What Accounts for Time Variation in the Price of Default Risk?*

Ronald W. Anderson†

May 2008. This version August 2008

Abstract

We study the market for credit default swaps (CDS) between 2003 and 2008 in order to understand origins of the well documented tendency for credit spreads on diverse issues to periodically undergo large, common adjustments in the same direction and of similar magnitudes. Our methodology allows us to distinguish co-movements that reflect common revisions in the statistical default distribution from common factors driving time variation in the market price of default risk. We estimate the *risk neutral* default distribution using a latent variable model which assumes that defaults on a name follow a jump process where the log intensity of arrivals of defaults itself follows an Ornstein-Uhlenbeck process. Estimates of this model are used to find the implied times series of the risk neutral default intensity for each firm. A principal components analysis suggests that a very high fraction of time variations in the implied default intensities of diverse firms is explained by a single common factor. We then combine these estimates with estimates of the *statistical* default process based on a hazard model in order compute the implied market price of default risk. We show that a relatively high fraction of the observed variation of this market price of default risk can be accounted for by a linear model of the market price of default risk using as observed covariates macro indicators, firm indicators and indicators of equity market and credit market conditions. Our estimates show a strong association between that credit market conditions and the market price of risk. The estimated coefficients have the correct signs. Overall, our results provide some evidence of the partial segmentation of credit markets.

** Preliminary and incomplete. Please do not circulate. Comments welcome*

†London School of Economics and CEPR. r.w.anderson@lse.ac.uk. I would like to thank Poornima Sankar, Xiao Wang and Ping Zhou for research assistance. This research has been supported by the EPSRC Grant No. EPRC522958/1, "Integrating Historical Data and Market Expectations in Risk Assessment for Financial Institutions". I have benefitted from comments by Aneel Keswani, K.G. Lim, Yves Nosbusch and participants at the FMG workshop on "Integrating Historical and Expectations Data in Financial Econometrics". Responsibility for all views expressed and all errors is my own.

What Accounts for Time Variation in the Price of Default Risk?

1 Introduction

In this paper we study the pricing of credit risk as reflected in the market for credit default swaps (CDS) between 2003 and 2008. Our focus is on the well documented common co-movement of yield spreads for a wide range of names in various sectors and of different credit quality. This common factor in credit spreads could be the reflection of changes in the expected credit losses. For example, Yu (2002) presents evidence that suggests that major changes in yield spreads anticipate major changes in realized default rates by approximately one year. However, in his sample some significant increases in default rates were not anticipated by an earlier increase in yield spreads (e.g., in early 1996). In other cases, major yield spread changes are not followed by any large change in default rates. These may be cases of forecasting mistakes. Or they may be the consequence of yield spreads being driven by other factors than expected credit losses alone.

An important possible explanation is that generalized credit spread changes reflect changes in the compensation that the market requires for bearing credit risk. Indeed the view that credit spread changes are driven by changes in risk appetites is widespread among practitioners and policy makers. For example, the sharp increase in credit spreads in the summer of 2007 was described by some central bankers as a consequence of the market correcting a widespread mispricing of credit risk in 2004-2006.[1] However, yield spreads also reflect a compensation for the relatively high degree of illiquidity faced by holders of defaultable securities. Changes in market liquidity over time might account for some of the changes in observed changes in yield spreads.

In an important earlier study of yield spreads on corporate bonds Collin-Dufresne, Goldstein and Martin (CGR) show that in disagreement with the predictions of structural credit risk models, changes in a firm's value (as reflected in equity prices) account for only a small fraction of changes in observed yield spreads on the firm's liabilities. In contrast, a large

[1]For example Ben Bernanke assessed the origins of the market turmoil of 2007 in the following terms. "Although subprime mortgages were the most obvious example, the loosening of credit standards and terms occurred more broadly, reflecting a general boom in credit markets that peaked and then reversed last summer. This boom was characterized by a general erosion of market discipline, underpricing of risk, and insufficient attention by investors to the quality or riskiness of the instruments they purchased." (Bernanke 2008). A similar assessment was expressed by the Financial Stability Forum (2008) and the Bank of England (2007).

fraction of yield changes on a wide spectrum of issues appears to follow movements in some common factor. Regressions using observations of a variety of macro and financial proxies leave a large fraction of these common movements unexplained.

These results motivate the use of latent variable models in much of the empirical literature on credit spreads. For example, using Kalman filter techniques applied to individual corporate bonds Duffee (1999) estimates a reduced form model in which the intensity of default follows a mean-reverting square root process and shows that the model produces reasonable parameter estimates and relatively good fits.[2] Generally, these applications employ observations of prices on traded instruments *for which no default has occurred.* Also, these applications attempt to estimate parameters which determine the dynamics of the market price of default risk.

Given the comments above about the distinguishing changes in yields driven by changes in expected credit losses from those driven by changes in the price of bearing a given risk, it may be surprising that estimates based on prices or yields alone can identify a market price of default risk. To understand this issue, it is important to distinguish two aspects of credit risk borne by an investor holding a security over a period of time. First, there is the risk that a default will occur over this holding period. Second, there is the risk of a change in the probability of a future default which will lead to a change of value of the security in the secondary market. The former type of risk has come to be known has the "jump to default" risk; whereas, the latter is denoted "mark to market" risk. In general, with risk averse investors, the expected return on a defaultable security reflect some compensation required by investors for bearing each type of risk. In estimating reduced form models from market prices alone, a market price of default risk is typically identified by assuming that the market price of risk associated with the change of measure from the statistical default distribution to the risk neutral default distribution is an affine function of the intensity (or log intensity) under the risk neutral measure (see, e.g., Pan and Singleton (2007)). Now as has been emphasized by Jarrow, Lando and Yu (2005) and Yu (2001), the market price of default risk estimated in this way captures only the "mark to market" component of default risk. To estimate a jump risk premium as well as a mark to market risk premium, it is necessary to draw upon information on actual defaults. Estimates based only on prices of securities that have not defaulted suffer from a bias akin to survivorship bias encountered in the analysis of equity returns.

Driessen (2005) attempts to overcome this difficulty in his estimates of a reduced form model using observations on corporate bonds between 1991 and 2000. He finds that liquidity measures and taxes important in explaining *cross sectional* patterns of credit spreads. To identify the market price of credit event (jump) risk, he employs Standard and Poors and

[2]Other examples of estimates of reduced form models include applications to interest rate swaps (Duffie and Singleton (1999)), sovereign bond issues (Pan and Singleton (1997)). See Duffie and Singleton (2003) for a general introduction to reduced form credit risk modeling.

Moody's historical default frequencies to infer the intensity of default under the statistical measure. He then estimates the market price of jump risk as the ratio of the risk neutral default intensity to the statistical default intensity, which he assumes to be a constant parameter, μ. In his benchmark model he find $\mu = 2.3$, implying a large market price of default risk. This large risk premium associated with what might be expected to be a diversifiable risk is a surprising finding. While the standard errors of Driessen's estimates are rather large, using a variety of alternative samples the estimated values of this jump risk premium are systematically greater than 1 and are frequently quite large. The apparently large risk premium paid for bearing jump risk has been the subject of a series of further analyses using different data and different methodologies (Berndt *et al.* (2005), Berndt and Obreja (2007) and Saita (2006)). Generally, the estimates confirm that the jump risk premia are very large, in stark contrast with what might be expected intuitively or what had been assumed in earlier applications of reduced form models (as discussed by Jarrow et al (2005)). This has led Berndt et al to suggest that large jump risk premia may be the consequence of financial market segmentation. We will comment on this literature when discussing our own findings below.

Driessen's methodology has clear limitations in relation to our primary interest on the time variation in the price of credit risk bearing. Since Driessen *assumes* a constant market price of default event risk, by design he cannot consider how this price may evolve over time. Furthermore, the use of bond ratings and historical default frequencies to proxy for the statistical default distribution has an important weakness if we are interested in changes in the market price of default risk over time. Specifically, it is well-documented that ratings exhibit a high degree of inertia and are not necessarily good estimates of the probability of default at a given point of time. As a consequence, an increase in credit spread might be due to increased probability of default (under physical measure) but not captured in the current rating. This change might be mistakenly ascribed to a change in risk tolerance. For this reason, to capture time changes in the pricing of default risk it would be good to have more direct estimates of the physical default distribution as discussed by Yu (2001). This is precisely the approach that we have taken.

Another possible weakness of Driessen, Duffee and other studies that have based estimates on yields spreads on corporate bonds is that these spreads will reflect a composite of compensation for market illiquidity and tax effects as well as a credit risk premium. For example, it might be that part of the large estimated jump risk premium obtained by Driessen could derive from weaknesses in the proxies that he uses to control for liquidity and taxes. For this reason, the growth of the CDS market is an important development for the study of credit risk because these homogenous derivatives contracts are typically much more liquid than the underlying bond contracts and because tax effects should be absent in their pricing.[3]

[3]See, Blanco et al (2005) for a discussion of relation of the CDS and corporate bond markets and for

Berndt et al (2005), Berndt and Obreja (2007) and Saita (2006) all use data from the CDS market to estimate reduced form models and use estimates of the statistical default distribution to identify the premium associated with jump to default risk. As estimates of the statistical default distribution, Berndt *et al.* and Berndt and Obreja employ the Moodys-KMV EDF (expected default frequency) for specific names. One possible criticism of this approach is that EDF's are based on a proprietary methodology which therefore cannot be subjected to independent validation. A more important weakness for our purposes is that movements over time of EDF will be driven in large part by changes in the firm's equity prices. As a result they may not be good representations of the changes in the firm's statistical default distribution. In particular, general descriptions of the Moodys-KMV make clear that the EDF is calculated as a non-parametric (and proprietary) function of the distance to default which was introduced in Merton (1974) (see, Crouhy, Galai and Mark (2001) for a discussion). Distance to default in turn is the difference between an estimate of firm value and the value of firm liabilities expressed in units of the volatility of firm value. Given the inertia in estimating the value of debt and of volatility, changes of this measure are dominated by changes in equity. Since the value of equity is also a forward-looking measure which will reflect the market's current price of risk bearing, changes in EDF may not simply reflect changes in the physical default distribution. Thus EDF based estimates of jump risk premium may suffer from an opposite bias from that of ratings based estimates. For example, an increase in CDS spreads that was driven by an increase in the price of jump risk that was positively correlated with an increase in the risk premium on equity may be improperly attributed to an increase in the statistical default probability because the fall in equity price will drive EDF's higher.

To overcome these possible problems, we derive statistical default intensities from estimates of hazard functions based on a large panel of firms including a significant number default observations.[4] A further difference with previous studies is we use data from a later time period which included the significant reversal in credit markets which took place in 2007. However, beyond these differences in methodology and data coverage, the main difference in our study as compared to Driessen, Berndt *et al.*, Berndt and Obreja and Saita is that we study the time series properties of our estimates of the market price of default event risk and identify observable proxies which have significant explanatory power in accounting for changes in this market price.

Our estimates show that the determinants of the market price of default event risk exhibit important differences across different sectors. However, there is a strong, general association between credit market conditions (as measured by indices of quality of banks' loan books) and the market price of default risk. This supports the argument of Adrian and Shin (2008)

evidence that CDS prices tend to lead bond prices. Descriptions of the development of the default swap market can be found in Duffie (BIS 2007) and Anderson and McKay (2008)

[4]For recent examples of estimates of the default distribution derived from credit histories see Shumway (2001), Campbell and Hilscher (2005), and Duffie, Saita, and Wang (2005).

that changes in aggregate balance sheets of intermediaries forecast changes in risk appetite. Our findings are robust across a variety of alternative proxies for credit market conditions and across sectors. In contrast equity market risk factors and general business conditions do not always have coefficient estimates of the right sign and are not always significant. However, there is some evidence that changes in the value firm premium are partially correlated with changes in the pricing of default risk. Overall, our results provide evidence of the partial segmentation of credit markets in line with the conjecture of Berndt *et al.*

The remainder of the paper is organized as follows. In section 2 we introduce our panel data set of CDS prices and provide some statistical characterizations of yield spread changes. In section 3 we present the latent variable model for CDS pricing, discuss estimation methodology and report parameter estimates. We study the time series behavior of risk neutral default intensities implied by our estimates derived from CDS spreads. In section 4 we combine risk neutral intensities with estimates of the statistical default intensities derived from a hazard model to obtain the implied market prices of default event risk. We use panel data methods to explore observable proxies that may account for changes in the market price of default event risk and consider the robustness of our findings by exploring some alternative estimations techniques including ratings based measures of statistical default intensities. Section 5 summarizes our conclusions.

2 Statistical Analysis of CDS Pricing

2.1 Data

Our CDS price data cover firms with 1, 3 and 5-year CDS contracts reported on a daily basis on Datastream between September 2003 and through January 2008. To facilitate comparison we have drawn our sample from two sectors, energy and media, from North America and Europe. Overall we have 41 firms across four subsamples allowing us to make two-way comparisons (across sectors and regions). For North American firms we have taken CDS contracts denominated in US dollars. For European firms the contracts are quoted in euros or pounds sterling. We summarize some results by rating category. Following market convention we assign rating to a name based on the rating of its senior, unsecured bonds or notes with two or more years to maturity. The source of most of our ratings data is the Mergent Fixed Income Data set. In a few cases we supplemented this with firm rating information obtained from the Standard and Poors website.

TABLE I Summary Statistics (prices in basis points)

Firm	Mean CDS Spread	Std Dev of Spread	Rating
North American Energy Sector			
ANADARKO PETROLEUM	34.01	7.84	BBB
APACHE	23.94	4.43	A
CHEVRON	11.44	3.73	AA
CONOCOPHILLIPS	22.45	5.48	A
DEVON ENERGY	36.17	12.52	BBB
EXXON MOBIL	7.23	3.19	AAA
MARATHON	31.84	8.69	BBB
MASSEY ENERGY	255.99	101.69	B
NEWFIELD EXPLORATION	128.14	49.66	BB
OCCIDENTAL PETROLEUM	26.01	7.20	A
PEABODY ENERGY	131.69	38.24	BB
PIONEER NATURAL RESOURCES	110.81	46.40	BB
SUNOCO	40.87	8.44	BBB
WILLIAMS COMPANIES	161.00	63.26	BB
XTO ENERGY	50.37	23.52	BBB
North American Media Sector			
BELO CORP	88.22	36.35	BBB
CHARTER COM	897.04	653.47	CCC
COMCAST	46.76	18.05	BBB
GANNETT	39.32	15.55	A
INTERPUBLIC	222.68	85.30	B
OMNICOM	31.39	11.92	A
TIME WARNER	51.11	16.78	BBB
VIACOM	49.96	15.28	BBB
WALT DISNEY	31.57	15.75	A
European Energy Sector			
BP	10.43	11.70	AA
ENI	13.31	12.09	AA
REPSOL	42.99	25.34	BB
SHELL	12.73	11.27	AA
STATOIL	15.15	10.83	AA
TECHNIP	34.98	24.92	BBB
TOTAL	13.22	11.29	AA
European Media Sector			
BSKYB	43.27	16.60	BBB
PEARSON	45.21	15.36	BBB
PROSIEBENSAT	176.96	122.48	BBB
PUBLICIS	52.04	27.00	BBB
REUTERS	26.55	8.64	A
SES	45.80	21.30	BBB
THOMSON	89.17	88.72	A
VIVENDI	54.84	21.43	A
WOLTERS	48.50	17.06	BBB
WPP	41.86	25.32	BBB

The firms included in our study as well as the rating (in July 2006), the mean and the standard deviation of the 5-year CDS spread are listed in Table I. It will be observed that our data set spans quite a wide range of firms with mean spreads going from a minimum of 7.23 basis points for AAA-rated Exxon-Mobil to 897 basis points for C-rated Charter Communications. Broadly speaking spreads are higher for media firms than energy firms. And spreads are higher for North American firms than European firms.

Within the sample there is a preponderance of BBB-rated names with A-rated and BB-rated names also being quite common. By and large, spreads are lower for more highly rated names as would be expected. However, there are a few exceptions to this. The differences of spreads across industrial sectors are apparent even after we control for rating. Table II reports the mean spread between September 2005 and August 2007 on the 5-year CDS's by ratings categories and for our four sub-samples. For the A and BBB category that represents a large fraction of our sample, we see that both in North America and in Europe media firms carry a higher spread than do energy firms within the same rating category.

TABLE II Mean CDS Spreads
(basis points)

Rating	NA Energy	NA Media	EU Energy	EU Media
AAA	5.12	*	*	*
AA	9.36	*	8.18	*
A	21.25	29.41	8.45	46.93
BBB	35.37	55.45	29.60	54.76
BB	114.80	*	30.58	*
B	313.30	179.92	*	*
C	*	895.23	*	*

As a control for possible common effects in time variation of CDS spreads we also use indices of spreads on large industrial firms. For North America we have constructed an index of Blue Chip CDS spreads from individual quotes for firms included in the Standard and Poors 500 equity index which had 5-year CDS's quotes available on Datastream for the period September 2003 through end of August 2007. In all 62 firms were included. The CDS index was calculated as the arithmetic average of the quoted spreads. Among the 15 energy companies the only ExxonMobil was also included in the calculation of the CDS index. Three of the North American media firms (Time Warner, Walt Disney and Viacom) appeared in the index as well. For European Firms we use a chained series from constructed from iTraxx 5-year, on-the-run spreads.

2.2 Linear Regressions

As noted in the introduction, previous analysis of corporate bond pricing has established that changes in yields on a firm's bond are only weakly related to the changes in firm value (as measured by equity changes) but strongly affected by a common factor that appears to drive a wide range of bonds. As an initial attempt to see if a similar pattern holds in CDS pricing we apply a regression model to balanced panels for our four subsamples. In particular, we consider the model,

$$\Delta lnCDS_{it}^{5} = \alpha_i + \beta \Delta lnS_{i,t} + \gamma \Delta lnIndxCDS_t^5 \tag{1}$$

where for firm i, $\Delta lnCDS_{i,t}^{5}$ is the weekly change of the logarithm of the spread on firm's 5-year CDS, $\Delta lnS_{i,t}$ is the corresponding log change of the firm's equity price and $\Delta lnIndxCDS_t^5$ is the log change of the index of CDS quotes. This specification allows us to control for a variety of sources of cross-sectional variation through the uses of firm effects (either fixed or random).

The results are reported in Table III. The results for the pooled least squares regression ($\alpha_i = \alpha$ for all i) for North American energy firms are given in the first column of Table III top panel. These result are very much in line with the results of previous work on corporate bond yields (CGR). That is, the movements of the firm's CDS spreads are negatively related to changes in the firm's equity price as theory predicts; however, the relation is weak and only marginally statistically significant. In contrast, the energy firm's CDS spreads are strongly related to an index of CDS spreads for very large liquid firms drawn from all industries. And this common factor is highly statistically significant.

Also for North American energy firms columns 2 and 3 of Table III report results for the same linear model using panel data methods for firm groups. The results using either fixed effects or random effects are virtually the same as those obtained in the pooled regressions. Columns 4 and 5 give results of panel methods allowing for first order serial correlation of errors. The coefficient estimates of the regressors are very similar to those obtained previously. It is noted however that the autocorrelation coefficient of the errors is -0.27 which is suggestive of some mean reversion of unobserved factors.

TABLE III Linear Model Estimates:
Dependent Variable, Weekly Change of log of CDS spread

(p-values in parentheses)

North American Energy Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	-.1135	-.1129	-.1135	-.1163	-.1186
	(0.084)	(0.087)	(0.084)	(0.093)	(0.085)
$\Delta lnIndxCDS5_t$	.6930	.6931	.6930	.6945	.6943
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	-.0002	-.0002	-.0002	-.0001	-.0001
	(0.875)	(0.875)	(0.875)	(0.944)	(0.935)
ρ				-.2738	-.2738
R-squared	0.0416	0.0416	0.0416	0.0416	0.0416
Number of obs	3120	3120	3120	3120	3120
North American Media Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	.0168	0.0200	0.0168	0.0318	0.0278
	(0.832)	(0.802)	(0.832)	(0.692)	(0.727)
$\Delta lnIndxCDS5_t$	0.846	0.8470	.8465	0.8503	0.8468
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	.00012	0.0001	.0001	0.0001	0.0001
	(0.925)	(0.925)	(0.925)	(0.965)	(0.926)
ρ				-.098	-.0938
R-squared	0.1124	0.1124	0.1124	0.1124	0.1124
Number of obs	2052	2052	2052	2052	2052
European Energy Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	-0.0425	-0.0416	-0.0425	-0.0598	-0.0613
	(0.654)	(0.662)	(0.654)	(0.541)	(0.530)
$\Delta lnIndxCDS5_t$	0.5463	0.5463	0.5463	0.4977	0.4994
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.0028	0.0028	0.0028	0.0022	0.0029
	(0.049)	(0.049)	(0.049)	(0.135)	(0.114)
ρ				-0.187	-0.187
R-squared	0.2428	0.2428	0.2428	0.2428	0.2428
Number of obs	931	931	931	931	931
European Media Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	-0.2961	-0.2896	-0.2961	-0.3058	-0.3090
	(.0014)	(0.000)	(0.000)	(0.000)	(0.530)
$\Delta lnIndxCDS5_t$	0.5659	0.5667	0.5659	0.5528	0.5521
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.0014	0.0014	0.0014	0.0012	0.0014
	(0.087)	(0.088)	(0.087)	(0.131)	(0.114)
ρ				-0.0965	-0.0966
R-squared	0.3786	0.3786	0.3786	0.3786	0.3786
Number of obs	1680	1680	1680	1680	1680

The results for North American Media firms are given in Panel 2 of Table III. Again, there is a strong, highly significant positive relation with movements of the general index of CDS spreads, and this is consistent across alternative estimation methods. In this case, the estimated relation to equity changes is positive rather than negative as predicted by theory, but it is statistically insignificant. Again, when we allow for autocorrelation of the residuals of a given firm, the estimated coefficient is negative suggesting possible mean reversion of unobserved factors.

In panels 3 and 4 of the Table the results for European firms by and large exhibit a similar pattern. There is a strong, significant and robust positive relation to changes in the broad CDS index. There is evidence of negative autocorrelation of residuals. The only slight surprise is that for European media firms the coefficient on changes in the firm's own equity is significant and negative. This suggests some hope that traditional structural models of credit risk might find some scope for application in that sector.

These results give strong evidence of the importance of some common factor driving changes of CDS spreads over time. The use of a broad CDS index to control for this is imperfect for two reasons. First there is some overlap of coverage between our subsamples and the universe of firms used to construct the index. Second, we have seen some evidence of omitted factors. In order, to examine these matters further in the next section we introduce explicitly a latent variable model of CDS pricing which will allow us to characterize the common factor across firms without imposing that this coincide with any particular reported index.

3 The Market Implied Default Intensity

3.1 A Latent Variable Model of CDS Pricing

As discussed in section 2, it is likely that not all the systematic determinants of CDS prices can be readily represented with empirically observed proxy variables. For this reason we wish to explore models that capture unobserved risk factors as latent variables. In credit risk modelling the most widely used class of models of this sort are reduced form models which treat the default event as a continuous time stochastic process.[5] In particular, following Saita and Berndt et.al. we assume that the default for a given name i arrives with a default intensity that is independent of the instantaneous risk-free rate. We indicate this intensity at time t under the risk-neutral process as $\lambda_i^Q(t)$. Then at time t the probability p_{it}^T that firm i will not default prior to some date T in the future is given by,

$$p_{it}^T = E^Q[e^{-\int_t^T \lambda_i^Q(s)ds}] \tag{2}$$

[5]See Duffie and Singleton chapter 5 for an introduction to reduced from models and chapter 8 for their application to CDS pricing.

Thus for example, the value d_{it}^T at time t of a promise by firm i to pay \$1 at time T assuming loss given default of 100% is, $d_{it}^T = e^{-r(T-t)} p_{it}^T$ where r is assumed to be the constant risk-free rate.

There is no firmly established empirical evidence on the behavior of latent default risk factor $\lambda_i^Q(t)$. The regression results of the previous section gave some evidence of mean reversion. This is consistent with the stochastic process adopted by Saita, namely that the log of the default intensity follows an Ornstein-Uhlenbeck process.[6] Setting $X_t^i = ln\lambda_i^Q(s)$, we assume,

$$dX_t^i = k_q^i(\theta_q^i - X_t^i)dt + \sigma^i dZ_t^{iq}, \tag{3}$$

where dZ_t^{iq} is a Brownian motion under the risk-neutral process.

3.2 Estimation

We will estimate the parameters of the risk-neutral process k_q^i, θ_q^i and σ^i from observations of the spreads of CDS's written on firm i. The estimating equation can be developed from CDS pricing relations as follows. Under the CDS the protection seller will receive a periodic payment of C at regular intervals until date T in the future or until default if this occurs prior to T. From date t suppose there are n payment dates $t(j)$ until $T = t(n)$. Then the value of the cash flows to the protection seller are, $C\Sigma_j^n d_{it}^{t(j)}$. The protection buyer will receive compensation for the loss of value on a bond issued by firm i incurred at default at some stochastic time τ in the future. Let the loss given default (LGD) be given as L, a possibly random amount that will be paid at the time of default. Thus the value of cash flows to the protection buyer is $E_t^Q e^{-r(\tau-t)}L$. The fair value of the CDS spread at any given time is the C which just equates the value of cash flows of the protection seller and the protection buyer. That is, it satisfies,

$$C\Sigma_j^n d_{it}^{t(j)} = E_t^Q e^{-r(\tau-t)}L \tag{4}$$

Let the spread that solves this pricing equation be written as $f(t, T, k_q^i, \theta_q^i, \sigma^i, \lambda_q^i(t))$. Note that in this expression we explicitly take into account that at time t all expectations are conditional upon the current value of the default intensity $\lambda_q^i(t)$. In the results reported below we have treated LGD as constant parameter and have set $L = 0.5$, approximately the result reported by Altman and Kishore (1996) for senior, unsecured debt.[7]

The parameters k_q^i, θ_q^i, and σ^i are estimated assuming that observed quotes on CDS spreads deviate from theoretical spreads by an additive normal error. Specifically for firm i

[6] Berndt *et al* p.24 also adopt the O-U process as part of a somewhat more complicated specification for the log default intensity.

[7] The results of Houwelling and Vorst (2003) suggest that valuation of CDS are relatively insensitive to changes of LGD within the range $(0.4, 0.6)$ which encompasses most empirical estimates.

we obtain a panel of observations on 1, 3 and 5-year CDS at discrete times $t = 1, M$. Let these quoted spreads be indicated as CDS_{it}^{T} for $T \in 1, 3, 5$. Then our statistical model is,

$$\begin{aligned} CDS_{it}^{T} = f(t, T, k_q^i, \theta_q^i, \sigma^i, \lambda_q^i(t)) + u_{it}^{T} \\ T \in 1, 3, 5 \\ t = 1, M \end{aligned} \tag{5}$$

We estimate this model using an iterative simulated quasi-maximum likelihood procedure very similar to that employed by Saita. Specifically, each iteration proceeds as follows:

1. *Given* values of the parameters k_q^i, θ_q^i, and σ^i we obtain a time series of implied default intensities $\lambda_q^i(t)$ by solving equation (5) for $T = 5$ assuming assuming $u_{it}^5 = 0$ for $t = 1, M$.

2. *Given* the time series $\lambda_q^i(t)$ for $t = 1, M$ choose k_q^i, θ_q^i, to minimize the sum of squared residuals $\Sigma_{T \in 1,3} \Sigma_{t=1}^{M} [CDS_{it}^{T} - f(t, T, k_q^i, \theta_q^i, \sigma^i, \lambda_q^i(t))]^2$.

The procedure is continued until convergence is obtained. The assumption that the theoretical model prices the 5-year CDS exactly is admittedly a bit arbitrary, but it is in line with market practice where the 5-year issue is often the most liquid, benchmark issue. Notice that a by-product of the procedure is an estimate of the time series of instantaneous default intensities, $\lambda_q^i(t)$ for $t = 1, M$. Implementation of this procedure is carried out by numerical integration to calculate the expectations in equation(4) and by simulating a discretized version of equation (3). More details on the appropriate numerical procedures are provided in Saita and in Berndt *et al.*

This procedure was applied to the 41 firms listed in Table I. Samples consisted of weekly observations between September 2003 and January 2008.[8] Note that the method was applied for each firm separately with no restrictions imposed across equations. In principle, it might be interesting to explore cross-equation restrictions on the parameters; however, in practice this would be difficult. Indeed, given the large number of Monte Carlo simulations involved in each separate function evaluation, the computations of estimates for the 41 firms separately was already very computer intensive. Systems estimation which would impose some cross equations restrictions while allowing for some firm specific effects would have increased the dimensionality of the optimization considerably.

The parameter estimates obtained for the four subsamples of firms are listed in Table IV.

[8] Not all 41 firms are quoted for this entire period. For reasons of data availability and in order to construct balanced panels for use in subsequent analysis, the periods covered are as follows: N.A. Energy, 11/9/03-29/8/07; N.A. Media, 27/08/03-26/12/07; EU Energy, 14/9/05-26/03/08; and EU Media, 12/1/05-26/3/08. Note that the European CDS's generally became available somewhat later than the North American CDS's.

TABLE IV Latent Variable Parameter Estimates

Firm	σ^i	k_q^i	θ_q^i
North American Energy Sector			
ANADARKO PETROLEUM	1.109	0.0097	-5.9739
APACHE	1.6821	0.3255	-6.461
CHEVRON	1.3694	0.1686	-7.9679
CONOCOPHILLIPS	0.6277	0.3089	-4.8142
DEVON ENERGY	0.8925	0.3297	-4.9476
EXXON MOBIL	0.8226	0.0159	-6.6214
MARATHON	0.6479	0.3625	-4.5898
MASSEY ENERGY	0.813	-0.1178	-4.7534
NEWFIELD EXPLORATION	0.2433	-0.041	-7.0053
OCCIDENTAL PETROLEUM	1.3633	0.0522	-8.01
PEABODY ENERGY	0.8944	0.0141	-7.1023
PIONEER NATURAL RESOURCES	0.8253	-0.0343	-7.9969
SUNOCO	0.1411	0.3336	-4.0925
WILLIAMS COMPANIES	1.2005	0.1675	-5.1114
XTO ENERGY	0.5289	0.4461	-4.3722
North American Media Sector			
BELO CORP	0.7838	-0.0229	-5.9746
CHARTER CO	0.8740	-0.1012	-4.8567
COMCAST	0.3011	0.0949	-2.1992
GANNETT	0.6544	0.2185	-3.9947
INTERPUBLIC	0.7010	-0.0752	-4.1653
OMNICOM	0.1517	0.2431	-3.9796
TIME WARNER	0.4063	0.1112	-2.5059
VIACOM	0.0299	-1.8518	-5.4096
WALT DISNEY	0.3552	0.2753	-4.1559
European Energy Sector			
BP	1.0367	0.0022	-6.0163
ENI	0.7736	0.0572	-6.0545
REPSOL	0.5993	0.2042	-3.7571
SHELL	0.9754	-0.0055	-6.0310
STATOIL	0.7885	0.1261	-6.0473
TECHNIP	0.9321	-0.0437	-5.9977
TOTAL	0.9379	0.0953	-6.0554
European Media Sector			
BSKYB	0.9422	0.0258	-9.6959
PEARSON	1.1919	0.1363	-5.4009
PROSIEBENSAT	0.8501	-0.2388	-4.3114
PUBLICIS	0.5584	0.2406	-3.5949
REUTERS	0.4710	0.2509	-4.4194
SES	1.2564	-0.2433	-4.1582
VIVENDI	0.7387	0.2619	-4.3320
WOLTERS	1.0647	0.0474	-6.0107
WPP	0.3678	0.1276	-2.4437

From these results we see that for most firms the estimated value of the parameter k_q^i is positive and for about half the firms it exceeds 0.1 suggesting CDS contracts are priced on the assumption of strong mean reversion in the default intensity process. However, for quite a few of the firms the estimated mean reversion parameter is close to zero or is negative. For these firms the O-U specification may not be appropriate. To explore this matter further, we graphed the likelihood surface in k_q^i X θ_q^i and confirmed for several of the firms the likelihood function was extremely flat in the neighborhood of $k_q^i = 0$. Thus for these firms, we cannot reject the hypothesis of that the log default intensity follows a random walk. Note these comments pertain to the *risk neutral* process and do not speak to the issue of mean reversion in statistical default intensities. Overall, our estimates of the mean reversion parameter were rather higher than those reported by Saita Table 2 and Appendix A. In contrast, the volatility of the intensity process, σ^i was rather precisely estimated and the ranged between 0.029 and 1.86 which was in line with the estimated reported by Saita.[9]

3.3 Time Series Behavior of Market Implied Default Intensity

Perhaps of even greater interest than the parameter estimates are the estimates of the time-series of the default intensities, $ln\lambda_{it}^Q$, implied by the estimated model. We are particularly interested in whether these estimates for the 41 firms estimated independently may exhibit any common patterns. To do so we carried out a principal components analysis for the four subsamples of firms. The results of these analyses can be seen in Table V where we report the proportion of the variation explained by the first five principal components.

TABLE V Principal Component Analysis of Implied Default Intensities

Component	1	2	3	4	5
North American Energy Sector					
Variance explained, marginal	0.6852	0.1156	0.0580	0.0402	0.0264
Variance explained, cumulative	0.6852	0.8008	0.8588	0.8990	0.9254
North American Media Sector					
Variance explained, marginal	0.7428	0.1828	0.0266	0.0215	0.0127
Variance explained, cumulative	0.7428	0.9255	0.9521	0.9736	0.9863
European Energy Sector					
Variance explained, marginal	0.9352	0.0209	0.0176	0.0109	0.0082
Variance explained, cumulative	0.9352	0.9561	0.9737	0.9846	0.9928
European Media Sector					
Variance explained, marginal	0.7039	0.1526	0.0657	0.0301	0.0168
Variance explained, cumulative	0.7039	0.8565	0.9222	0.9523	0.9691

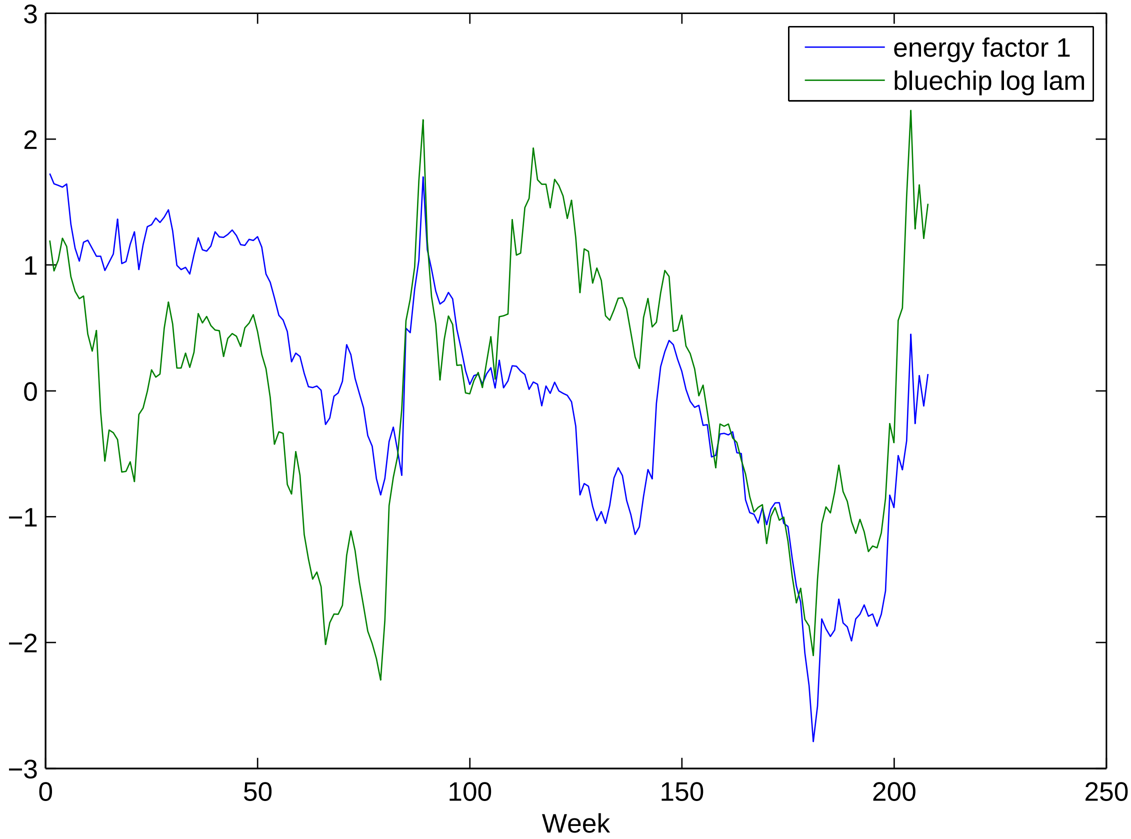
From this we see that a large fraction, ranging from 68% to 93%, of the time series variation of the instantaneous default intensities implied by the the first principal component

[9] Our sample covers different names than those used by Saita. Furthermore, he included observations taken between June 1998 and June 2004 which overlapped with our sample for less than one year.

of calculated for weekly observations between September 2003 through January 2008. This is strong evidence of a common determinant of price of credit risk within each of the four subsamples. Now this factor could reflect determinants that are specific to that sector, or it may reflect more general determinants of the market price of credit risk. To investigate this further we compare the implied time series of the latent factor implied by the first principal component of default intensities in the energy sector with the default intensity implied by the index of CDS spreads. The results for the North American Energy Sector are summarized in Figure 1.

Figure 1: Energy Common Factor and Blue Chip CDS Factor

This figure plots the log intensities implied by the CDS Index for US firms included in the S&P 100 index and the common factor implied by the first principal component of the log intensities of the fifteen energy companies over the 208 weeks from 10/9/03 through 29/8/07. For visual comparability, both series have been normalized by subtracting the sample mean and dividing by the sample standard deviation. The correlation of the two series is 0.47.



The correlation between the common energy default factor and the default factor for the Blue-chip factor is quite high (47%). In the figure it is striking the many of the extreme moves in one series are very precisely mirrored in the other series. At other times, the two series appear to be poorly correlated. This pattern suggests that there may be both a broad-based credit risk factor that influencing credit markets generally as well as a sectoral factor that may be specific to the energy industry. What seems remarkable here is that the dominant common factor that emerges from the components identified in the default intensities for fifteen energy firms estimated *independently* should emerge so clearly as closely linked to the central tendency of default risk captured in the default swaps of 62 firms of which 61 do not overlap with our energy sample.

A similar pattern holds for the other subsamples. The first principle component in the estimated log intensities of our independently estimated model accounts for a very high proportion of the total variation of these intensities. Furthermore, the underlying factor reflected in this component is highly correlated with the general index of CDS spreads. For the four subsamples the correlations between the first factor as above and the index of CDS spread (SPIdxCDS for North America and iTraxx5 for Europe) are:

Sample	N.Am. Energy	N.Am Media	Eu.Energy	Eu.Media
Correlation	-0.444	-0.5582	-0.9137	-0.9036

To summarize, we have estimated a latent variable model for CDS pricing for 41 firms in four distinct sectors and covering a wide range of credit quality. We have estimated the models independently and have explored the extent to which the estimated implied risk-neutral default intensities follow some common tendency. We find that in each sector studied a common factor accounts for a large proportion of the variation of the implied default intensity. Furthermore, this common factor is highly correlated with movements of a general index of CDS prices. Now this common factor could reflect co-movements in the statistical probability of default. Or it could reflect time variation in a common market price of default risk. We attempt to explore this issue in the next section.

4 The Market Price of Default Risk

4.1 The Relation of Market Implied and Historical Default Intensities

The market price of default risk reflects the discount on a defaultable security in addition to that which is justified by the statistical default process. An advantage of the reduced form model that we have adopted here is that this price of default risk has a natural interpretation as the ratio of the intensity of default under the risk neutral process and the intensity from the statistical distribution. Thus to identify the market price of default risk we will combine our estimates of the intensity of default derived from CDS prices with estimates that have been derived from historically observed instances of default or bankruptcy.

There have been several recent attempts to estimate statistical default process from historical episodes of financial distress.[10]. In comparing those studies with estimates of the risk neutral process such as those given above it is important to emphasize differences in the two estimation problems. *First*, the most important point is that financial distress is a rare event. That is, most firms whose securities are traded in the market have never defaulted and have never experienced financial distress. Thus, inevitably to obtain estimates of the probability of financial distress we will need to work with large *cross sections* of firms including both those that have experienced distress and those that have not. *Second*, in dealing with large cross-sections of firms it will be necessary to control firm characteristics which are reflected in their financial reports which are available on a quarterly or annual basis. Thus in capturing time variations of the physical intensity of default we will work at a much higher level of temporal aggregation than we do when estimating risk neutral default processes from market quotes. *Third*, in working with panel data with financial ratios as covariates there may be significant problem of missing observations. This is particularly true for firm experiencing financial distress where early stages of distress may involve difficulty in producing audited financial statements. For this reason, estimates of the physical default process potentially may be prone to sample selection bias.

Our estimates of the physical distress process for our sample of firms are derived from Zhou (2007) who employs a methodology similar to Shumway (2001) and Campbell *et al* (2005) but corrects for possible sample selection bias induced by the earlier studies' treatment of missing observations. In particular, working with quarterly observations for North American firms between 1995 and 2005 she documents the fact that important accounting variables frequently missing from the data set. Given that missing accounting variables may be associated with the on-set of financial distress, a method based on simply deleting firm/quarters with some missing explanatory variables, as in Campbell *et al* is potentially exposed to self-selection bias. Zhou shows that the estimates of the model are sensitive to the method adopted in treating missing observations and argues that the method of multiple imputations is best equipped to correct for this problem.

Following this methodology our estimate of the physical default intensity can be written as:

$$\lambda^P = e^{4(X'\hat{\beta}})\tag{6}$$

where X is a vector of regressors entering into the hazard function estimation and $\hat{\beta}$ is the associated vector of parameter estimates. Note that in this expression we multiply the

[10]See Shumway (2001), Campbell *et al* (2005) and Duffie *et al* (2005)

coefficient estimates by 4 to express Zhou's quarterly estimates as an intensity per year. Using the results in her Table 14, this can be expressed as:

$$\begin{aligned} ln(\lambda^P) = 4 * (&-9.3022 - 10.3148NITA + 4.8065TLTA \\ &-1.3812PRICE - 0.2514EXRET + 1.8190SIGMA) \end{aligned} \tag{7}$$

The definition of variables in this equation are given in Table VI which describes our quarterly data set including those variables used in the regression analyses reported below.

TABLE VI Quarterly Data Descriptions

Variable	Description	Source
$ln(\lambda^Q)$	log intensity of default in risk neutral distribution	Own calculations
$ln(\lambda^P)$	log intensity of default in physical distribution	Zhou (2007), own calculations
NITA	net income over total assets	Compustat
TLTA	total liabilities over total assets	Compustat
PRICE	log of min(share price, $15)	Datastream
EXRET	log excess monthly return on share over S&P500	Datastream
SIGMA	standard deviation of daily stock returns in past three months	Datastream
GDPGTH	growth rate of GDP	US Dept of Commerce
OILPRICE	West Texas intermediate	FRED, St.Louis Fed
RETSP	Return on S&P 500 composite index	CRSP
NPCMCM2	Nonperforming Com. Loans Banks w/ Assets from $300M to $1B	FRED, St.Louis Fed
NPCMCM5	Nonperforming Com. Loans Banks with Total Assets over $20B	FRED, St.Louis Fed
NPTLTL	Nonperforming Total Loans	FRED, St.Louis Fed
USROE	Return on Average Equity for all U.S. Banks	FRED, St.Louis Fed
FRBSURVEY	Percent Tightening Standards for Commercial Loans	Fed Senior Loan Officer Opinion Survey
MKTRF	Market return in excess of risk free	Ken French Data Library
SMB	Small-minus-big (small firm premium)	Ken French Data Library
HML	High-minus-low (value firm premium)	Ken French Data Library
RF	Three month Treasure rate	Ken French Data Library

The variables included in calculation of the statistical default intensity are those also used by Campbell *et al.* As discussed in the introduction, an alternative approach to estimating the statistical default process is to infer it from observations of the Moodys-KMV EDF's which are monotonic functions of the distance-to-default (Berndt *et al*). Zhou finds that adding DTD to the specification above does significantly increase the explanatory power of the model. This result is in agreement with the finding of Campbell *et al* and Shumway.

It should be noted that the measure of financial distress employed by Zhou and Campbell *et al* is either bankruptcy or the assignment of a 'D' rating. This may a stricter definition than that which applies in the documentation for a given firm's default swap. As a consequence, the estimate of the physical default intensity may be systematically below that would have obtained had a broader default definition been adopted. For example, if conditional on triggering a CDS credit event, the probability of bankruptcy is a constant 0.5, then the physical credit event intensity will be approximately twice the the corresponding physical bankruptcy intensity. For this reason, in our discussion below of our calculated ratios of risk neutral to physical default intensities, λ^Q/λ^P, we emphasize our findings on the factors that may account for the *variations* of this ratio. This is in contrast with the recent literature that is primarily concerned with the *level* of the intensity ratio (e.g., Driessen, Saita, and Berndt *et al*).

An advantage of the hazard approach to estimating the statistical default intensity is that the model appears to account for a significant fraction of the observed increase in default frequencies during the 1980's and their subsequent decline much of the 1990's (see Campbell *et al* for a discussion). In contrast, the average default frequencies which underly the ratings based approach are sensitive to the time-period over which the frequencies are measured. As acknowledged by Driessen, this can have important implications for the level of the estimated jump risk premia. We will return to this issue below when we consider the robustness of our findings on the determinants of default event risk premia by employing a ratings based approach as an alternative to our hazard estimates of the statistical default process.

Given the important differences in accounting conventions in Europe and North America and given that the estimates of Zhou have been based on a sample of North American firms, we also confine our analysis to our North American firms. Our sample of 15 North American energy firms spans sixteen quarters from Q1 2003 through Q4 2006; our sample of 9 North American media firms covers fifteen quarters from Q2 2003 through Q4 2006. Our quarterly estimates of the risk neutral intensities of default were derived from our estimates reported in Table IV. Specifically, we have calculated the quarterly averages of the weekly default intensities implied by those estimates.

Some important characteristics of the resulting estimates of the physical and risk neutral default intensities can be seen from a two-way analysis of variance allowing for quarter and firm effects. These are reported in Table VII. Our results show that in both the energy and media subsamples risk-neutral intensities are much more variable than statistical intensities. This is particularly noticeable for the energy subsample where the total sum of squared deviations of the risk neutral intensities exceed that of the physical intensities by a factor of 3. This is perhaps not surprising since the energy subsample consists of relatively highly rated firms where the pure credit component of spreads may be relatively low.

A high proportion of observed variation in both kinds of intensities is accounted for by firm level differences. There is a high positive correlation between risk neutral and statistical default intensities. We would expect this, but it is still an important result. Given that the two types of intensities were derived independently and using very different methodologies, the positive correlation encourages us in believing that the quarterly, *backward-looking* physical default model is capturing influences perceived as important by the market *on a forward-looking basis.*

Given this result, we then calculate the estimated implied market price of default risk as the natural log of the ratio of risk neutral and physical default intensities.[11] A two-way ANOVA of these estimates is also reported in Table VII. Again firm effects account for a high proportion of total variation. However, we see the time effect is also quite important, accounting for 16% and 17% of total variation in the energy and media subsamples respectively. In the next section we will try to explore factors that may account for this time variation in the market price of credit risk.

TABLE VII Two-way ANOVA of Physical and Risk Neutral Intensities

Sample Dependent variable	*N.American Energy* $ln(\lambda^P)$	*N.American Energy* $ln(\lambda^Q)$	*N.American Energy* $ln(\lambda^Q/\lambda^P)$	*N.American Media* $ln(\lambda^P)$	*N.American Media* $ln(\lambda^Q)$	*N.American Media* $ln(\lambda^Q/\lambda^P)$
Number of obs	233	233	233	118	118	118
R-squared	0.8726	0.9095	0.7920	0.8864	0.7953	0.7167
Model SS	124.27	441.99	215.47	73.32	123.37	77.46
per cent	87.26	90.95	79.20	88.64	79.53	71.67
Firm SS	121.91	396.96	176.22	71.01	106.25	63.50
per cent	85.60	81.69	64.77	85.86	68.49	58.75
Time SS	4.31	62.92	43.59	2.16	19.89	18.60
per cent	0.22	12.95	16.02	2.61	12.82	17.21
Residual SS	18.14	43.977	56.59	9.39	31.75	30.63
per cent	12.74	9.05	20.80	11.36	20.47	28.33
Total SS	142.42	485.96	272.06	82.71	155.13	108.09
per cent	100.00	100.00	100.00	100.00	100.00	100.00
Correlation	0.6791			0.5727		

[11]It should be noted that our risk neutral intensities were obtained from an estimate of the *marginal* distribution of defaults which assumed mean reversion of the latent variable. In contrast, our statistical default intensities are based on estimates *conditional* upon observed covariates. The *unconditional* statistical default distribution will exhibit mean reversion if the conditioning variables exhibit mean reversion.

4.2 Determinants of the Market Price of Default Risk

In this section we explore whether the variation in the market price of default risk that we have identified may be accounted for by observable factors either specific to the firm or general factors reflecting business conditions. In particular, we wish to explore whether specific indicators of credit market conditions appear to account some of observed variation and whether any such influence is robust to including general financial market conditions. Such a finding would be evidence in support of a possible segmentation of credit markets from other financial markets as has been conjectured by Berndt *et al.*

The variables used for external factors in are summarized in Table VI. In addition to standard macroeconomic and firm accounting variables we include information on the condition in the chief suppliers of credit as represented by the banking sector. These are derived from two principles sources. The first set of variables come from the Federal Reserve System's "Reports of Condition and Income for All Insured U.S. Commercial Banks" and available on the website of the the St. Louis Fed. The second source of credit condition information is the Fed's "Senior Loan Officer Opinion Survey on Lending Practices". We use these data in estimating linear models applied to the default risk premium of our North American Energy and Media firms as estimated above. As suggested by the analysis of variance results reported in Table VI, we include firm fixed effects in all of our estimates reported here. We have also estimated the models excluding fixed effects but including more firm financial ratios as controls. The results are qualitatively the same as those we report here.

Our results for North American Energy Firms are reported in Table VIII, Panel A. The first column reports our benchmark model. Earnings (NITA) is included as an indicator of firm specific business conditions. It enters with a positive sign which may be surprising. However, it is insignificant, which suggests that firm specific influences are largely captured in the constant fixed-effect. GDP growth is included as a general business conditions indicator. It is marginally significant. It is not immediately clear what the direction this influence should be on the market price of default risk. The negative sign obtained here might be suggestive of a "credit cycle" as commonly discussed among practitioners. The oil price is included and may serve both as a control for general business conditions and as a sector-specific indicator relevant to the energy sector as a whole. It enters with a positive sign and is marginally significant.

TABLE VIII Panel A:
Linear model estimates of the market price of credit risk
N.American Energy(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	233	233	233	233	233	233
R-SQ(within)	0.3335	0.3354	0.3112	0.2938	0.2818	0.2497
Firm F.E.	yes	yes	yes	yes	yes	yes
NITA	3.794	3.774	3.863	4.050	3.297	4.081
	0.122	0.125	0.122	0.109	0.197	0.117
GDPGTH	-17.298	-20.549	-12.216	-.421	-19.462	-2.902
	0.057	0.039	0.183	0.965	0.042	0.777
OILPRICE	.012	.013	.0109	.004	-.027	-.020
	0.058	0.053	0.127	0.506	0.000	0.000
RETSP		-4.505				
		0.419				
NPCMCM2	2.462	2.551				
	0.000	0.000				
NPCMCM5			.553			
			0.000			
NPTLTL				1.877		
				0.000		
USROE					.674	
					0.000	
FRBSURVEY						.008
						0.012
CONSTANT	-3.061	-3.111	-1.270	-2.049	-6.586	1.044
	0.000	0.000	0.016	0.007	0.001	0.000

In this benchmark regression a measure of non-performing commercial loans is included as an indicator of credit market tightness. Its role in the credit channel is clear– increases in non-performing loans will lead to increases in loan loss provisions and typically a reduction of regulatory capital ratios. This argument has been elaborated by Adrian and Shin (2008). The credit variable NPCMC2 enters the regression with a positive sign, as we would expect if there is a credit supply effect on the market price of default risk, and it is highly significant.

Column 2 in Table VIII Panel A reports the result of including an index of stock market returns as a control for changes the market price of equity. This variable enters with a negative sign as we would expect, but it not significant. The inclusion of this control variable has no effect on the qualitative effects of the other variables in the regression. In particular, the credit supply variable remains very highly significant and has the correct sign. In the remaining regressions we omit the stock return variable, but the results are robust to its inclusion.

In the remaining columns of Table VIII Panel A we experiment with alternative proxies of credit market tightness. In column 3 we include NPCMCM5 which is a measure of non-performing commercial loans in very large banks (in contrast with NPCMCM2 which is a measure of non-performing loans in relatively small banks). This variable enters with the expected positive sign. It is highly significant, albeit at a somewhat lower level than NPCMCM2 as can be seen from the R-squared. This might suggest that performance of loan portfolios of small, less diversified, banks may more informative than the loan portfolios of large banks. In column 4, non-performing loans for the banking system as whole is our proxy for credit market tightness. Again it enters with the expected sign and is significant. Column 5 uses average return on equity in the banking sector as the credit supply proxy, and this has the correct sign and is significant. Finally, in Column 6, we use the Fed's lending officers' survey variable as a credit sector indicator. It enters with the expected positive sign and is significant.

The general point that emerges from these regressions is that credit market tightness appears to be a significant determinant of the market price of credit risk after controlling for firm specific effects, general business conditions, and equity market conditions. This conclusion does not depend greatly on the precise way in which credit market tightness is measured. However, we have found that the best single proxy appears to be an indicator of non-performing loans at smaller commercial banks. The effects of non-credit variables in the regression are largely robust to the choice of the credit tightness proxy used. The sole exception is the oil price variable which sometimes enters with a positive sign and sometimes with a negative sign.

The results for this framework applied to the North American media sector are reported in Table VIII Panel B. Again, firm fixed effects are included. The contrast with North American energy firms is interesting because of exposure of the sectors to different economic conditions (i.e., greater exposure to commodities and business cycle in the energy sector) and because media firm are typically less highly rated with higher CDS spreads on average. The results in the table show that indeed these differences do appear to be manifested in the way the market price of credit risk is determined in the media sector. The GDP growth variable is generally insignificant as we might expect for a sector less exposed to business cycle influences. However, the oil price variable enters significantly in most specifications although not always with the same sign. Also, the return on the equity index now is marginally significant.

However, the main result for the North American media firms is the same as for energy firms. The most important explanatory variable for the market price of default risk is the proxy for credit market tightness. Again the best proxy appears to be the index of non-performing loans in smaller commercial banks. But similar results are obtained using non-performing loans in large banks. Overall, the evidence for the two sectors suggest that credit market conditions are important determinants of the market price of default risk even after taking into account firm specific effects, general business conditions and equity market conditions.

TABLE VIII Panel B:
Linear model estimates of the market price of credit risk
N.American Media(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	118	118	118	118	118	118
R-SQ(within)	0.2523	0.2756	0.2111	0.1830	0.1423	0.1367
Firm F.E.	yes	yes	yes	yes	yes	yes
NITA	6.537	6.655	5.485	5.238	5.311	5.356
	0.216	0.203	0.311	0.342	0.347	0.345
GDPGTH	1.730	-8.656	11.058	24.050	17.320	20.959
	0.902	0.564	0.432	0.093	0.236	0.167
OILPRICE	.027	.029	.020	.011	-.005	-.014
	0.013	0.009	0.079	0.298	0.587	0.001
RETSP		-15.565				
		0.060				
NPCMCM2	3.214	3.506				
	0.000	0.000				
NPCMCM5			.622			
			0.001			
NPTLTL				1.998		
				0.012		
USROE					.187	
					0.343	
FRBSURVEY						.002
						0.673
CONSTANT	-4.799	-4.976	-2.109	-2.797	-2.648	.430
	0.000	0.000	0.014	0.035	0.421	0.219

Of course, in this analysis of the market price of default risk there is a wide variety of alternative variables that could be tried. We have explored some of these possibilities including such firm measures as leverage or equity volatility and general business conditions measures such as industrial production, other commodity prices and the University of Michigan index of consumer sentiment. Two conclusions emerge from all these explorations. First, none of these additional control variables turns up as significant across both subsamples and across the various alternative specifications. Second, credit market tightness proxies remain consistently significant and of the right sign across these alternative specifications.

The results in Table VIII suggest that after controlling for firm level and sectoral differences a significant part of the time variation in the market price of default risk is accounted for by time variation in credit market tightness. This is consistent with the idea that the market for default risk may be segmented from other financial markets as has been conjectured by Berndt *et al.* We pursue this idea by augmenting our benchmark model to include the Fama-French risk factors that have been widely used in the analysis of equity markets. Specifically, we use the quarterly average of the monthly data reported on Ken French's Data Library (as described in Table VI).

The results for the North American energy sector are presented in Table IX, Panel A. The first three columns show the result of introducing individually each of the three Fama-French factors into our benchmark model. The excess return on the market and the small firm premium are both insignificant; however, the HML variable enters with a negative sign which is highly significant. This suggests that controlling for other factors, periods of relatively high returns on value stocks are associated with low market prices of default risk. Column 4 reports results with the short-term Treasury rate included. It enters with a negative sign but is insignificant. When the three Fama-French factors are included jointly (column 5), HML again enters with a significant negative sign and the two others are insignificant. Interestingly, when both HML and the risk free rate are included (column 6) both are negative and significant.

Thus we find evidence that the factors that appear as significant risk factors in equity markets do account for some of the common time variation of the market price of default risk. However, a striking finding in Table IX, Panel A is that the estimated coefficients of the credit market tightness variable (NPCMCM2) are almost identical across all specifications and are very highly significant. This suggests that while equity market conditions do seem to some impact credit markets, specific credit supply factors remain highly important in accounting for the time variation in default risk pricing.

TABLE IX Panel A:
Equity market risk factors
N.American Energy(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	233	233	233	233	233	233
R-SQ(within)	0.3410	0.3336	0.3534	0.3401	0.3624	0.3680
Firm F.E.	yes	yes	yes	yes	yes	yes
NITA	3.705	3.801	3.049	3.807	2.910	2.901
	0.130	0.123	0.211	0.120	0.232	0.230
GDPGTH	-20.229	-16.794	-15.042	-23.919	-15.535	-24.757
	0.029	0.092	0.095	0.018	0.249	.013
OILPRICE	.008	.0123	.011	.0243	.006	.029
	0.251	0.053	0.087	0.018	0.360	0.005
NPCMCM2	2.284	2.462	2.241	2.578	2.054	2.370
	0.000	0.000	0.000	0.000	0.000	0.000
MKTRF	-.038				-.0338	
	0.110				0.360	
SMB		-.004			-.0149	
		0.900			0.791	
HML			-.0961		-.106	-.117
			0.009		0.020	0.002
RF				-1.205		-1.860
				0.135		0.023
CONSTANT	-2.567	-3.055	-2.710	-3.418	-2.215	-3.184
	0.002	0.000	0.000	0.000	0.009	0.000

Table IX, Panel B reports the results for North American Media Firms. The results for the equity risk factors are very similar to those for the energy firms. Movements in the value premium do seem to be partially correlated with movements in the market price of default risk while equity market premium and the small firm premium are not. Again, when the risk free rate is include along with the HML variable, both are negative and significant. As with the energy firms, the effect of the credit market tightness variable is rather insensitive to the inclusion of the equity market risk factors– its coefficient is negative and highly significant in all cases.

TABLE IX Panel B:
Equity market risk factors
N.American Media(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	118	118	118	118	118	118
R-SQ(within)	0.2526	0.2527	0.2842	0.3020	0.2909	0.3646
Firm F.E.	yes	yes	yes	yes	yes	yes
NITA	6.688	6.417	5.498	8.006	5.912	6.967
	0.211	0.229	0.291	0.121	0.262	0.160
GDPGTH	.423	.181	-.776	-18.977	.328	-29.304
	0.978	0.991	0.955	0.223	0.989	0.056
OILPRICE	.0274	.028	.030	.060	.029	.075
	0.016	0.013	0.005	0.000	0.010	0.000
NPCMCM2	3.230	3.220	3.362	3.658	3.409	4.017
	0.000	0.000	0.000	0.000	0.000	0.000
MKTRF	-.009				-.018	
	0.816				0.781	
SMB		.011			-.032	
		0.804			0.711	
HML			-.127		-.156	-.186
			0.027		0.022	0.001
RF				-3.185		-4.212
				0.006		0.000
CONSTANT	-4.764	-4.819	-4.964	-5.930	-4.875	-6.535
	0.000	0.000	0.000	0.000	0.000	0.000

To summarize, a large fraction of the variation in the market price of default risk is accounted for by constant firm effects; however, there is significant common time variation. After controlling for macroeconomic and sectoral factors, we find changes in credit market tightness, measured with a variety of empirical proxies, is a significant explanatory variable that is robust to the inclusion of a wide variety of other variables. Beyond this we find that changes in the value premium in equity markets appear to account for some of the variation of the price of default risk.

The results so far are consistent with the conjecture that there may be some friction that impedes capital flows between equity and credit markets. Within credit markets it is often argued that since some institutional investors are specifically prohibited from holding non-investment grade instruments (rated BB or below) a similar friction may be present within the credit markets themselves. As previously discussed, ratings do not enter into our calculation of the default event risk premium. Furthermore, they do not enter into the regression analysis (Tables VIII and IX) where we have controlled for cross sectional heterogeneity with firm fixed effects as well as accounting variables. So to explore this conjectured ratings based segmentation within credit markets themselves, we now introduce ratings into the analysis.

Table X summarizes the default event risk premium ($ln(\lambda^Q/\lambda^P)$) by ratings class for the two North American sectors between September 2003 and August 2007. For the Energy sector the premia on non-investment grade names is significantly above that for investment grade names. However, this is not the case for the Media sector. Overall, there does seem to be a rough tendency for the default event risk premium to vary inversely with credit quality.

TABLE X: Default Event Risk Premia by Ratings Class

Rating	NA Energy Mean	NA Energy St.Dev.	NA Media Mean	NA Media St.Dev.
AAA	1.27	.112	*	*
AA	1.25	.132	*	*
A	1.87	.059	1.91	.144
BBB	1.86	.109	3.10	.113
BB	3.0	.133	*	*
B	2.84	.214	3.08	.081
C	*	*	3.35	.260

We now ask whether the fact a name carries an investment grade rating is a significant determinant of the default risk premium once we control for other factors. We define a dummy variable IGRADE which takes on the value of 1 if for a name if it carries a rating of BBB or above in a given quarter and zero otherwise. The results from introducing this variable into benchmark specifications (with and without the HML factor included) are reported in Table XI.

TABLE XI Results with Investment Grade Dummy (p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$	NA Energy	NA Energy	NA Media	NA Media
Number of obs	233	233	118	118
R-SQ(within)	0.3451	0.3636	0.2599	0.2901
Firm F.E.	yes	yes	yes	yes
NITA	6.973	6.057	9.717	8.314
	0.017	0.037	0.110	0.166
GDPGTH	-18.67	-16.41	2.528	-.0116
	0.039	0.068	0.858	0.999
OILPRICE	.0119	.0107	.027	.0307
	0.069	0.101	0.013	0.006
NPCMCM2	2.508	2.291	3.229	3.371
	0.000	0.000	0.000	0.000
HML		-.0927		-.12
		0.011		0.032
IGRADE	-.181	-.1706	-.1428	-.125
	0.046	0.058	0.286	0.342
CONSTANT	-3.006	-2.672	-4.750	-4.916
	0.000	0.000	0.000	0.000

The investment grade dummy enters with a negative sign in these regressions. This is consistent with the idea that, all else equal, non-investment grade issues will carry an additional premium perhaps reflecting reduced liquidity due to limited participation in this segment of the credit market. However, the coefficients are only marginally significant for the energy sector and are insignificant in the media sector. Overall, we see that once we account for other determinants of the default risk premium the effect of the investment grade classification is minor at best. Stated otherwise our evidence suggests that an increase in yield spreads associated with a downgrade from investment grade to non-investment grade will largely correspond to the fair compensation for higher expected credit losses in the latter segment of the bond market. Otherwise, comparing Table XI with the corresponding results in Tables VIII and IX shows that our previously qualitative conclusions are unchanged.

4.3 Ratings-based statistical default intensities

We have argued that the hazard approach to estimating the statistical default process has desirable features for the purposes of understanding the market price of default risk, especially if we are interested studying the time variation of that risk premium. We now consider how our results would differ if we were to take the alternative approach of representing the statistical default distribution using the historical default frequencies reported by ratings agencies for bonds of a given ratings category. This is potentially interesting for two reasons.

First, it is a check on the robustness of our qualitative conclusions on the determinants of the default risk premium. Second, if we find that the results do not change, this would suggest that we might be able to employ a simple ratings based approach to modeling the statistical default process rather than the more data intensive econometric approach used above.

To represent the statistical default distribution in this approach, we calculate the intensity of default, $\lambda_{i,t}^{P*}$, for firm i at time t by assuming that the corresponding five-year probability of default equals that reported by Moodys for firms in i's rating class. Moodys (2000) reports cumulative default frequencies observed for all firms between 1920 and 1999 (Exhibit 30) and 1983 and 1999 (Exhibit 31). Typically the reported default rates are higher for the longer time-period, and this was particularly the case for BBB rating category which are most prevalent in our data set. We use both in our analysis.

The main difference in the results between ratings based estimates for the two time periods is in the level of default risk premium. For example, for North American energy firms the average market price of risk $ln(\lambda^Q/\lambda^{P*})$ based on the 1920-1999 sample is -1.312 as compared to -0.678 when based on the 1983-1999 sample. The difference between the two measures is a direct consequence of the fact that higher cumulative default frequencies reported by Moodys in the earlier sample imply a higher statistical default intensity. Notice that in both cases, the estimated price of default risk is *negative*. One possible explanation of this result is that during the 2003-2007 period covered in our North American CDS data, investors judged that default intensities were more in line with those implied by the 1990's default rates. Indeed in using the hazard model to take account of possible time variations in the statistical default distribution, the average our own estimates of the market price of default was 2.17 for the North American energy sample. A very similar pattern holds for the North American media sample as well.

A second difference is that the time variability of the default risk premia is higher when calculated using the ratings based statistical default distribution rather than the hazard based calculation. For example, in the North American energy sample the standard deviation of the monthly average default risk premia is 0.54 and 0.59 for the estimates based on Moodys 1920-1999 and 1983-1999 samples respectively. This compares to 0.43 for the hazard based estimates. For the North American media data the comparable standard deviations are 0.41 and 0.41 for the ratings based estimates and 0.35 for the hazard based estimate. This result is due to the lower time variability of the ratings based default intensities as a consequence of ratings inertia, as discussed in the introduction.

This increased time variability of ratings based default risk premia has some consequences for the regressions used to identify factors that may account for that variability. Table XII reports the result of the regression analyses for our benchmark models from Tables VIII and IX rerun taking as dependent variable $ln(\lambda^Q/\lambda^{P*})$ based on the 1920-1999 Moodys default frequencies.

TABLE XII Regression with ratings based statitical default probabilities (p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^{P*1})$	NA Energy	NA Energy	NA Media	NA Media
Number of obs	233	233	118	118
R-SQ(within)	0.5205	0.5270	0.2493	0.2737
Firm F.E.	yes	yes	yes	yes
NITA	-.462	-.9021	1.8096	.874
	0.830	0.677	0.739	0.871
GDPGTH	-22.407	-21.075	-8.551	-10.807
	0.005	0.009	0.557	0.454
OILPRICE	.0167	.0159	.0377	.040543
	0.004	0.007	0.001	0.000
NPCMCM2	3.165	3.034	3.821	3.954
	0.000	0.000	0.000	0.000
HML		-.0567		-.115
		0.081		0.055
CONSTANT	-3.840	-3.633	-5.732	-5.881
	0.000	0.000	0.000	0.000

For North American energy firms, in column 1 of Table XII the coefficients GDP growth and the price of oil are of the same sign as those obtained in column 1 of Table VIII Panel A but are now highly significant. This suggests that these controls for economic activity are picking up some of the greater time variability in the ratings based premia. When the value firm factor HML is included (column 2) it is now insignificant. In both regressions however the credit market tightness proxy (NPCMCM2) is positive and very highly significant as was the case in Tables VIII and IX. Columns 3 and 4 present comparable regressions for North American media firms. As in Tables VIII and IX, the oil price is positive and significant, and both NITA and GDP growth are insignificant. The HML variable is now only marginally significant. However, in both cases the estimated coefficients of NPCMCM2 are very similar to those obtained in Tables VIII and XI and are very highly significant.

When other regressions are run with other explanatory variables as in Tables VIII, IX and XI with ratings-statistical default intensities based on Moodys 1920-1999 and 1983-1999 default frequencies there are some changes in results on some of the explanatory variables. However, the striking result is that the coefficient on the credit market tightness proxies remain significant and of the same signs of those reported here. Overall, the important conclusion is that credit tightness appears to exert an important influence on the market price of default event risk and that this result appears to be robust to inclusion of a variety of other explanatory variables, including equity market risk factors, and to alternative measures of the statistical default distribution.

5 Conclusion

In this paper we study the pricing of credit risk as reflected in the market for credit default swaps (CDS) between 2003 and 2008. This market has newly emerged as the reference for credit risk pricing because of its use of standardized contract specifications and has achieved a higher level of liquidity than typically prevails in the markets for the underlying notes and bonds of the named corporate issuers.

We have explored factors that might account for the well documented common co-movements of yield spreads for a wide range of names in various sectors and of different credit quality. We have argued that these co-movements might reflect common revisions in the statistical default distribution or common factors driving time variation in the market price of default risk. Our methodology allows us to disentangle these influences.

We employ a panel dataset of 1, 3 and 5 year CDS prices on 41 firms that were traded between between September 2003 and through January 2008 and covering four distinct subsamples: North American energy, North American media, European energy, and European Media. We start our analysis by estimating of a linear regression model and find a strong positive association between spread changes on individual names and a broad-based index of CDS price changes. In contrast, the association with equity prices is very weak, generally statistically insignificant, and often of the wrong sign. These results are robust to inclusion of firm fixed or random effects. We find a negative autocorrelation of residuals in these panel estimates which we interpret as evidence of mean reversion in unobserved risk factors. All these results are consistent across our four subsets, i.e., they hold for North American Energy and Media and European Energy and Media.

We pursue our study by exploring a latent variable model recently introduced in the literature which assumes that defaults on a name follow a jump process where the log intensity of arrivals of defaults itself follows an Ornstein-Uhlenbeck process. After developing a continuous time model of CDS pricing with this underlying stochastic process, we estimate our model for our 41 firms individually, applying no restrictions across firms. In line with previous work we find that some firms do seem have mean reverting default intensities and others do not. Overall the evidence of mean reversion is stronger in our study than that found previously.

The estimated models are then used to produce an implied time-series of instantaneous default intensities for our 41 firms observed at weekly intervals. We carry out a principal components analysis of the panels of default intensities for our four sector-region combinations. In all cases a very high fraction of weekly variations in the implied default intensity is explained by a single common factor. We find that the implied common factor for each subsample is highly correlated with the default intensity implied by the index of CDS spreads on Blue-chip names. This is strong evidence confirming the presence of a general credit risk factor whose existence has been proposed in a number of recent contributions.

We then ask what our estimates of default intensities derived from CDS prices imply for the market price of default risk. In order to answer this question we need to compare our estimates of the *risk neutral* intensity process with estimates of the *statistical default* process. We argue that recent studies which have used the Moodys-KMV EDF (estimated default frequencies) are essentially confounding information about the risk-neutral and statistical default distributions. Other estimates based on ratings suffer from the well-know problem of inertia in ratings changes. We therefore calculate statistical default intensities using a dynamic econometric model derived from a large panel data set of North American firms. Specifically, we use the estimates recently derived by Zhou (2007) who employs a methodology similar to Shumway (2001) and Campbell *et al* (2005) but corrects for possible sample selection bias induced by the earlier studies' treatment of missing observations. These estimates are implemented for our North American firms only. Our results show that in both the energy and media subsamples risk-neutral intensities are much more variable than statistical intensities. A high proportion of observed variation in both kinds of intensities is accounted for by firm level differences. There is a high positive correlation between risk neutral and statistical default intensities.

We then combine estimates to find the implied market price of risk measured as the natural logarithm of the ratio of risk-neutral intensity and statistical intensity of default. We show that a relatively high fraction of the observed variation of this market price of default risk can be accounted for by a common time variation. In order to identify this factor, we explore a linear model of the market price of default risk using as observed covariates macro indicators, firm indicators and indicators of equity market and credit market conditions. Our estimates show a strong association between that credit market conditions and the market price of risk. The estimated coefficients have the correct signs. These are robust findings across a variety of alternative proxies for credit market conditions and across our two subsamples. In contrast equity market conditions and general business conditions do not always have coefficient estimates of the right sign and are not always significant. However, there is some evidence that changes in the value firm premium are partially correlated with changes in the pricing of default risk.

We compare our analysis of the market price of default risk obtained using the dynamic econometric model of the statistical default process with those obtained using a ratings based distribution derived from historical default frequencies by ratings class. The results differ in several ways. First estimated default risk premia are much lower when statistical default processes are calibrated off the Moodys 1920-1999 or 1983-1999 default frequencies. Second, the time variability of the market price of default risk is considerably greater with the ratings based approach reflecting the largely static nature of the assumed statistical default distribution. Third, in the regression analyses of default premia the business cycle controls appear more highly significant and the equity market risk factors less significant than in our benchmark regressions. However, credit market tightness proxy variables continue to be very significant both statistically and economically.

Overall, our results suggest that a large fraction of the changes in credit spread over time reflect changes in the market price of default risk. The factors driving this price appear to differ across different industry sectors. However, our evidence suggests that financial health of major suppliers of credit exerts a common influence across across diverse sectors. This is a stronger and more robust influence than those exerted by the generally recognized equity market risk factors. Thus our results provide some evidence of the partial segmentation of credit markets.

References

Adrian, T. and H.S. Shin, 2008, "Liquidity and Financial Cycles," BIS Working paper, 256.

Altman, E.I. and A.M.Kishore, 1996, "Almost Everything You Wanted to Know about Recovery Rates on Defaulted Bonds," *Financial Analysts Journal.* 52:6, 57-64.

Anderson, R. W. and K. McKay, 2008, "Derivatives Markets" in X.Freixas, P.Hartmann, and C.Mayer (eds.), *European Financial Markets and Institutions.* Oxford University Press.

Bank of England, 2007, *Financial Stability Review* October, p.6.

Bernanke, B., 2008 "Addressing Weaknesses in the Global Financial Markets: The Report of the President's Working Group on Financial Markets" Federal Reserve Board, April 10.

Berndt, A., R. Douglas, D. Duffie, M. Ferguson, and D. Schranz, 2005, "Measuring Default Risk Premia from Default Swap Rates and EDF's" Stanford University, working paper.

Blanco, R., S Brennan, I.W. Marsh, 2005 "An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps," *Journal of Finance.* 60, 2255-2281.

Campbell, J. and Hilscher, J. and Szilagyi, J., 2005, "In Search of Distress Risk", Working paper, Harvard University.

Collin-Dufresne, P., R.A. Goldstein, and J. Martin, 2001, "The Determinants of Credit Spread Changes," *Journal of Finance.* 56, 2177-2208.

Crouhy, M., D. Galai, and R. Mark, 2001, *Risk Management.* McGraw-Hill.

Driessen, J., 2005, "Is Default Event Risk Priced in Corporate Bonds?" *Review of Financial Studies.* 18, 165-195.

Duffie, D., 2007, "Innovations in Credit Risk Transfer: Implications for Financial Stability" Stanford University, working paper.

Duffie, D. and D. Lando, 2001, "Term Structures of Credit Spreads with Incomplete Accounting Information," *Econometrica* 69, 633-664.

Duffie, D., L. Saita, and K. Wang, 2005, "Multi-Period Corporate Default Prediction With Stochastic Covariates", Working paper, Stanford University.

Duffie, D., and K. Singleton, 2003, *Credit Risk.* Princeton University Press.

Financial Stability Forum, 2008, *Report of the Financial Stability Forum on Enhancing Market and Institutional Resilience*, April 7, p.5.

Houweling, P. and T. Vorst, 2005, "Pricing Default Swaps: Empirical Evidence" *Journal of International Money and Finance.* 24, 1200-1225.

Jarrow, R.A., D. Lando, and F.Yu, 2005, "Default Risk and Diversification: Theory and Empirical Implications" *Mathematical Finance.* 15, 1-26.

Moody's Investor Services, 2000, "Historical Default Rates of Corporate Bond Issuers, 1920-1999" Global Credit Research, Special Comment, January.

Saita, L., 2006, "The Puzzling Price of Corporate Default Risk," Stanford University, working paper.

Shumway, T., 2001, "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," *Journal of Business.*74, 101-124.

Yu, F., 2002, "Modeling Expected Returns on Defaultable Bonds," *Journal of Fixed Income.* 12, 69-81.

Zhou, P., 2007, "Forecasting Bankruptcy and Physical Default Intensity'" manuscript, London School of Economics.