n} e^{-z_j jh}(1-\phi_j)e^{-\lambda_j(j-1)h}(1-e^{-\lambda_j h})\right]}{hE\left[\sum_{j=1}^{n} e^{-z_j jh}e^{-\lambda_j(j-1)h}\right]}, \quad (5)$$

where z_j is the zero-coupon discount rate for period j. Of course, λ_j is the default intensity for period j. Noting that λ is a function of $\mathbf{B}$ and $\mathbf{X}$ from Eq. (4), we may undertake a least-squares fit of the CDS spread c as follows, across all observations:

$$\mathbf{B}^* = \operatorname{argmin}_{\mathbf{B}} \sum_i \sum_t [CS_{it} - \widehat{CS}_{it}]^2, \quad (6)$$

where CS_{it} is the actual observed value of the CDS spread and $\widehat{CS}_{it}$ is the fitted value for firm i at time t. Thus, $\mathbf{B}^*$ is the best fit value of the parameters. In the special case where $\lambda_j = \lambda$, i.e. constant conditional on the given state vector $\mathbf{X}$, and the recovery rate is constant, i.e. $\phi_j = \phi$, we obtain a simplified expression of Eq. (5), i.e.,

$$CS[\lambda] = \frac{(1-\phi)(1-e^{-\lambda(\mathbf{B})h})}{h}. \quad (7)$$

Taking logarithms, we obtain an approximate linear estimation equation:

$$\begin{aligned}\log\{CS[\lambda]\} &= \log\left[\frac{(1-\phi)}{h}\right] + \log[(1-e^{-\lambda(\mathbf{B})h})] \\ &\approx \log\left[\frac{(1-\phi)}{h}\right] + \log[\lambda(\mathbf{B})h] = \log\left[\frac{(1-\phi)}{h}\right] + \mathbf{B}'\mathbf{X}h,\end{aligned}$$

where we have exploited the fact that $\lambda(\mathbf{B}) = \exp[\mathbf{B}'\mathbf{X}]$. The expression highlights the fact that it is natural to regress the natural logarithm of CDS spreads on explanatory variables. Indeed, as may be noticed in the work of Aunon-Nerin et al. (2002), regressions in the logarithm of spreads do fit better than in levels directly.

3. Data

3.1. Sample collection and description

Our data collection was initiated by obtaining a list of all the CDS securities with spreads available on Bloomberg. Bloomberg lists 10,503 CDS securities covering 1563 unique debtor entities. From this list we eliminated all CDS securities where the notional value is not dollar denominated reducing the sample to 4168 CDS securities covering 960 unique debtor entities. On this sample, we collected the CDS constant maturity spreads at the end of each quarter over the period 2001–2005 from Bloomberg. Cossin and Lu (2005) argue that this CDS quote represents the market price for the credit risks of the borrower and is thus adequate for our purposes. We are able to obtain spread information on 790 CDS securities on 340 unique debtor entities. The sample is then merged with the COMPUSTAT Quarterly Industrial database and the CRSP daily stock file. This last procedure eliminates from the sample all non-publicly traded entities and non-US firms. Eventually, to determine our final sample, we further require that each firm possess at least 50 trading days of stock price returns prior to the end of each quarter and that data on total assets be available. Following standard practice, we exclude financial firms from the sample identified using the Fama and French (1997) 17 industry classification. Our final sample comprises 2860 quarterly CDS spreads on 506 CDS securities representing 230 unique firms. Table 1 presents the time profile of the sample by CDS maturity.

Table 1

Number of observations. Our sample consists of 2860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

Quarter	CDS maturities					
	1	2	3	5	10	All maturities
2001Q3				8		8
2001Q4				8		8
2002Q1				23		23
2002Q2				72		72
2002Q3				108		108
2002Q4				121		121
2003Q1	5		4	156		165
2003Q2	33		32	228		293
2003Q3	34	2	34	248		318
2003Q4	22		22	244		288
2004Q1	52		53	221		326
2004Q2	77		78	215	14	384
2004Q3	72		73	209	15	369
2004Q4	67		67	192	14	340
2005Q1	6		6	24	1	37
All quarters	368	2	369	2077	44	2860

Table 2 presents the industry profile of sample firms. We assign a company to one of 16 industries (financials are excluded from our analysis) determined by Fama and French (1997), and located on Kenneth French's website, by using the CRSP primary SIC code (COMPUSTAT SIC codes often differ from those in CRSP).

In Table 3, we present the mean and medians of CDS spread values by maturity and year. In Table 4, we report the mean and median CDS spreads by industry. Overall, we find that there is considerable time variation in CDS spreads within a given industry group. In Table 5, we report spreads by rating. Given the sample period, the spreads have declined from 2002 to 2005, as the general quality of issuers in the credit markets improved. Furthermore, as in bond spreads, we notice a considerable overlap in spread ranges for adjoining rating categories and as has been well-documented in prior studies (e.g. Ericsson et al., 2004), there is a dramatic increase in spreads when moving from investment grade firms to those in non-investment grade.

3.2. Variable construction

3.2.1. Accounting-based variables

We construct our accounting-based variables following the Moody's Private Debt Manual published on the Moody's-KMV website. We use 10 variables to proxy for (1) firm size, (2) profitability, (3) financial liquidity, (4) trading account activity, (5) sales growth and (6) capital structure. We choose to use the Moody's accounting ratios rather than the *Z*-score (Altman, 1968) or *O*-score (Ohlson, 1980) measures of distress for several reasons. First, the *O*-score or the *Z*-score (e.g. Hillegeist et al., 2004) measures are restrictive functional specifications. A score in essence summarizes information and will necessarily possess less explanatory power than the inclusion of its components in a multivariate regression. Secondly, using the Moody's variables allows us to consider potentially important variables not included in either score such as interest coverage. We list the variables and their construction below:

(i) *Firm size:* We use the value of total assets (COMPUSTAT-Quarterly item 44) divided by the Consumer Price Index on all-urban consumers, all items with the period 1982–1984 as a base.
(ii) *Three ratios that gauge profitability:* Return on assets (ROA), net income growth, and interest coverage. ROA is

Table 2
Industry profile of our sample by year. In this table each firm is allowed to be included only once per reported period. We use the Fama and French (1997) 17-industry classification based on SIC codes obtained from CRSP. Our sample consists of 2860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

Industry	2001		2002		2003		2004		2005		All years	
	N	%	*N*	%	*N*	%	*N*	%	*N*	%	*N*	%
Automobiles			4	3.92	7	3.76	7	3.41	2	10.53	10	4.35
Chemicals			4	3.92	9	4.84	8	3.90	3	15.79	9	3.91
Construction and construction materials			1	0.98	6	3.23	6	2.93			12	5.22
Consumer durables			2	1.96	5	2.69	5	2.44			5	2.17
Drugs, soap, perfumes, tobacco	1	25.00	2	1.96	10	5.38	14	6.83	2	10.53	15	6.52
Fabricated products												
Food			8	7.84	13	6.99	12	5.85	3	15.79	13	5.65
Machinery and business equipment			14	13.73	19	10.22	22	10.73	5	26.32	24	10.43
Mining and minerals					1	0.54	1	0.49			1	0.43
Oil and petroleum products			9	8.82	13	6.99	16	7.80	1	5.26	17	7.39
Retail stores	1	25.00	12	11.76	20	10.75	22	10.73	1	5.26	23	10.00
Steel works, etc.			1	0.98	3	1.61	3	1.46			3	1.30
Textiles, apparel and footware					1	0.54	4	1.95			4	1.74
Transportation			10	9.80	13	6.99	14	6.83			16	6.96
Utilities			10	9.80	22	11.83	24	11.71			25	10.87
Other	2	50.00	25	24.51	44	23.66	47	22.93	2	10.53	53	23.04
All industries	4	100.00	102	100.00	186	100.00	205	100.00	19	100.00	230	100.00

Table 3
Spread descriptive statistics. Our sample consists of 2860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

	CDS maturity											
	1-Year			3-Year			5-Year			10-Year		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
2001							16	90.41	88.75			
2002							324	175.4	100			
2003	94	36.88	24	92	52.06	35.66	876	103.4	55.69			
2004	268	30.26	19.38	271	49.61	31.32	837	79.44	47.01	43	89.78	65.1
2005	6	15.11	11.67	6	31.73	26.54	24	85.8	48.61	1	35.95	35.95
All years	368	31.7	20.5	369	49.93	33.4	2077	104.7	57.83	44	88.56	64.84

constructed as net income (item 69) divided by total assets. Net income growth is calculated as net income minus the previous quarter's net income divided by total assets. Interest coverage is calculated as pretax income (item 23) plus interest expense (item 22) divided by interest expense.

(iii) *Financial liquidity:* We use the quick ratio and the cash to asset ratio. The quick ratio is constructed as current assets (item 40) minus inventories (item 38) over current liabilities (item 49) and the cash to asset ratio is cash and equivalents (item 36) over total assets.
(iv) *Trading account activity:* The ratio of inventories to cost of goods sold (item 30).
(v) *Quarterly sales growth:* Sales (item 2) divided by the previous quarter sales minus one.
(vi) *Capital structure:* The ratio of total liabilities (item 54) to total assets and the ratio of retained earnings (item 58) to total assets.

In some instances of flow items, COMPUSTAT reports a missing value in the first and third quarter of the year when the data reported in the second and fourth quarters are semi-annual numbers. When this event occurs, we set the first and second quarter data to one-half the semi-annual reported value in the second quarter. We proceed similarly in the third and fourth quarter using the fourth quarter semi-annual numbers.[4]

In order to account for seasonal effects, we take the trailing four quarter average of ROA, sales growth, interest coverage, and inventories over cost of goods sold before including these variables in the model. We follow Blume et al. (1998) by transforming the interest coverage ratio in two ways. First, before taking the trailing four quarter average, we set any quarterly interest coverage ratio to zero if they are negative. Second, any trailing four quarter average interest coverage ratio that exceeds 100 is censored on the assumption that further increases in value convey no additional information. We also follow Blume et al. (1998) in changing the specification of the model to allow the data to determine the shape of the nonlinearity. Specifically, let IC_{it} be the interest coverage for firm i in quarter t, we then include the interest coverage ratio in the regression model as $IC_{it} = \sum_{j=1}^{4} \kappa_j c_{jit}$, where c_{jit} is defined in the following table as

	c_{1it}	c_{2it}	c_{3it}	c_{4it}
$IC_{it} \in [0, 5)$	IC_{it}	0	0	0
$IC_{it} \in [5, 10)$	5	$IC_{it} - 5$	0	0
$IC_{it} \in [10, 20)$	5	5	$IC_{it} - 10$	0
$IC_{it} \in [20, 100]$	5	5	10	$IC_{it} - 20$

This specification allows the regression model to determine different coefficient parameters on each increment of the interest coverage ratio.

[4] This occurs only in 24 cases in our sample.

Table 4
Mean and median CDS spreads by industry. We use the Fama and French (1997) 17 industry classification based on SIC codes obtained from CRSP. Our sample consists of 2860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

Industry	2001			2002			2003		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
Automobiles	2	160.88	160.88	22	251.77	212.5	40	220.12	196.75
Chemicals				12	71.51	63.08	47	49.92	44.56
Construction and construction materials				9	138.89	130	41	61.38	60.5
Consumer durables				5	95	64.17	30	86.9	62.95
Drugs, soap, perfumes, tobacco	4	94.28	90.81	13	97.7	98.17	47	114.95	40
Food				14	60.61	54.25	43	45.2	31.67
Machinery and business equipment				42	176	77.5	117	92.1	34.75
Mining and minerals							4	74.06	75
Oil and petroleum products				25	91.49	65	60	60.87	44.13
Retail stores	2	22.38	22.38	41	133.32	80	122	70.27	50.31
Steel works, etc.				3	45.08	48.5	9	92.11	56.5
Textiles, apparel and footware							1	37.25	37.25
Transportation				30	139.1	87.17	97	62.55	43
Utilities				23	236.29	156.67	84	126.07	79.13
Other	8	87.88	88.13	85	255.16	207.5	322	107.3	57.4
All industries	16	90.41	88.75	324	175.36	100	1064	93.04	50.25
	2004			2005			All years		
	N	Mean	Median	*N*	Mean	Median	*N*	Mean	Median
Automobiles	56	143.93	139.96	2	182.6	182.56	122	189.3	179.79
Chemicals	63	34.07	32.5	3	26.06	17.67	125	43.43	36.06
Construction and construction materials	73	43.58	32.83	2	128.2	128.18	125	57.64	45.67
Consumer durables	39	79.22	61.02				74	83.4	62.25
Drugs, soap, perfumes, tobacco	71	90.43	55.75	2	38.83	38.83	137	98.89	66
Food	54	32.81	26.69	5	26.97	19.18	116	40.51	30.28
Machinery and business equipment	171	57.74	29.92	16	51.98	29.22	346	83.45	36.19
Mining and minerals	1	46.5	46.5				5	68.55	71.25
Oil and petroleum products	82	56.6	32.72	1	31.25	31.25	168	63.17	41.77
Retail stores	150	52.54	39.05	1	220	220	316	70.21	46
Steel works, etc.	12	49.43	48.42				24	64.89	50.5
Textiles, apparel and footware	7	39.12	41.03				8	38.89	40.52
Transportation	104	37.71	33.01				231	61.31	41.06
Utilities	131	67.42	47.04				238	104.4	58
Other	405	76.98	45.33	5	76.21	28	825	107.3	56.55
All industries	1419	64.77	39.87	37	64.22	31.44	2860	87.95	48.5

Table 5
Mean and median CDS spreads by S&P credit rating. Our sample consists of 2860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis. The S&P credit ratings were obtained from Compustat. Pluses or minuses associated with the credit rating were removed prior to grouping.

S&P rating		2001	2002	2003	2004	2005	All years
AAA	Mean		67.45	27.33	23.45		34.35
	Median		62.96	17.63	26.17		26.5
	N		4	8	7		19
AA	Mean	22.38	42.36	22.78	18.35	13.5	24.91
	Median	22.38	35.25	20	16.31	13.5	19.88
	N	2	16	31	30	1	80
A	Mean	78.91	94.77	42.48	33.27	26.07	48.77
	Median	84.25	73.42	34	27.36	20	35
	N	7	108	225	231	8	579
BBB	Mean	109.83	208.41	107.02	69.68	78.39	109.22
	Median	90.5	146.88	71.25	54.3	48.61	68.33
	N	3	166	363	390	8	930
BB	Mean		687.27	351.18	190.81	149.71	277.55
	Median		737.5	278.18	173.5	128.18	214.38
	N		11	60	97	4	172
B	Mean			571.07	351.13	271.25	390.55
	Median			530	340	271.25	343.75
	N			7	26	2	35

3.2.2. Market-based variables

Two common market-based approaches to estimating the probability of default are the Merton (1974) distance to default (DTD) measure and the default intensity obtained from the calibration of reduced-form models. We focus on the former distance to default for several reasons. First, as Arora et al. (2005) find, reduced-form models are difficult to calibrate because of the differing quality of bond pricing information on the reference entities. Secondly, the distance to default remains the mostly widely used market-based credit risk metric. Additionally, the distance to default is of particular interest since Hillegeist et al. (2004) find that it outperforms accounting information in the prediction of default.

We numerically solve the standard system of simultaneous equations in equity E and stock volatility σ_e in the Merton model to obtain the firm value V and the volatility of the firm σ_v and calculate the distance to default as

$$DTD = \frac{\log(V/F) + (\mu - \sigma_v^2/2)T}{\sigma_v\sqrt{T}}. \quad (8)$$

The input σ_e is the annualized standard deviation of returns and is estimated from the prior 100 trading days of stock price returns from CRSP. μ is estimated as the annualized mean equity returns on the prior 100 trading days. Similar to Bharath and Shumway (2008), we require that at least 50 trading days be available in the computations. E the market value of equity is computed from

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Table 6
Variable name and description for each firm i at quarter t. Predicted sign in the regression with $log(CS_{it})$ as the dependent variable are included in the table.

Variable	Description	Sign
Accounting variables		
$size_{it}$	Asset/CPI	–
ROA_{it}	Return on asset	–
$incgrowth_{it}$	Income growth	–
c_{1it}	Interest coverage $\in [0,5)$	–
c_{2it}	Interest coverage $\in [5,10)$	–
c_{3it}	Interest coverage $\in [10,20)$	–
c_{4it}	Interest coverage $\in [20,100]$	–
$quick_{it}$	Quick ratio	–
$cash_{it}$	Cash to asset ratio	–
$trade_{it}$	Inventories to cost of goods sold ratio	+
$salesgrowth_{it}$	Sale growth	–
$booklev_{it}$	Total liabilities to total asset	+
$retained_{it}$	Retained earnings to total asset	–
Market-based variables		
DTD_{it}	Distance to default	–
ret_{it}	Annualized prior 100-trading day equity return	–
σret_{it}	Annualized prior 100-trading day equity volatility	–
Macroeconomic variables		
r_t^{3month}	3-Month constant maturity US-Treasury bill rate	–
$indret_{it}$	Prior-year return in the same Fama-French industry	–
$invgrade_{it}$	Equal to 1 if firm is rated above BBB; 0 otherwise	–
$S\&P_t^{-1yr}$	Prior-year S&P returns	–
Contract-specific variables		
$seniority_{it}$	Equal to 1 if underlying debt is senior; 0 otherwise	–
$maturity_{it}$	Maturity of CDS contract (1, 2, 3, 5, 10 years)	+

COMPUSTAT as the number of shares outstanding times the end of quarter closing stock price. Following Vassalou and Xing (2004), we take the face value of debt F to be debt in current liabilities (item 45) plus one-half of long-term debt (item 51). The risk-free rate r is obtained from the Federal Reserve Bank of Saint-Louis.

3.2.3. Macroeconomic variables

We use the risk-free rate r estimated as the 3-month treasury constant maturity rate. This rate is the same across all firms in the same period and therefore also acts as the time dummy variable accounting for the time clustering in the data. We also include the prior year (trailing 12-month) return on the S&P 500, and the prior year return on the Fama and French (1997) industry group that the firm belongs to. Since periods of low interest rates are usually related to economic downturns, we expect a negative relation between the risk-free rate and CDS spreads. Duffee (1998), Collin-Dufresne et al. (2001) and Bharath and Shumway (2008) find a negative relationship between changes in interest rates and changes in default risk. We also expect a negative coefficient on the S&P 500 and industry returns, as low market returns are associated with higher probabilities of default.

Table 7 presents descriptive statistics on our accounting-based and market-based determinants of CDS spreads for the sample firms. In this table, every given firm is represented as many times as CDS spreads are available on that company. Notably, the average firm value V is roughly \$35 billion with a median of approximately \$14.5 billion, suggesting that a few companies have very large firm values, thereby skewing the distribution. The volatility of equity appears to be well distributed around a mean of 28%.

4. Results

Table 8 reports the mean and median CDS spreads for quartiles of the sample sorted on the basis of the firm-level accounting variable of interest. Quartile 1 stands for the lowest values of the variable. We find strong results that suggest accounting-based variables play an important role in explaining CDS spread values.

Table 7
Descriptive statistics. Our sample consists of 2860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which accounting data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis. Accounting ratios are calculated following the Moody's Private Firm model. Total assets/CPI is the deflated value of the firms total assets using the CPI obtained from the Bureau of Labor Statistics. Net income growth is calculated as the trailing four quarter average of net income over assets minus the previous quarter net income over assets. Interest coverage is calculated as the trailing four quarter average of pretax income plus interest expense over interest expense. The quick ratio is calculated as current assets minus inventories over current liabilities. Cash to asset is cash equivalent to total assets. Inventory/COGS is the ratio of inventories to cost of good sold. Sales growth is the trailing four quarter average of the quarterly growth in sales. Liabilities to assets ratio is total liabilities over total assets. The distance to default is calculated by iteratively solving the Merton model described in the text using the firms equity value during the quarter, the previous 100 trading day volatility of equity returns from CRSP, the 3-month constant maturity T-Bill obtained from the Federal Reserve Bank, and the face value of debt computed as current debt plus 1/2 of long-term debt.

Variable	N	Mean	Median	First quartile	Third quartile
Panel A: Accounting ratios					
Size					
Total assets/CPI	2860	232.77	105.48	55.63	203.67
Profitability					
ROA	2860	0.01	0.01	0	0.02
Income growth (1000×)	2860	0.95	0.57	−0.4	1.74
Interest coverage	2860	6.19	3.35	1.64	6.56
Liquidity					
Quick ratio	2593	0.96	0.93	0.69	1.16
Cash to asset	2860	0.07	0.04	0.02	0.09
Trading accounts					
Inventory/COGS	2860	0.65	0.49	0.21	0.79
Sales growth					
Sales growth	2860	0.04	0.03	0.01	0.05
Capital structure					
Liabilities to asset ratio	2860	0.67	0.67	0.57	0.77
Retained earnings to asset	2701	0.18	0.19	0.06	0.31
Panel B: Market-based measures of default					
Distance to default	2860	10.12	10.00	6.99	13.17
Equity volatility	2860	0.28	0.25	0.2	0.34
Volatility of assets	2860	0.25	0.23	0.19	0.31
Equity value	2860	31,938	13,555	6974	31,551
Face value of debt	2860	9615	3211	1571	7305
Firm value	2860	34,697	14,561	7743	35,785

The univariate analysis in Table 8 is complemented by three multivariate empirical models: (i) An accounting-based multivariate model of the determinants of credit spreads, compared in explanatory power to (ii) a model which uses market information and (iii) a comprehensive model which includes both accounting- and market-based information.

4.1. Accounting-based model (model 1)

For each firm i and quarter t we estimate the following least-squares regression where $\log(CS_{it})$ is the natural log of the CDS spread at the end of quarter t for firm i.

$$\begin{aligned}\log(CS_{it}) = {} & \beta_0 + \beta_{1i}Size_{it} + \beta_{2i}ROA_{it} + \beta_{3i}incgrowth_{it} + \beta_{4i}c_{1it} \\ & + \beta_{5i}c_{2it} + \beta_{6i}c_{3it} + \beta_{7i}c_{4it} + \beta_{8i}quick_{it} + \beta_{9i}cash_{it} \\ & + \beta_{10i}trade_{it} + \beta_{11i}salesgrowth_{it} + \beta_{12i}booklev_{it} \\ & + \beta_{13i}retained_{it} + \beta_{14i}r_t^{3month} + \beta_{15i}S\&P_t^{-1yr} \\ & + \beta_{16i}indret_{it} + \beta_{17i}invgrade_{it} + \beta_{18i}maturity_{it} \\ & + \beta_{19i}seniority_{it} + \epsilon_{it}. \end{aligned} \tag{9}$$

Table 8
Spread quartiles. This table presents the mean and median CDS spreads by quartile of firm-characteristic. Only 5-year maturity CDS spreads on senior debt are used in this table. Our sample consists of 2860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis. Accounting ratios are calculated following the Moody's Private Firm model. Total assets/CPI is the deflated value of the firms total assets using the Consumer Price Index obtained from the Bureau of Labor Statistics. Net income growth is calculated as the trailing four quarter average of net income over assets minus the previous quarter net income over assets. Interest coverage is calculated as the trailing four quarter average of pretax income plus interest expense over interest expense. Cash to asset is cash equivalent to total assets. Inventory/COGS is the ratio of inventories to cost of good sold. Sales growth is the trailing four quarter average of the quarterly growth in sales. Liabilities to assets ratio is total liabilities over total assets. Retained earnings/assets is the ratio of retained earnings to total assets. Bold font denotes fourth quartile spreads that are statistically significant from the first quartile at the 5% level.

Variable		Quartile			
		1	2	3	4
Size					
Total assets/CPI	Mean	97.94	131.89	85.19	97.99
	Median	53	71.46	55.38	55
	N	453	454	454	454
Profitability					
ROA	Mean	186.29	105.23	66.21	**55.48**
	Median	135.34	66.02	47.75	31.92
	N	453	454	454	454
Income growth	Mean	113.84	92.91	86.12	120.17
	Median	61.25	52.62	50.25	64.25
	N	453	454	454	454
Interest coverage	Mean	170.92	128.66	69.93	**43.67**
	Median	108.75	82.69	48.28	32.68
	N	453	454	454	454
Liquidity					
Quick ratio	Mean	96.94	99.43	99.45	109.28
	Median	60.17	55.33	49.98	50
	N	417	417	417	417
Cash to asset ratio	Mean	89.38	103.12	108.19	112.3
	Median	56.5	60.56	59.41	48.38
	N	453	454	454	454
Trading accounts					
Inventory/COGS	Mean	119.26	106.47	100.31	**85.38**
	Median	65.71	64.38	50	48.75
	N	447	448	448	447
Sales growth					
Sales growth	Mean	109.77	111.45	94.19	97.63
	Median	63.17	61.08	47.58	58.17
	N	453	454	454	454
Capital structure					
Liability to asset ratio	Mean	63.3	94.89	104.27	**150.49**
	Median	41.25	52.48	66.38	85
	N	453	454	454	454
Retained earnings/asset	Mean	184.91	92.31	76.98	**57.04**
	Median	142.19	57.42	51.58	34.5
	N	430	430	431	430

Table 6 provides a description of the short-hand variable names as well as their predicted signs. Table 9, column 1, presents our findings on this regression model. As a result of missing firm-level data, the number of observations in our model drops to 2242 firm-quarters. We find a negative and statistically significant (at the 1% level) relationship between the book value of size and CDS spreads meaning that larger firms present less risk of credit default. Corroborating our univariate results, we find a strong negative relationship between accounting performance as measured by ROA and CDS spreads. Furthermore, as we hypothesized earlier the relationship between interest coverage and spreads is overall negative and non-linear. When the interest coverage is between 0 and 5 the parameter coefficient is −0.08 and is significant at more than the 1% level of statistical significance. This coefficient decreases to −0.02 when the interest coverage is between 5 and 10 and the level of significance decreases but is still below 5% level of statistical significance. Between 10 and 20 the interest coverage ratio is not significant, whereas beyond 20 the coefficient is negative but very close to zero and significant at the 5% level. The quick ratio which appeared to produce mixed results in the univariate setting is positively related to spreads in the multivariate regression with a coefficient of 0.07, which is significant at the 5% level. This result is somewhat counterintuitive as one would expect a higher quick ratio to be associated with lower spreads. This could be due to two reasons. First, firms with deteriorating credit are less able to finance their current liabilities on longer credit terms, resulting in reducing current liabilities, and an increase in the firm's quick ratio. Second, poorly performing firms will generally face longer terms on sales causing accounts receivables to rise and inventory to fall, again increasing the firm's quick ratio. The fact that the positive relationship no longer remains once market-based variables are included in the model suggest that these latter variables are better indicators of firm performance. The cash to asset ratio and sales growth measure, as in our univariate results, produce no significant association with the CDS spreads.

In the regression we control for macroeconomic factors as we discussed earlier by including the risk-free rate, the prior year S&P 500 returns, and the return on the industry. We find a negative relationship between all three variables and the CDS spreads suggesting that the security is very sensitive to the current macroeconomic environment and, in particular, to stock market conditions. This is consistent with the findings of Duffie et al. (2005). Not surprisingly, we find that investment grade firms have significantly lower spreads. Finally, we control in our model for characteristics of the CDS contract including maturity and whether the underlying debt is senior.

Since our goal is to assess the comparative explanatory power of market-based and accounting-based models, our main focus will remain on the R^2 in the regressions. The explanatory power of our accounting-based model is high and it is able to explain 65% of the variation in our sample of CDS spreads. Overall, the explanatory power of this model, which does not include a single firm-level market variable, compares very favorably to market-based models reported in other studies (e.g. Berndt et al., 2003).

4.2. Market-based model (model 2)

There is accumulating evidence that equity market information may be used to explain credit spreads, as in papers by Collin-Dufresne et al. (2001), Das et al. (2006), Duffie et al. (2005), Zhang et al. (2005), and Bystrom (2005). Therefore, our market-based model contains both firm and market-wide equity variables.

For each firm i and quarter t we estimate the following least-squares regression where $\log(CS_{it})$ is the natural log of the CDS spread at the end of quarter t for firm i:

$$\log(CS_{it}) = \beta_0 + \beta_{1i}DTD_{it} + \beta_{2i}ret_{it} + \beta_{3i}\sigma ret_{it} + \beta_{4i}r_t^{3month} + \beta_{5i}S\&P_t^{-1yr} + \beta_{6i}indret_{it} + \beta_{7i}invgrade_{it} + \beta_{8i}maturity_{it} + \beta_{9i}seniority_{it} + \epsilon_{it}. \tag{10}$$

In Table 9, column 2, we present the results of the preceding regression model where market variables are used to determine CDS spreads. Our main variable of interest in this model is the distance to default (DTD) which is often regarded as a sufficient statistic to

Table 9
OLS regressions of the log of CDS spreads to accounting measures (model 1), market-based measures (model 2) and both (model 3). The sample size is kept constant across models and consists of 2242 quarterly CDS spreads from 2001Q3 to 2005Q1 from Bloomberg on which accounting data for the underlying entity is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms (excluding financial firms). Log of assets is the logarithm of the deflated value of total assets. Net income growth is the trailing four quarter average of net income over assets minus the previous quarter net income over assets. Interest coverage is calculated as the trailing four quarter average of pretax income plus interest expense over interest expense and transformed using the methodology of Blume et al. (1998). The quick ratio is calculated as current assets minus inventories over current liabilities. Cash to assets is cash equivalent to total assets. Inventory/COGS is the ratio of inventories to cost of good sold. Sales growth is the trailing four quarter average of the quarterly growth in sales. Liabilities to assets ratio is total liabilities over total assets. Retained earnings/asset is the ratio of retained earnings to total assets. The distance to default is calculated by iteratively solving the Merton model using the equity value during the quarter, the previous 100 trading day volatility of equity returns from CRSP, the 3-month constant maturity T-Bill obtained from the Federal Reserve Bank, and the face value of debt computed as current debt plus 1/2 of long-term debt. Mean and volatility of equity returns are included separately. The 3-month T-Bill, the previous 12-month value-weighted industry and S&P 500 returns are included as macroeconomic variables. Investment grade dummy is a variable taking on the value of 1 if the bond is rated BBB or above. Maturity is the maturity in years of the CDS contract and seniority is a dummy variable equal to 1 if the underlying bond is senior.

Variables	Log of CDS spread		
	Model 1	Model 2	Model 3
Intercept	5.42***	4.84***	4.86***
	37.89	42.82	31.34
Log of assets	−0.14***	–	−0.13***
	−9.74	–	−9.91
ROA	−8.56***	–	−3.71***
	−7.19	–	−3.36
Income growth	2.17	–	1.74
	1.47	–	1.31
Interest coverage 1	−0.08***	–	−0.07***
	−8.25	–	−8.44
Interest coverage 2	−0.0**	–	−0.01
	−1.98	–	−1.26
Interest coverage 3	0.00	–	0.00
	0.08	–	0.26
Interest coverage 4	0.00**	–	0.00
	−2.3	–	−0.74
Quick ratio	0.07**	–	−0.01
	2.08	–	−0.35
Cash to asset	0.09	–	−0.14
	0.42	–	−0.69
Inventory/COGS	−0.07***	–	−0.05***
	−4.11	–	−3.23
Sale growth	0.04	–	0.26
	0.25	–	1.81
Liabilities to asset ratio	0.70***	–	0.60***
	7.64	–	7.20
Retained earnings/asset	−0.50***	–	−0.50***
	−8.40	–	−9.24
Distance to default	–	−0.08***	−0.04***
	–	−20.93	−9.76
Equity return	–	0.07*	−0.11***
	–	1.95	−3.43
Volatility of equity return	–	0.96***	1.51***
	–	5.94	9.52
3-Month T-Bill rate	−36.18***	−13.77***	−17.85***
	−15.14	−5.38	−7.76
Previous 1-year industry return	−2.39***	−0.58**	−0.62***
	−8.63	−1.97	−2.36
Previous 1-year S&P returns	−1.21***	0.01	−0.12***
	−16.15	0.10	−1.49
Investment grade dummy	−1.06***	−1.19***	−0.89***
	−20.66	−23.69	−19.06
CDS maturity	0.18***	0.20***	0.18***
	23.11	25.57	26.69
Seniority dummy	−0.05	0.07*	−0.01
	−1.34	1.76	−0.36
R^2	64.55%	63.59%	71.69%
Adj. R^2	64.30%	63.45%	71.40%
N	2242	2242	2242

* T-statistics are reported below the coefficients with 10% level of significance.
** T-statistics are reported below the coefficients with 5% level of significance.
*** T-statistics are reported below the coefficients with 1% level of significance.

determine the probability of default. We control for the CDS contract characteristics in the same manner as model 1. Additionally, we include the last 100 trading days average of the equity returns for firm i at quarter t, which we denote in the model as ret_{it}. This

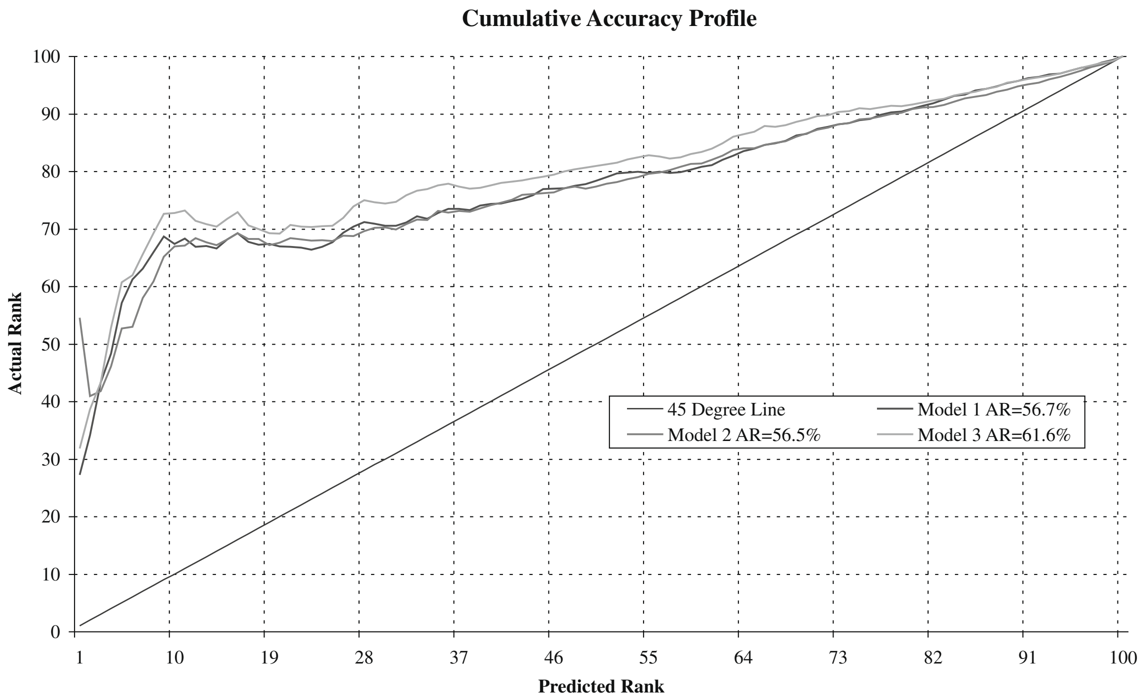

Fig. 1. Cumulative accuracy profile (CAP) and accuracy ratio for spreads models. The cumulative accuracy profile consists in ranking the predicted values of $\log \widehat{CS}_{it}$ (log credit spreads) and the corresponding actual values $\log CS_{it}$ independently from highest to lowest. We then create 100 bins and assign the top 1% of all predicted values to the first bin, the top 2% to the second bin and so on and so forth until the 100th bin is populated which of course would consist of the total number of observations. We then repeat this exercise for the actual values. Once our bins are populated we compare how many predicted values in a given bin also have their actual values in that same bin. We then plot that percentage for each bin; the resulting graphic is the cumulative accuracy profile of our model. The accuracy ratio associated with a given cumulative accuracy profile is defined in the manner of Duffie et al. (2005) as twice the area that lies between the curve and the 45 degree line.

measure is used by Duffie et al. (2005) in combination with distance to default (DTD) to measure firm default intensity.[5]

As expected, we find that the distance to default is strongly negatively related to CDS spreads at more than the 1% level of significance. Overall, we find that the explanatory power of the market-based model is comparable to our accounting-based model with an R^2 of 64% versus 65% in the latter model.

4.3. Comprehensive model (model 3)

We now ask the question as to whether market-based measures of default add any value if they are used in combination with accounting measures by performing the following regression model (which we call "comprehensive"):

$$\begin{aligned}\log(CS_{it}) = {} & \beta_0 + \beta_{1i} Size_{it} + \beta_{2i} ROA_{it} + \beta_{3i} incgrowth_{it} + \beta_{4i} c_{1it} \\ & + \beta_{5i} c_{2it} + \beta_{6i} c_{3it} + \beta_{7i} c_{4it} + \beta_{8i} quick_{it} + \beta_{9i} cash_{it} \\ & + \beta_{10i} trade_{it} + \beta_{11i} salesgrowth_{it} + \beta_{12i} booklev_{it} \\ & + \beta_{13i} retained_{it} + \beta_{14i} DTD_{it} + \beta_{15i} ret_{it} + \beta_{16i} \sigma ret_{it} \\ & + \beta_{17i} r_t^{3month} + \beta_{18i} S\&P_t^{-1yr} + \beta_{19i} indret_{it} \\ & + \beta_{20i} invgrade_{it} + \beta_{21i} maturity_{it} + \beta_{22i} seniority_{it} \\ & + \epsilon_{it}. \end{aligned} \tag{11}$$

The variables that are included in the comprehensive model are simply the union of variables in model 1 and model 2. In this model, we find strong results indicating that market-based information is complementary to firm-level accounting-based data or *vice versa*. Indeed, the variables which constituted the basis of the accounting-based model are still strongly significant with the same signs (except for the quick ratio whose coefficient was pushed down to zero). The previous statement applies equally to the market-based variables which retain their signs and levels of significance except for the prior 100-day firm equity returns which now switches sign to the predicted direction. The explanatory power of the comprehensive model is 72% which is a strong improvement over the previous two models.

Overall these results suggest two things. First, the distance to default may not be a sufficient statistic in modeling the cross-section of credit default swap spreads. Second, accounting variables possess valuable information in determining spreads which is not captured by the traditional market-based measures of default.

4.4. Robustness

In this section, we conduct several robustness checks. First, we estimate the models using only 5-year CDS spread data. The number of observations drops to 1624 but our results are qualitatively unchanged. The accounting-based model R^2 decreases to 62%, the market-based model R^2 decreases to 61%, whereas the comprehensive model R^2 stands at 69%. All coefficients and degrees of significance remain virtually identical.

Second, many studies use the probability of default (defined as $N(-DTD)$), rather than the distance to default. We re-estimate all three models with the full sample of 2242 CDS-quarters and, overall, find weaker results for both the market-based and comprehensive model which under this new specification can explain 50% and 66% of the variance in the logarithm of CDS spreads. We also re-

[5] Rather than use DTD, a volatility adjusted measure of leverage, Carr and Wu (2005) employ option volatility and find this simpler variable also provides high explanatory power for the few firms they examine in their paper; similar ideas permeate the paper by Cossin and Lu (2005). Ericsson et al. (2004) show that a model with leverage and volatility variables can explain over 60% of the levels of CDS spreads. Chen et al. (2005) employ a similar market-based regression as the one above in a four-factor model and find that two interest rate factors, and a credit and liquidity factor are all significant in explaining CDS spreads.

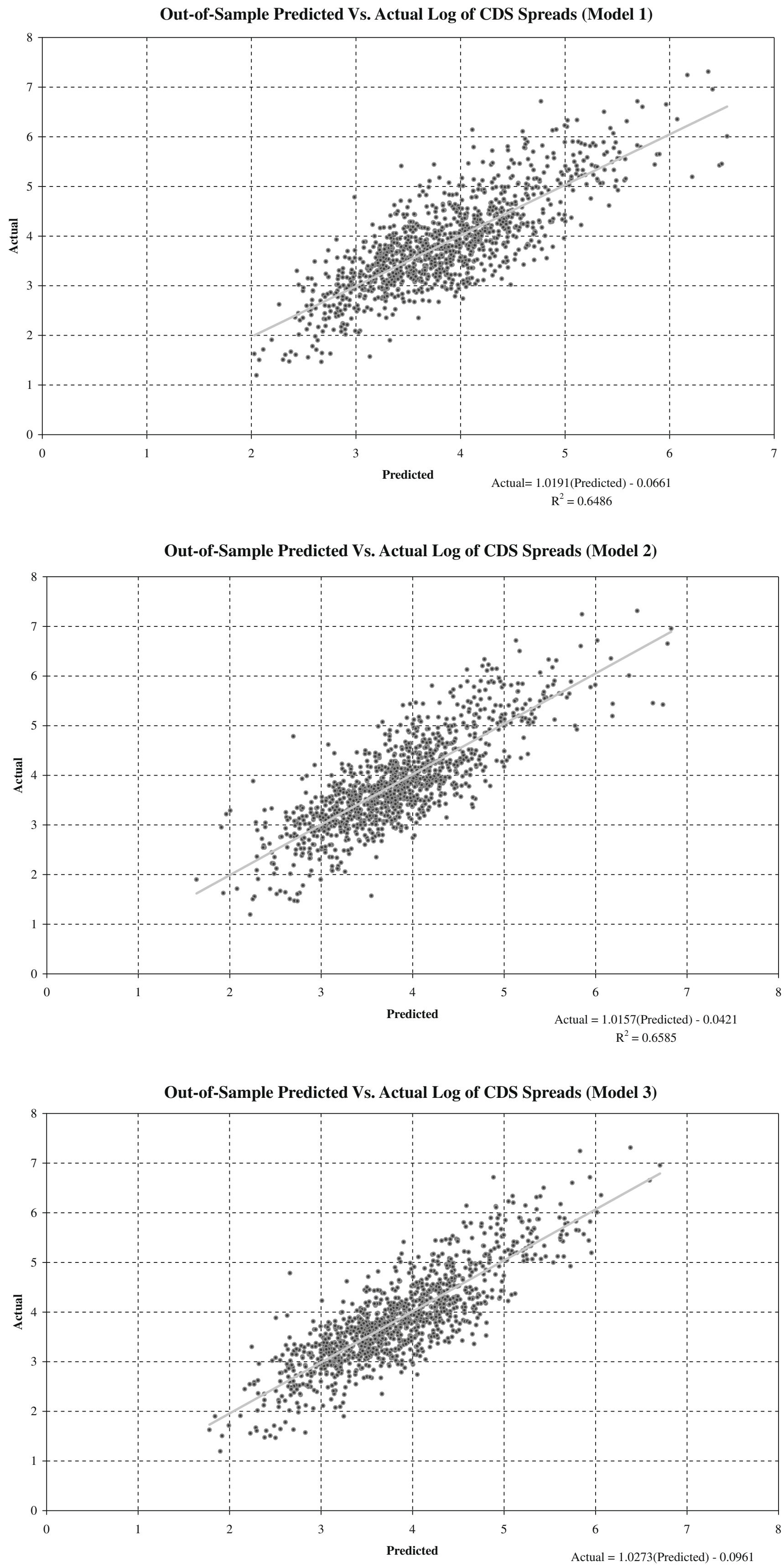

Fig. 2. Regression of actual log of spreads ($\log CS_{it}$) on out-of-sample forecasted log of spreads ($\log \widehat{CS}_{it}$) using the comprehensive model. The pooled sample is randomly split into an in-sample and out-of-sample of approximately the same size. Models 1–3 are estimated in-sample and the parameters are used to forecast out-of-sample predicted values. If the predictive ability of the model is strong regressing actual values on predicted values should yield an intercept close to zero and a slope close to one.

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estimate the market-based model and comprehensive model with the logarithm of the probability of default and find R^2's of 58% and 68%, respectively. Therefore, the models are sensitive to non-linear scaling of distance to default; our results suggest that using distance to default directly provides better results.

Third, we re-estimate the accounting and comprehensive model with only the accounting variables that are significant at the 5% level or higher (not reported). We find that both models do not suffer as a result. The R^2s for the accounting-model and the comprehensive model remain at 65% and 72%, respectively. This suggests that the cash to asset ratio, the sales growth, and income growth identified by Moody's-KMV as important variables in determining credit worthiness are superfluous in a model of CDS spreads.

Fourth, as mentioned previously AAA-rated firms have higher spreads than AA-rated firms and Ericsson et al. (2004) eliminated AAA-rated firms their sample. As a robustness check, we eliminate AAA-rated firms and re-estimate our three models. The results are virtually unchanged.

Fifth, we address the concern that accounting-based data is not actually known at the end of the quarter but is reported at some subsequent time. Sengupta (2004) finds that this delay is on average around 40 days, although it has been widespread over the period for managers to offer earnings guidance prior to the official press release (Noe et al., 1998). This problem is not an issue in uncovering the determinants of CDS spreads *per se* but is relevant in assessing whether some trading strategies are implementable in real-time. To verify this we re-examine all three models using the next quarter CDS spreads as the dependent variable. The findings are that the accounting-based model retains strong explanatory power with an R^2 of 62%.[6] The market-based model fairs relatively worse at explaining the leading spreads with an R^2 of 60% and the comprehensive model is able to retain most of its explanatory power with an R^2 of 69%.

Sixth, we test the out-of-sample performance of our models. We randomly split our pooled sample of CDS spreads into an in-sample and out-of-sample of approximately equal sizes (the in-sample and out-of-sample contain 1124 and 1136 observations, respectively). We then re-estimate all three models in-sample and use the resulting parameters to determine the out-of-sample predicted values. Fig. 2 shows the results of regressions of actual versus predicted values for all three models. Models 1 and 2 have R^2s of 65–67% range, respectively. The coefficients on both models are statistically no different than one and the intercepts are statistically no different than zero. An *F*-test of the joint hypothesis that the slope is equal to one and the intercept is zero fails to be rejected at any conventional level of significance. For model 3 the fit is much stronger with an R^2 of 71% and the joint hypothesis that the slope is one and the intercept is zero also fails to be rejected.

Finally, we use the panel feature of our data to perform a CDS contract and time fixed-effects regression. Fixed-effects regressions have the advantage that they eliminate any unobserved effects which might be correlated with the explanatory variables. However, the disadvantage of fixed-effects regressions is that they cannot be used for the purpose of prediction and will sometimes interact with existing variables resulting in sign reversals.[7] The R^2s are higher for all three models with the inclusion of CDS and time fixed-effects. The purely accounting model has an R^2 of 92.25% which is now slightly lower but still comparable to the purely market-based model with an R^2 of 92.45%. The comprehensive model explains 93.10% of the variation in spreads. Accounting variables remain statistically significant even after the inclusion of fixed-effects. Overall, including time and firm fixed-effects does not change the relative performance of market-based and accounting-based models.

[6] Table not reported, results available on request.

[7] The results are summarized here, and the tabulated results are available on request.

4.5. Rank-order predictability

Predicting the relative ranking of CDS spreads rather than their point estimates is of central interest to hedge fund managers and CDS traders. Relative trading strategies consist in selling a CDS whose credit quality is expected to improve *relative to another company* whose CDS is being bought. Therefore we investigate how the accounting-based model compares to the market-based model in terms of relative rankings of CDS spreads by constructing cumulative accuracy profile (CAP) curves and the associated accuracy ratio (AR) statistics.

Fig. 1 presents the cumulative accuracy profile for all three models and their corresponding accuracy ratios. The accuracy ratio is 61.6% for our comprehensive model, 56.7% for our accounting-based model and 56.5% for the market-based model. These results suggest that the relative rankings of CDS spreads are more difficult to model than actual default events where Duffie et al. (2005) find accuracy ratios of 88% based on the distance to default measure and economy-wide level data. Hamilton and Cantor (2004) find accuracy ratios of 65% based on Moody's Credit Ratings. Also, Blochwitz et al. (2000) find accuracy ratios of 59.7% for the KMV Private Firm Model. Credit spreads may also contain other elements like liquidity and tax effects, though our use of CDS spreads is an attempt to mitigate the influence of such factors. Also, CDS spreads contain default risk premia, which are harder to rank and explain. Out-of-sample cap curves result in the same accuracy levels as those in-sample. There appears to be little loss of power in our out-of-sample predictions. This result supports the robust cross-sectional fit of the model.

5. Conclusion

Credit default swaps are derivatives that offer protection against firms defaulting on their debt obligations. CDS spreads provide a reliable measure of default risk as they are the compensation that market participants require for bearing that risk. Using a large sample of 2860 CDS spreads, we find that models using accounting data explain CDS spreads at least as well as structural models that make use of market data. This finding is robust to different specifications and holds out-of-sample. In addition, accounting data has an advantage over market data since it can be used to quantify credit risks for firms that do not have traded equity or are infrequently traded. Finally, models that make use of both sources of information, accounting and market-based, explain a substantially larger proportion of CDS spreads. We conclude that rather than viewing accounting and market information as substitutes, they should be viewed as complementary in the prediction of default.

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