Exploring the relationship between credit spreads and default probabilities

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Abstract

Contrary to theory, recent empirical work suggests that changing default expectations can explain only a fraction of the variability in credit spreads. This paper takes a fresh look at this question, relating credit spreads for a sample of investment-grade bonds issued by UK industrial companies to default probabilities generated by the Bank of England's Merton model of corporate failure. For the highest quality corporate issues, where the probability of default is low, this factor explains relatively little of the variation in credit spreads. For such bonds, common market factors – perhaps related to liquidity conditions – appear to be of greater importance. This is consistent with previous empirical work. For lower-rated investment-grade bonds, however, the probability of default is found to be a more important determinant of credit spreads, explaining around a third of variability in a pooled regression. When coefficients are allowed to vary at the level of the individual issue, explanatory power rises to 50% for this group. This is much higher than previous studies have found, reflecting both the more direct application of the Merton model and the recognition that idiosyncrasies in factors such as liquidity conditions and expected recovery rates are likely to undermine results from pooled estimation.

Key words: Credit spreads, implied default probabilities, Merton models.

JEL classification: G12, G13.

Summary

Theoretically, changes in the yield spread between risky and risk-free bonds should reflect changing expectations about the likelihood of loss from default, which will itself be determined by variability in the probability of default and expected recovery. Our principal interest in this paper is to explore the extent to which variability in sterling corporate credit spreads corresponds to the theory, drawing, in particular, upon the predictions of a structural (Merton-style) model of corporate failure. Although credit spreads are often cited as indicators of such expectations, the empirical literature has found little evidence that idiosyncratic default risk is the principal driver of variability in credit spreads.

The recent empirical literature has generally adopted one of two approaches to examine the validity of structural models of default. Researchers have either compared actual credit spreads with those implied by a fully calibrated structural model or else they have regressed changes in spreads upon a reduced form of the model. In this study we take a different approach. First, we adopt an error-correction method in order to capture both the long-run relationship between spreads and default probabilities, and short-run deviations from trend. Second, while analysis of a reduced form of the structural model allows the key relationships to be identified, the non-linear interactions between the model inputs are not exploited. Hence, some of the power of the model is lost. In this paper, therefore, we apply the structural approach more directly, employing a Merton-style model, developed at the Bank of England, to generate a panel of implied default probabilities. Finally, much of the previous work in this area has drawn upon data from the US non-government bond market. Our work, by contrast, employs a sample of 78 sterling bond issues by 42 UK industrial companies. For each, we have up to 83 monthly observations for both asset swap credit spreads and Merton-generated implied probabilities of default, thereby creating a diverse data set, covering a segment of the market that, to our knowledge, has not previously been studied in this way.

The application of this approach is revealing. In a pooled regression, we find that variability in the implied probability of default can explain just 8% of the probability of default in the highest quality credit spreads (AAA/AA), and 11% of that in A-rated credits. With the probability of default for these issuers generally low, and often lacking variability, the relative importance of systematic factors tends to increase. Indeed, we find that the addition of time dummies to the specification increases explanatory power considerably, perhaps reflecting the influence of common factors such as liquidity conditions not explicitly included in the specification. Our results for lower investment-grade issues, those rated BBB, are more supportive of the structural model. Here we find that the probability of default explains around a third of the variation in credit spreads in a pooled regression, which is higher than previous empirical studies have found.

Comparison with a broadly equivalent specification to that employed elsewhere suggests that this is a reflection of the more direct application of the Merton approach; in particular, capturing the non-linearity inherent in the structural model, which is most important for companies that are closer to the default point.

In a further round of tests, we allow for heterogeneity in responses across individual issues in the ratings subgroups. Heterogeneity does indeed appear to be an important feature of the data set, with explanatory power increasing to 28% for high-quality issues, and almost 50% for BBB issues. This argues in favour of not only applying the Merton model directly, but also allowing for potential idiosyncrasies in factors such as liquidity and recovery rates.

Finally, we consider whether we are losing valuable information in the annualisation process for our implied default probabilities. If investors have short horizons, they may place greater weight on near-term default probabilities, and this will perhaps be more important for lower-grade bond issues. This hypothesis is supported by the data. Returning to a pooled specification with common coefficients, but retaining differences across ratings, we find once again that almost half of the variability in BBB credit spreads is explained by the regression specification. Explanatory power remains at just 12% for high-quality issues.

Many of these results would appear to have an intuitive interpretation. Previous research has established that the theoretical relationship between credit spreads and default expectations does not hold fully in practice, and this paper concurs with that finding. Spreads would appear to be influenced by market factors, such as liquidity premia, and these are likely to be time varying. Thus, it is intuitive that, for high-quality issuers, where both the level and variability of the probability of default is likely to be lower, the relative contribution of default expectations is likely to be much smaller.

1. Introduction

Theoretically, changes in the yield spread between risky and risk-free bonds should reflect changing expectations about the likelihood of loss from default, which will itself be determined by variability in the probability of default and expected recovery. Our principal interest in this paper is to explore the extent to which variability in sterling corporate credit spreads corresponds to the theory, drawing, in particular, upon the predictions of a structural model of corporate failure.[(1)] This is an important question, not only for practitioners in the financial markets, who require a better understanding of the factors influencing the value of their bond portfolios, but also for banking supervisors, central bankers and policymakers, who seek reliable measures of default expectations. Although credit spreads are often cited as indicators of such expectations, the empirical literature has found little evidence that idiosyncratic default risk is the principal driver of variability in credit spreads.

The recent empirical literature has generally adopted one of two approaches to examine the validity of structural models of default. Researchers have either compared actual credit spreads with those implied by a fully calibrated structural model (notably, Huang and Huang (2003)), or else they have regressed changes in spreads upon a reduced form of the structural model (Longstaff and Schwartz (1995) and Collin-Dufresne *et al* (2001)). In this study we take a different approach. First, we adopt an error-correction method in order to capture both the long-run relationship between spreads and default probabilities, and short-run deviations from trend. Second, while analysis of a reduced form of the structural model allows the key relationships to be identified, the non-linear interactions between the model inputs are not exploited. Hence, some of the power of the model is lost. In this paper, therefore, we apply the structural approach more directly, employing a Merton-style model, developed at the Bank of England (described in Tudela and Young (2003a, 2003b)), to generate a panel of implied default probabilities. Finally, much of the previous work in this area has drawn upon data from the US non-government bond market. Our work, by contrast, employs a sample of 78 sterling bond issues by 42 UK industrial companies. For each, we have up to 83 monthly observations for both asset swap credit spreads and Merton-generated implied probabilities of default, thereby creating a diverse data set, covering a segment of the market that, to our knowledge, has not previously been studied in this way.

The application of this approach is revealing. In a pooled regression, we find that variability in the implied probability of default can explain just 8% of that in the highest quality (AAA/AA) credit spreads, and 11% of that in A-rated credits. With the probability of default for these issuers generally low, and often lacking variability, the relative importance of systematic factors tends to increase. Indeed we find that the addition of time dummies to the specification increases explanatory

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(1) Structural models see default as arising out of the dynamics of a firm's value process. Such models draw upon the essential insight of Merton (1974), that bondholders may be seen as having bought a riskless bond and granted the shareholders a put option on the value of the firm, with a strike price equal to the face value of the debt. Thus, one may employ option-pricing techniques to determine the value of this put option and hence evaluate the probability of default, requiring data only on the drift and volatility of the company's asset/liability ratio. The principal alternative approach to modelling credit risk is often referred to as the 'reduced-form' approach. In the latter class of models, default is modelled as a stochastic process. A good, recent review of both classes of model may be found in Giesecke (2003).

power considerably, perhaps reflecting the influence of common factors such as liquidity conditions, not explicitly included in the specification. Our results for lower investment-grade issues, those rated BBB, are more supportive of the structural model. Here we find that the probability of default explains around a third of the variation in credit spreads in a pooled regression, which is higher than has been found in previous empirical studies. This can be attributed to the more direct application of the Merton model, rather than differences in the data set. Indeed, we show that adopting an equivalent approach to Collin-Dufresne *et al* (2001), we obtain a broadly comparable R^2 to that in the authors' original US study.

When we allow for heterogeneous responses across issues in the panel, explanatory power for the BBB sample rises further, to approximately 50%. This argues in favour of, not only applying the Merton model directly, but also allowing for potential idiosyncrasies in factors such as liquidity and recovery rates.

This paper proceeds, as follows. We begin, in Section 2, with a brief introduction to the theoretical relationship between credit spreads and default probabilities. In Section 3, we turn to the empirical literature on this topic, highlighting some of the key recent contributions. Our own empirical work is presented in Section 4, with some extensions in Section 5. Section 6 concludes.

2. The theoretical relationship between credit spreads and default probabilities

From a contingent claims perspective, all traded securities should have a risk-neutral expected return equal to the risk-free rate. If this were not so, profitable arbitrage opportunities would exist, and the market could not be in equilibrium. If we assume continuous compounding, the return on a default-free zero-coupon bond is given by:

$$R_{0,T}^{f} = e^{r_{0,T}T} \qquad \textbf{(1)}$$

where r is the spot risk-free rate at period 0, on a T-period bond, and $R_{0,T}^{f}$ is one plus the risk-free rate of return between periods 0 and T. The promised return on a defaultable (risky) bond, is given by:

$$R_{0,T}^{d} = e^{(r_{0,T}+s_{0,T})T} \qquad \textbf{(2)}$$

where s is the annualised spot credit spread at period 0, on a T-period bond. According to the 'no arbitrage' condition, if s>0 it must be that the bondholder attaches a probability of less than one to receipt of the full promised return. The credit spread thus represents compensation for expected loss, which itself comprises the probability of default and the extent of loss given default. If q_T^{cum} is the risk-neutral cumulative probability of default over the life of the bond, and z is the recovery rate in the event of default, the no arbitrage condition can be expressed, as follows:

$$e^{r_{0,T}T} = [1 - q_T^{cum} + q_T^{cum} z] \cdot e^{(r_{0,T}+s_{0,T})T} \qquad \textbf{(3)}$$

Rearranging and taking logs of both sides, one can obtain an expression for the spot credit spread in terms of the probability of default and the recovery rate:

$$s_{0,T} = \frac{\ln\{[1-q_T^{cum}+q_T^{cum}z]^{-1}\}}{T} = -\frac{\ln(1-q_T^{cum}+q_T^{cum}z)}{T} \quad \textbf{(4)}$$

Thus, the annualised spot credit spread is equivalent to the annualised risk-neutral probability of loss. If $z = 0$ this is equivalent to the annualised probability of *default*:

$$s_{0,T} = q_{0,T}^{Ann} = \frac{\ln[(1-q_T^{cum})^{-1}]}{T} = -\frac{\ln(1-q_T^{cum})}{T} \quad \textbf{(5)}$$

However, if $z \neq 0$, the relationship between credit spreads and the *annualised* probability of default is more complex. Rearranging equation **(5)** and substituting for q_T^{cum} in equation **(4)**,
yields:

$$s_{0,T} = -\frac{\ln[(1-z)\cdot e^{-q_{0,T}^{Ann}T}+z]}{T} \quad \textbf{(6)}$$

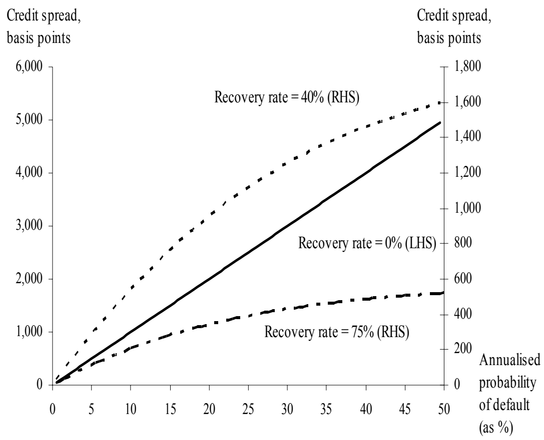
Thus, we can see that, when the recovery rate is non-zero, the credit spread is a non-linear function of $q_{0,T}^{Ann}$, with the first derivative of **(6)** being:

$$\frac{\partial s_{0,T}}{\partial q_T^{Ann}} = \ln[(1-z)\cdot e^{-q_{0,T}^{Ann}T}+z]^{-1}\cdot(1-z)\cdot e^{-q_{0,T}^{Ann}T} \quad \textbf{(7)}$$

This is illustrated in Chart 1, in which we assume a zero-coupon bond with a maturity of five years and recovery rates of 0%, 40% and 75%.(2) With a recovery rate of zero, plotted on the left-hand axis, it is clear that the relationship is one-for-one. As we move to a non-zero recovery rate, plotted on the right-hand axis, the relationship becomes non-linear, with the degree of non-linearity increasing in z. Note both the shift of scale and the change in the shape of the function.

(2) A recovery rate of approximately 40% is consistent with empirical observations. In a sample of more than 700 defaulting bond issues between 1978 and 1995, Altman and Kishore (1996) calculate an average recovery rate of $41.70 per $100 face value. Recovery outcomes vary significantly across industries. Those industries in which assets tend to be more liquid and more tangible enjoy higher liquidation values.

Chart 1: The theoretical relationship between credit spreads and annualised default probabilities[(a)]



(a) Assumes a zero-coupon bond, with maturity of 5 years.

The literature has, however, identified a host of reasons why the theoretical relationship outlined above might break down. One of the most crucial is likely to be the existence of liquidity premia. As pointed out by Schultz (1998), corporate bond markets tend to lack liquidity, making it costly to trade, and often making it difficult, if not impossible, to hedge or exit positions.[(3)] As a result, the market will impose a yield premium by way of compensation. A related issue is that in the presence of short-selling constraints, prices may not immediately reflect new information, creating a further source of divergence of theoretical and actual prices. This will be a particular problem if bonds are infrequently traded, which is often the case in the sterling market where a small number of buy-and-hold investors dominate. A further potential source of deviation from the theoretical relationship is taxation. Elton *et al* (2001) find, in a study of the US corporate bond market, that differential tax treatment of corporate relative to government bonds explains a significant proportion of the credit spread. It should be noted, however, that while liquidity premia are likely to vary considerably over time, the taxation factor may be less variable.

3. The empirical literature

As discussed earlier, our interest is in investigating the relationship between credit spreads and default probabilities. A number of authors have considered this empirical question, with the majority finding that only a fraction of the observed variability in credit spreads can be explained by changes in default expectations. In this section, we introduce some recent contributions to this literature, and discuss some of the key findings.

It is instructive to begin with a review of the key predictions of the structural approach to determining the probability of default, which are best expressed in terms of the implicit put option on

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[(3)] Indeed, as Blanco, Brennan and Marsh (2004) point out, if it is costly to short-sell, the true credit spread is the option-adjusted spread plus the repo cost.

the value of the firm granted by bondholders to the company's shareholders.[(4)] First, an increase in asset value (or a decrease in debt) will lower the probability of default; by taking the company further from its default point,[(5)] it reduces the value of the shareholders' put option on the firm. Second, an increase in volatility raises the likelihood that, for a given asset/liability ratio, asset value will fall to the default point. This therefore increases the value of the put option. The option-pricing methodology also allows us to make predictions about changes in the sensitivity of the put value to these factors as the asset/liability ratio itself changes (ie the rate of change of the option delta and option gamma). The key predictions here are that the option delta and the option gamma increase as the asset/liability ratio approaches the default point, thus yielding a non-linear relationship between default probability and the distance from default.

Longstaff and Schwartz (1995), henceforth LS, present a version of the original Merton model in which the risk-free rate is stochastic and default can occur whenever asset value reaches a certain threshold, rather than only at maturity. The authors also drop the assumption of strict absolute priority among claimants in the event of default. LS stress the distinction between the 'risk-neutral' and the 'actual' processes for the value of the firm. In the former, the drift term in the firm's value process is equal to r, the risk-free rate, while in the latter, it is equal to the actual mean equity return, μ. Thus, in valuing a risky bond, it is not sufficient to look only at the actual risk of default, as this may differ from the risk-neutral measure. The key message of LS is therefore that credit spreads will be positively related to actual default risk, but negatively related to the risk-free rate. The intuition for the latter association is that by increasing the risk-neutral drift in the firm's value process, an increase in the risk-free rate will drive the firm further away from the default threshold. LS go on to test the predictions of this model using a reduced form, rather than directly employing the predictions of a structural model. With a data set comprising 25 years of corporate bond yield averages for US industrials, utilities and railroads, LS regress spread changes on equity returns (for the appropriate index), and the change in the 30-year US Treasury yield. The authors find strong support for their variant of the structural model, with the coefficients on both regressors significantly negative, and most of their regressions exhibiting a high level of explanatory power. A further prediction of the model, as discussed above, is that these inverse relationships should be more

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[(4)] To illustrate briefly the structural approach, we draw upon the example in Giesecke (2003). Let us assume a simple firm, financed by a mix of equity and a zero-coupon bond, with face value B and maturity T. If, at T, the asset value of the firm, V_T, is insufficient to repay B, default occurs and the bondholders acquire the residual assets of the firm. In this case, the equity holders get nothing. If, on the other hand, the asset value is greater than B, the bondholders are paid in full, and the equity holders get the residual value: $V_T - B$. The value of equity is therefore equivalent to the pay-off of a European call option on V, with strike price B, and maturity T. Thus, making the assumption that V_t follows a random walk, with drift equal to μ, the equity value may be given by the Black-Scholes call option formula: $BS_c(\sigma, T, B, \mu, V_0)$, where σ is asset volatility, and the expected discounted default loss of the bondholders is then equal to the value of the put option: $BS_p(\sigma, T, B, \mu, V_0)$. Once again, from a contingent claims perspective, all assets should have a risk-neutral expected return equal to the risk-free rate. Thus, if μ is set to be equal to r, the risk-free rate, the resultant implied default loss is risk-neutral.

[(5)] In the context of the Merton model, the default point is a threshold asset value, at which the company is deemed to be in default. In the Bank's Merton model (Tudela and Young (2003a, 2003b)), employed in our econometric analysis, the default point is equal to all the company's short-term, and half its long-term liabilities.

pronounced as firms approach the default point. This prediction also finds support in LS's empirical tests: the R^2 of the reduced-form model increases as credit quality declines.

In a more recent study, adopting a similar approach, Huang and Kong (2003) investigate the explanatory power of a broader array of factors, including realised default rates, interest rate variables, equity market factors, liquidity indicators and macroeconomic indicators. Regressing spread changes in Merrill Lynch's corporate bond indices upon these variables, the authors find that the combined explanatory power is as high as two thirds for the lowest quality high-yield indices, declining to approximately half for the low investment-grade indices and to around a third for the high investment-grade indices.

Collin-Dufresne, Goldstein and Martin (2001), henceforth C-DGM, employ a disaggregated data set to test the structural approach more explicitly. Their key finding is that such models can explain only a fraction of the pricing of credit risk in the financial markets. According to a structural model of the credit spread, $Spread_t = f(V_t, r_t, \{X_t\})$, where V_t is the firm's value, r_t is the risk-free rate and $\{X_t\}$ is the set of all other state variables which might affect either the risk-neutral probability of default or the recovery rate in the event of default. Using a large US data set of 688 bonds, spanning 261 issuers and up to 56 months, C-DGM consider variants of the following specification:

$$\begin{aligned}\Delta Spread_{t,i} = {} & \beta_{0i} + \beta_{1i}\Delta leverage_{t,i} + \beta_{2i}\Delta r_t + \beta_{3i}(\Delta r_t)^2 + \beta_{4i}\Delta Slope_t + \beta_{5i}\Delta VIX_t + \\ & \beta_{6i}\Delta jump_t + \beta_{7i}\Delta S\&P_t + \varepsilon_{t,i}\end{aligned} \quad \textbf{(8)}$$

where *leverage* captures the relationship between firm *i*'s asset value and its debt obligations, *VIX* captures volatility, *jump* is the probability of a large equity decline, reflecting the risk of a sizable adverse shock to the firm's value process, and finally the return on the *S&P* and the yield curve *slope* are proxies for the business climate, which might be expected to determine the recovery rate. The estimated regression coefficient for each factor generally carries the expected sign, with some evidence of greater sensitivity for firms with higher leverage (ie closer to the default point).(6) However, despite adopting a more detailed specification, C-DGM find that the explanatory power is extremely low: only around a quarter of the variation in spreads appears to be explained by the determinants of a structural model. Furthermore, the most significant factors in their specification are common (such as the return on the S&P index), as opposed to idiosyncratic factors. Performing a principal components analysis of the residuals, C-DGM find that over 75% of the variation is due to the first component. This strengthens their conclusion that the most important drivers of variability in credit spreads are common systematic factors. Though the authors add proxies for time variation in liquidity and risk premia to their specification, a great deal remains unexplained.

Blanco, Brennan and Marsh (2004), henceforth BBM, perform an empirical analysis of

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(6) This is particularly notable for the interest rate and leverage, which is consistent both with the predictions of the structural model and the findings of Longstaff and Schwartz (1995). Surprisingly, however, there is no evidence of a systematic increase in R^2 as credit quality declines.

higher-frequency spread changes for a small sample of investment-grade corporates. These authors also find relatively low explanatory power from this specification, but interestingly do not find such a strong influence from changes in the broad equity index. BBM find considerable heterogeneity in estimated coefficients on firm-specific equity prices and volatility and, consistent with the structural model, observe that their absolute magnitudes tend to increase as credit quality decreases. The specific focus of BBM is on the dynamic relationship between corporate bond spreads and credit default swap (CDS) premia, rather than on the explanatory power of structural models of credit risk *per se*. An interesting finding in their paper is the fact that the CDS market appears to be more closely integrated with the equity market and tends to lead the corporate bond market in price discovery. The authors find that the basis between the two markets appears with a positive and highly statistically-significant coefficient when added to their regression specification for corporate bond spread changes, and suggest that the lagged response might reflect relative illiquidity and short-selling constraints in the cash market.

Huang and Huang (2003) calibrate a variety of structural models to match observed default loss experience and use these to predict the level of credit spreads. Though this is a markedly different approach, the authors reach a similar conclusion. For investment-grade bonds, credit risk accounts for around 20% of the observed spread, with the proportion rising to 30% for lower investment-grade spreads (ie Baa-rated issues). For high-yield bonds, however, credit risk is a much more important determinant of the spread. Elton, Gruber, Agrawal and Mann (2001), henceforth EGAM, also conclude that default risk can explain only a fraction of the credit spread. Here the authors split the level of the credit spread into three component parts: (i) a default premium, (ii) a tax premium, and (iii) a risk premium. Using a large US database, the authors empirically estimate how much of the observed credit spread can be explained by each component part, and find that, for ten-year corporate bonds, default risk plus taxation can account for little more than half of the observed credit spread.[7] Using the Fama-French (1993) 3-factor model,[8] the authors find that 85% of the remaining spread may be explained by the very systematic factors employed in the literature to analyse risk premia in the equity market. C-DGM also find support for these risk premium terms. Including all three in their specification, they find each to be statistically significantly negative, with their importance increasing as credit quality (as measured by absolute leverage) deteriorates.

The message from the recent empirical literature is consistent: though there is some support for structural models, the relationship between credit spreads and default probabilities appears to deviate significantly from that predicted by the theory. In particular, factors such as risk and liquidity premia seem to play a significant role.

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(7) Elton *et al* (2001) also estimate the appropriate premium for default risk by extracting marginal default probabilities for each ratings class from transition matrices generated by S&P and Moody's.
(8) The Fama-French model seeks to explain excess equity returns in terms of the excess return on the market portfolio, the return premium on a portfolio of small versus large stocks, and the return premium on a portfolio of high versus low book-to-market stocks.

4. Empirical analysis

4.1 Introduction

The objective of our empirical analysis is to determine the extent to which variability in sterling corporate credit spreads reflects variability in default expectations. Our analysis draws upon implied default probabilities for a sample of UK companies, generated by a structural model of corporate credit risk developed in-house at the Bank of England (described in detail in Tudela and Young (2003a, 2003b)).

As discussed in Section 3, the literature has previously applied the structural approach to this type of analysis, but generally the essential inputs (leverage and volatility) have been treated separately; often within a linear model specification. In this way, the interactions between these inputs and the rich, non-linear structure of these models has not been fully exploited. In contrast, the approach taken here allows the structural model to generate the implied default probability, and only then incorporates this in a linear regression, expressed in error-correction form.

We begin our analysis with a discussion of the data and data sources, going on to outline the essential features of the Merton model employed in our econometric work. We then undertake some preliminary graphical analysis, before turning to our formal econometric analysis.

4.2 Data and data sources

The principal source of corporate bond data is the Merrill Lynch Global Index System. We restrict our attention to investment-grade issuance, given that the UK high-yield sector is very small and notoriously illiquid. Merrill Lynch specifies a number of criteria for inclusion in these indices, which ensure that constituent bonds meet certain standards of investability. In particular, the minimum issue size (for investment-grade issues) is £100m, bonds must have at least one year remaining to maturity and the coupon schedule must be fixed. Prices are 'bid' and obtained from a combination of Merrill Lynch trading desks and external sources.

Our focus is on sterling issuance by UK industrial companies;[9] thereby excluding financial companies, which are not covered by the Bank's Merton model, and utility companies, for which the regulatory environment may affect investors' perceptions of risk. We have therefore filtered the Merrill Lynch Sterling Corporate Index accordingly, retaining in our data set all issues still outstanding on 30 November 2003, for which at least ten monthly observations for the asset swap

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[9] We exclude the financial and utility sectors as both are subject to ongoing regulatory and supervisory pressures that will affect the perceived risk associated with their issued securities. Furthermore, financial companies are not covered by the Bank's Merton model. Our criterion for inclusion is that issuers be rated no lower than BBB- by Standard and Poor's.

spread are available,[10] and for which implied default probabilities are available for the issuer in the Bank's model.[11] Data are available from January 1997, yielding an unbalanced panel with up to 83 observations per issue. In the early part of the period under review, we have observations for only a small number of issues. By January 2001, however, data are available for half of the bonds in the data set.

Our final data set contains 42 issuers, with a total of 78 individual bond issues (see Annex C for a full list).[12] This compares with 64 UK-domiciled industrial issuers, with a total of 124 individual issues, included in the Merrill Lynch Sterling Corporate Index at end-November 2003. Furthermore, the prevailing combined market value of the 78 bonds in our data set was more than £23 billion, constituting around two thirds of the value of this segment of the index. In this sense, our data set captures some of the most important UK issuers and issues. In Table A, we present the industrial breakdown of the relevant segment of the Merrill Lynch index. Comparison of this with our final sample reveals that we have retained a reasonably similar spread of issuers, with the only notable mismatch being in the real estate sector (for which data are incomplete in the Bank's Merton model).

Table A: The sectoral breakdown of sterling issuance by UK industrials

	£ issues by UK industrials – Merrill Lynch index system (30/11/03)			Our sample		
	% Mkt Cap	No. issuers	% issuers	% Mkt Cap	No. issuers	% issuers
Basic industry	3.8%	4	9.5%	3.0%	3	7.1%
Capital goods	9.3%	7	16.7%	9.3%	6	14.3%
Consumer cyclical	12.5%	8	19.0%	8.7%	5	11.9%
Consumer non-cyclical	24.9%	14	33.3%	32.8%	10	23.8%
Energy	7.2%	5	11.9%	6.6%	4	9.5%
Media	4.5%	4	9.5%	7.0%	4	9.5%
Real estate	7.6%	9	21.4%	0%	0	0%
Cyclical services	13.8%	8	19.0%	16.1%	6	14.3%
Non-cyclical services	0.6%	1	2.4%	1.1%	1	2.4%
Telecom & technology	15.8%	4	9.5%	15.5%	3	7.1%
	100%	64	100%	100%	42	100%

Source: Merrill Lynch.

[10] This is defined as the option-adjusted spread over LIBOR of a match floating rate bond. The asset swap spread is increasingly adopted as a measure of the credit spread, despite the fact that swap rates are not truly risk-free. This reflects the fact that the yield on government bonds became an increasingly unreliable reference rate in the late 1990s, as liquidity in the government market diminished.

[11] We also include data for outstanding bond issues by three formerly investment-grade companies – British Airways, Corus Group and Cable and Wireless – but only up until the time of their downgrade to sub-investment grade. Data for issues by Reuters and BP are also included, up until the time (during 2003) that the remaining maturity of their sterling bonds fell below one year. Finally, data for an outstanding bond by Six Continents has also been included up until the time of its withdrawal from the index, also during 2003.

[12] Fourteen of the issues in our sample are callable. This should not introduce any bias into our results, given that the spreads employed are option-adjusted. We have checked our key results using a sample of non-callable bonds only, with no discernible differences.

4.3 The Bank of England's structural model

The other important set of data employed in our analysis is, of course, the series of implied default probabilities generated by an in-house Merton model developed at the Bank of England. The model, presented in detail in Tudela and Young (2003a), adopts a similar philosophy to the original Merton approach and applies this to the generation of implied cumulative default probabilities for one to five years. Importantly, however, the Bank's model allows for default to take place at any time, once a certain threshold has been reached, rather than only at maturity as in the original Merton model. As shown in Tudela and Young (2003a), the implied probabilities of default generated by this model are fairly successful in establishing the likelihood of failure. In a study of UK quoted company defaults between 1990 and 2001, the authors found that the mean value of the one year ahead default probability for defaulting companies was 32%, and that for non-defaulting companies was 5.2%.

It should be noted that the value of the firm's assets is essentially unobservable. The model thus takes the ratio of the equity value to liabilities and applies a mapping, described in Tudela and Young (2003a), pages 15-16. The principal inputs to the model are then: data on stock market capitalisation for each company in the sample, and accounting data on each company's long and short-term liabilities.(13) The key variable, $k=A/L$, the asset-liability ratio, is assumed to follow a stochastic process, $dk = (\mu_A - \mu_L)kdt + \sigma_A k dz$, where μ_A and μ_L represent the drift in the asset and liability value processes respectively, σ_A captures asset volatility and $dz = \varepsilon\sqrt{dt}$, with $\varepsilon \sim N[0,1]$. The authors then define $\mu_A - \mu_L = \mu_k$ and $\sigma_A = \sigma_k$.

In mapping equity to asset values, the authors work with a risk-adjusted measure of drift for the asset process, $\mu_A^* = r - \partial$ (where r is the risk-free rate of return and ∂ is the firm's payout ratio), and set the risk-neutral rate of return on a firm's equity, X, equal to dividend income plus capital gains received by equity holders, $dE_t(X)/dt$; ie $rX = \partial(A - L) + dE_t(X)/dt$. The value for k, consistent with this expression, is ultimately employed in the model;(14) hence, implied probabilities of default generated by the model are risk-neutral. Given that the theory outlined in Section 2 predicts an association between credit spreads and risk-neutral default probabilities, the measures generated by the model are appropriate for our purposes in this study.

Default is deemed to occur if k falls below the default point $\underline{k}$, which is defined as the point at which assets equal total short-term liabilities, plus half the company's long-term liabilities. Maximum likelihood techniques are employed to determine the values of μ_k and σ_k, with these values then employed in the calculation of the implied default probability. The probability of the firm not defaulting until date T is the probability that $k_T > \underline{k}$, conditional on $k_\tau > \underline{k}\ \forall \tau \quad t \leq \tau < T$.(15)

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(13) These data are all obtained from Thomson Financial Datastream.
(14) The authors solve the expression: $rX = \partial(A - L) + dE_t(X)/dt$, for k, using the Newton-Raphson scheme.
(15) A formal mathematical treatment may be found in Tudela and Young (2003a).

4.4 Graphical analysis

We begin with a brief graphical analysis of the mechanics of the structural model. In Charts 2(a) – (d), we present a series of plots for four of the issues in our data set. For each, the top panel contains four time series, which illustrate the principal inputs to the structural model (asset value, default point and asset volatility) and the implied probability of default generated by the Bank's model.(16) Below this, we present, for each company, a second chart showing the implied probability of default and the asset swap spread, and a third tracing the path of the company's S&P issuer rating over the sample period.

In Charts 2(a) and (b), we examine data for two of the lower-rated companies in the sample. These charts suggest that default probabilities generated by the structural model explain a great deal of the variation in credit spreads. In the first panel of Chart 2(a), which plots data for British Airways (BA), we can see quite clearly that asset value was in steady decline for much of the period, while its default point, which proxies the firm's liability structure, was rising. The spike in the implied probability of default in late 2001 was coincident with a sharp fall in asset value (associated with expectations of lower profitability post-September 11th) which brought it close to the default point. In the second panel, we can see that BA's credit spread also rose dramatically at this time, and that there has indeed been a strong association between the implied default probability and credit spreads throughout the period under review.(17) The third panel reveals that, from 1999, BA's credit rating was also in decline and that the stronger association between the credit spread and default probability has been most evident since the company fell into low investment-grade territory. Similar observations may be made for Carlton Communications, in Chart 2(b).

Turning to the higher-rated companies, in Charts 2(c) – (d), the picture is quite different. In each case, the top panel reveals that asset values have remained some distance from the default point throughout the period. Thus, implied probabilities of default have also been low throughout (note the scales), and, by and large, less variable than those for the likes of BA and Carlton. Spreads for the companies shown in the charts, Tesco and BAA, did not exceed 80 basis points during the period under review (while those for the lower-rated companies above reached several hundred basis points in 2002/03), and such variability as has been observed must have been driven largely by other factors.

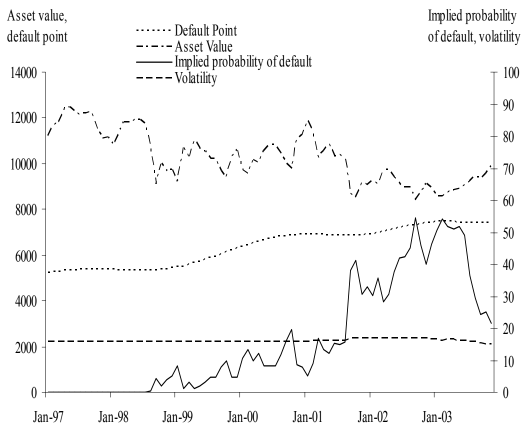
One qualification is that those highly-rated companies for which equity market volatility was particularly high during the stock market decline of 2000-03 – such as telecommunications companies – did experience a dramatic increase in implied default probability and a concomitant increase in credit spreads. Nevertheless, for A-rated companies such as Vodafone and BT (see Chart

(16) In these charts we present the annualised five-year implied cumulative probability of default. The choice of this measure is discussed later in this section.
(17) BA's credit spread is shown in the chart (and included in our analysis) to July 2003 only, at which time Standard and Poor's downgraded the company to sub-investment grade.

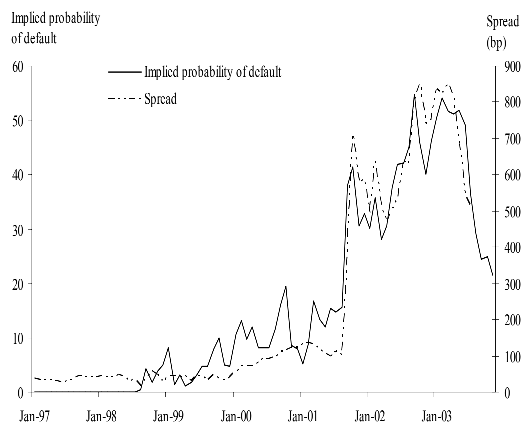
Charts 2(a) – 2(b)

2(a) British Airways

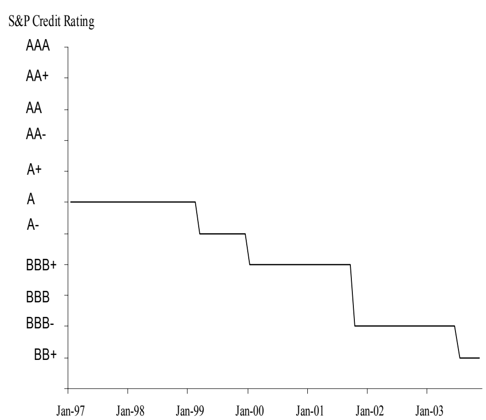
(i) Structural model inputs



(ii) IPD and asset swap spread

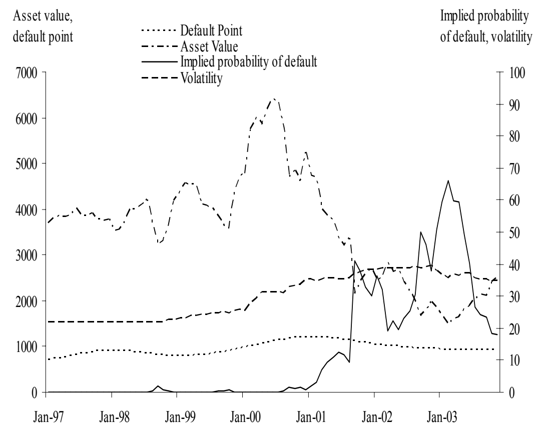


(iii) S&P credit rating

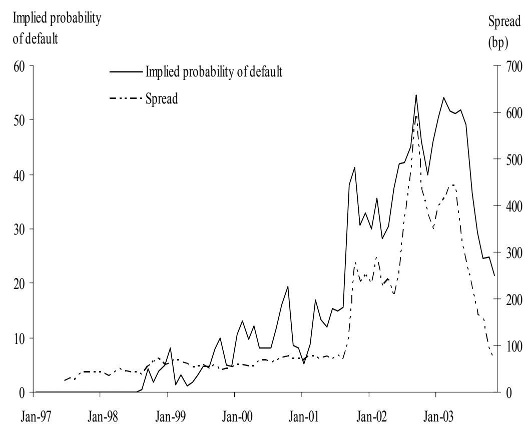


2(b) Carlton Communications

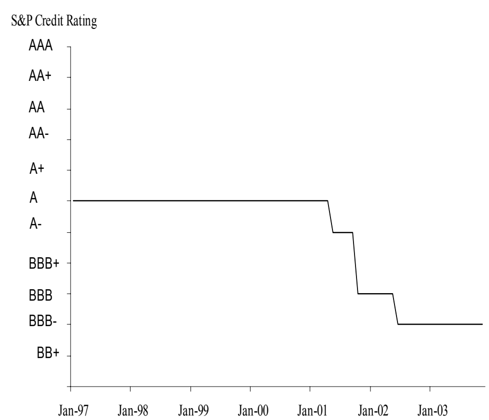
(i) Structural model inputs



(ii) IPD and asset swap spread



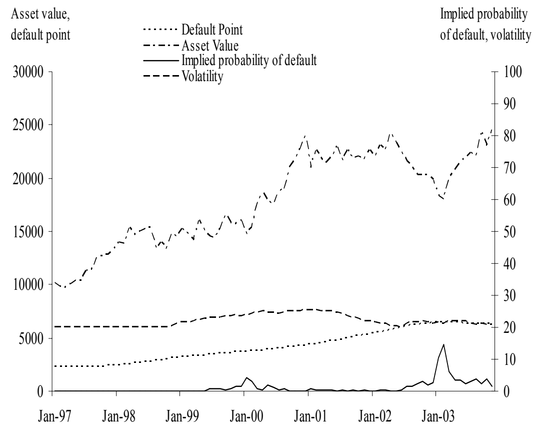
(iii) S&P credit rating



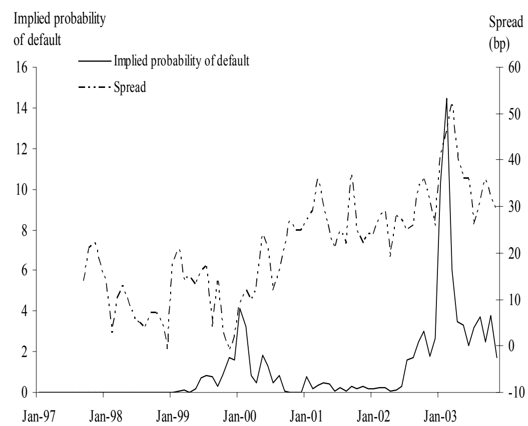
Charts 2(c) – 2(d)

2(c) Tesco

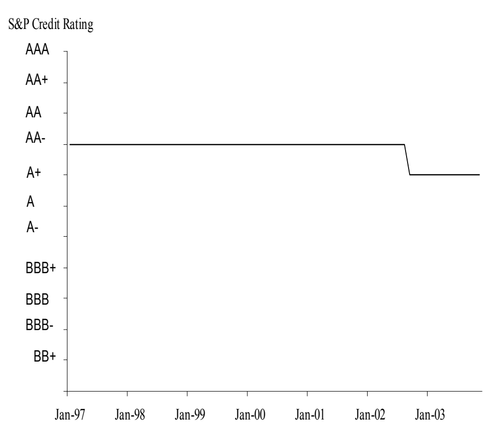
(i) Structural model inputs



(ii) IPD and asset swap spread

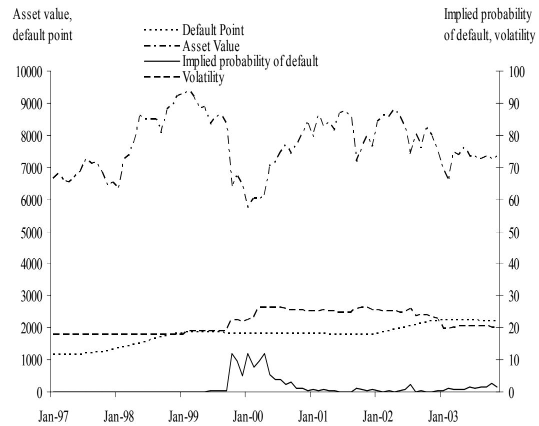


(iii) S&P credit rating

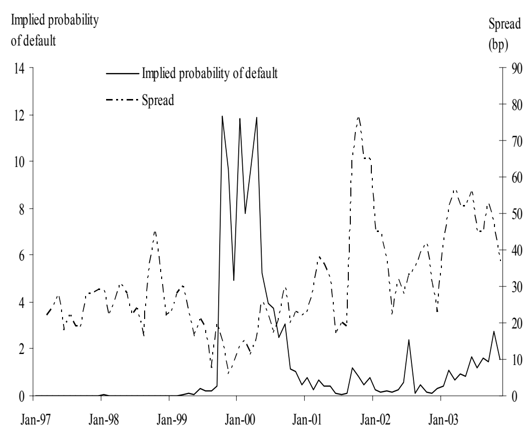


2(d) BAA

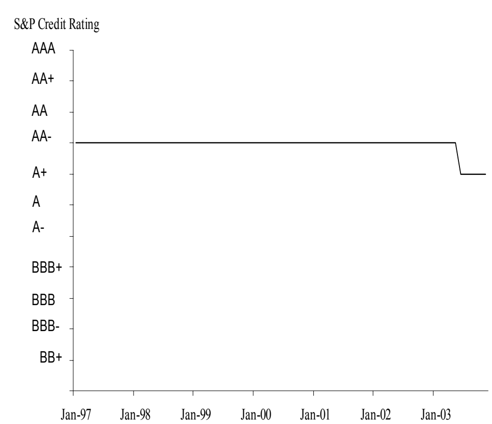
(i) Structural model inputs



(ii) IPD and asset swap spread



(iii) S&P credit rating



A1(a) and (b) in Annex A), credit spreads still barely breached 150 basis points, suggesting that the marginal response to changes in default risk was more muted than for lower-rated companies.[18]

A plausible, and quite compelling, explanation for these observations is that there is some segmentation between the high and low-quality investment-grade markets.[19] The high-quality tier of the market attracts investors with a limited appetite for credit risk, who might otherwise invest solely in gilts and supranational bonds. Such investors seek only a small margin above the risk-free return, a reward which does not justify detailed credit analysis. Hence, common, broad-market signals are more important than idiosyncratic factors. By contrast, investors in the low investment-grade segment of the market are more likely to be credit specialists, probably also investing in the high-yield market. By virtue of the higher returns available, these investors will be willing to incur the high cost of detailed credit analysis and as a result will likely be more responsive to idiosyncratic news.

4.5 Panel estimation

As we saw in Section 2, the theory predicts a positive relationship between annualised credit spreads and annualised default probabilities, which with non-zero recovery rates is non-linear. We initially adopt a linear approximation of this relationship, although by allowing coefficients to vary, first by rating, and later by issue, we go on to allow for some non-linearity.

As discussed above, the Bank's in-house Merton model generates cumulative implied probabilities of default for periods of one to five years. These are converted into annualised probabilities using the annual-compounding equivalent of equation **(5)**.[20] The bonds in our sample span a much broader range of maturities; indeed, the median maturity is 8.8 years, with the 25th and 75th percentile maturities being 6.0 and 13.9 years, respectively.[21] Although the theory predicts a relationship only between the spot credit spread and the annualised probability associated with that bond's maturity, the Bank's model generates probability estimates only for fixed one to five-year horizons. Thus, in our econometric work we take the longest of these – the annualised *five*-year probability − as a proxy (in a second round of tests, we consider the one-year probability).

We saw in equation **(5)** that, with zero recovery, the strict theoretical relationship between the credit spread on a zero-coupon bond and the risk-neutral annualised probability of default is:

$$Spread_{t,i} = \gamma IPD_{t,i} \qquad \textbf{(9)}$$

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[18] This is inconsistent with the theory, in which the non-linear relationship presented in Chart 1 suggests that the marginal response decreases as default probability increases.
[19] The author would like to thank an anonymous referee for suggesting this as a plausible explanation.
[20] This is: $q_{0,T}^{Ann} = 1-(1-q_T^{cum})^{1/T}$
[21] Maturities are slightly longer and more variable for the higher-rated bonds in our data set: The 25th, 50th and 75th percentiles are 5.8, 8.9 and 14.9 years, respectively, for bonds rated A- or higher, and 6.2, 8.5 and 10.7 years for those rated between BBB- and BBB+.

With both the probability of default (IPD) and the credit spread expressed in basis points, γ=1. This relationship may be rewritten:

$$Spread_{t-1,i} + \Delta Spread_{t,i} = \gamma(IPD_{t-1,i} + \Delta IPD_{t,i}) \quad \textbf{(10)}$$

which, rearranged, yields an expression in error-correction form:

$$\Delta Spread_{t,i} = \gamma \Delta IPD_{t,i} + \gamma IPD_{t-1,i} - Spread_{t-1,i} \quad \textbf{(11)}$$

(11) forms the basis for the specification to be adopted in our econometric analysis. We do, however, wish to introduce a little more flexibility into the specification to allow for departures from the strict relationship in **(9)**. In particular, we must allow for the fact that recovery rates will be non-zero, that the bonds in our sample are all coupon-bearing, and that there are likely to be departures from the theory due to the existence of factors such as time-varying liquidity premia and taxation. Furthermore, although the theory does not predict any relationship between the spread change in period *t* and lagged changes in the implied probability of default, we include a lag to allow for any delay in the transmission of information on default probabilities to the bond markets. As Blanco, Brennan and Marsh (2004) point out, news appears to be impounded into prices more slowly in the presence of short-selling constraints, though a long lag-length would seem implausible, and would suggest a high degree of segmentation between equity and bond markets.[22]

Our base-line specification is, therefore:

$$\Delta ASWAP_{t,i} = \beta_{0i} + \beta_1 ASWAP_{t-1,i} + \beta_2 5IPD_{t-1,i} + \beta_3 \Delta 5IPD_{t,i} + \beta_4 \Delta 5IPD_{t-1,i} + \varepsilon_{t,i} \quad \textbf{(12)}$$

where *ASWAP* is the asset swap spread, in basis points, and 5*IPD* is the five-year annualised implied probability of default (x100). The negative of the ratio of the coefficients on the lagged levels of implied probability of default and the asset swap spread, $-\beta_2/\beta_1$, will yield an estimate of the long-run relationship, while coefficients β_3 and β_4 represent estimates of the short-run effects.

Our chosen estimation methodology is least squares, with panel-corrected standard errors. Although our model is dynamic, the dimensions of our panel continue to argue in favour of a least-squares methodology. Judson and Owen (1999) present results from a Monte Carlo study, which compares the biases of alternative estimators, in panels of various dimensions. The authors show that with a sufficiently large *T* (=30), the residual mean-squared error from least-squares estimation is smaller than that from GMM, unless *N* is very large. When *T*=20, performance is broadly equivalent, but with a small *T*, GMM dominates. Here, even in our ratings sub-samples, *T* averages at least 25, and hence least-squares remains an appropriate approach.

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[22] As a robustness test, however, we do consider a specification which includes two lags of the change in default probability, finding that the coefficient on the second lagged term is not statistically significant at conventional levels, and that the inclusion of the second lag has no discernible effect on the other estimated coefficients.

The results in column (1) of Table B reveal that all estimated coefficients carry the expected sign and are statistically significant. The long-run effect is higher than the estimated short-run effects, although according to the theory a coefficient of 4.2 is consistent with a much higher recovery rate than has been observed empirically. Indeed, given a mean five-year annualised probability of default for the whole sample of the order of 10%, the implied recovery rate using the formula in **(7)** is close to 90%, which compares with an empirically observed recovery rate of close to 40%. As we shall discuss later in this section, our estimated coefficients may be difficult to interpret for a number of reasons. Hence, our prime emphasis will be on the overall explanatory power of our regressions and upon the relative magnitudes of estimated coefficients. The R^2 of our regression, at just 0.17, is towards the lower end of explanatory power in the US study of Collin-Dufresne *et al* (2001).

In column (2), we report the results from least-squares estimation of the specification in **(13)**, below (again, with panel-corrected standard errors). Here we also include time dummies, to capture any time-varying systematic factors omitted from our original specification. These might include liquidity premia and taxation factors, common to all bond issues.

$$\Delta ASWAP_{t,i} = \beta_{0i} + \beta_{0t} + \beta_1 ASWAP_{t-1,i} + \beta_2 5IPD_{t-1,i} + \beta_3 \Delta 5IPD_{t,i} + \beta_4 \Delta 5IPD_{t-1,i} + \varepsilon_{t,i} \quad \textbf{(13)}$$

The inclusion of time dummies has a marked effect on our regression results, with all estimated coefficients somewhat lower in absolute magnitude than those in column (1). This suggests that some of the effect attributed to the included variables was, in fact, due to correlation between the implied probability of default and omitted systematic factors. The explanatory power of the regression rises to a third.

By way of a test of the validity of our error-correction method, we carry out a Durbin test of autocorrelation in the residuals. For each specification, we extract the estimated residuals and regress these upon two lags of themselves (thereby testing for autocorrelation up to the second order) and all of the regressors in the original equation. In order to be consistent with our initial method, we again correct for panel-level heteroskedasticity when estimating these regressions. In the final row of Table B, we present the p-values from Wald tests of joint significance of the two lagged residual terms, and in each case fail to reject the null of zero autocorrelation with at least a 10% level of significance.

Table B: Pooled regression results

	All issues		Representative issues	
	(1)	(2)	(3)	(4)
$\Delta SWAP_{t\text{-}1}$	-0.071	-0.065	-0.051	-0.047
	$(-4.32)^{***}$	$(-3.85)^{***}$	$(-2.85)^{***}$	$(-2.57)^{***}$
$5IPD_{t\text{-}1}$	0.295	0.233	0.258	0.223
	$(5.15)^{***}$	$(4.61)^{***}$	$(3.95)^{***}$	$(3.89)^{***}$
$\Delta 5IPD_t$	1.814	1.233	1.838	1.238
	$(13.20)^{***}$	$(9.63)^{***}$	$(11.43)^{***}$	$(8.38)^{***}$
$\Delta 5IPD_{t\text{-}1}$	1.135	0.827	1.181	0.877
	$(8.58)^{***}$	$(6.77)^{***}$	$(7.62)^{***}$	$(6.18)^{***}$
Issue dummies	Yes	Yes	Yes	Yes
Time dummies	No	Yes	No	Yes
$\mathbf{R^2}$	**0.172**	**0.332**	**0.163**	**0.322**
Long-run effect	**4.185**	**3.573**	**5.051**	**4.731**
Observations	2,753	2,753	1,756	1,756
Issues[(a)]	71	71	39	39
Av. obs. per issue	38.8	38.8	45.0	45.0
Durbin test (p-value)	0.114	0.109	0.147	0.103

The dependent variable in our error-correction specification is the change in the asset swap spread. The estimation methodology is least squares, with panel-corrected standard errors. The long-run relationship reported in the table is calculated as $-\beta_2/\beta_1$ in specification **(12)**. t-statistics are reported in brackets, where * = coefficient statistically significant at the 10% level; **=coefficient statistically significant at the 5% level; and *** = coefficient statistically significant at the 1% level. In the final row of Table B, we report the results of a test of autocorrelation in the residuals. The residuals from each regression have been regressed against two lags of themselves and all of the regressors in the original regression. A Wald test of joint significance of the two lagged residual terms has then been carried out, with the p-value reported in the table.
(a) Given some evidence of autocorrelation in the residuals from these regressions, several issues have been dropped from the analysis.

There may be some concern over potential bias associated with the inclusion of multiple issues for several of the issuers in our data set. Alongside our core regression, therefore, we estimate specifications **(12)** and **(13)** including a single representative issue for each issuer (this is generally the issue for which we have the largest number of observations). Encouragingly, the results in columns (3) and (4) of Table B are very similar to those in columns (1) and (2) – both the explanatory power and the estimated short-run effects are almost identical, although the estimated long-run effects are slightly higher. Given the similarity of these results, we continue to work with the full data set for the remainder of the paper.

Clearly, a great deal remains unexplained in this pooled regression, and as mentioned above, the estimated long-run coefficient implies an implausibly high recovery rate. A number of factors may also be at work here. First, it is somewhat restrictive to impose a common coefficient across all issues. For example, there may be considerable heterogeneity in recovery rates. Second, our specification does not take account of heterogeneity in the response to factors subsumed in the time dummies − it would not be unreasonable, for example, to expect liquidity conditions to differ across issues and this could significantly affect the equilibrating force of arbitrage in the market. There may also be interactions between default probability and such omitted factors, which are not taken into account in our specification.(23)

Some of the heterogeneity in liquidity, risk premia, or recovery rates, may be related to the issuer's credit rating, and as was noted in the discussion supporting our graphical analysis, spreads appear to be more closely linked to default probabilities for lower-quality bond issues. Segmentation of the high and low tiers of the investment-grade market, as discussed above, may also argue in favour of a 'structural break' between ratings groups. Furthermore, to the extent that implied probabilities of default are higher for lower-rated issuers,(24) we capture some of the non-linearity in the spread-default probability relationship outlined in Section 2.

In Tables C(i) and (ii), we examine whether there is any evidence that coefficients vary by issuer rating. We work with three 'broad' ratings bands, based on Standard and Poor's credit ratings: (i) issuers rated AAA to AA-; (ii) issuers rated A+ to A-; and (iii) those rated BBB+ to BBB-.(25) We allow for transitions between ratings, and thus the composition of our sub-samples changes over time.(26) The A+ to A- sample is the largest, containing observations for a total of 56 issues, by 30 companies, with an average of 28 observations per issue. The highest quality sample is the smallest, with 20 issues across just 7 issuers, but with 35 observations, on average, for each issue. Finally, the BBB+ to BBB- sample comprises 36 issues, by 25 companies, with an average of 26 observations per issue.

Results for each group estimated separately are presented in Table C(i). These confirm the impression given by our earlier graphical analysis: the explanatory power of the Merton model increases as credit quality declines.

The model explains just 8% of the variability in AAA/AA spreads (column (1)), increasing modestly to 11% for single-A spreads (column (3)), and ultimately to 32% for the BBB sample (column (5)). Nevertheless, even for lower investment-grade credits much remains unexplained, which either constitutes a further challenge to the strict validity of the theoretical model, or argues in favour of further modification to our estimation methodology. Furthermore, the absolute magnitude of estimated coefficients – both long-term and short-term – tends to increase as credit quality declines. This finding is contrary to the theory – in which the relationship is concave − but consistent with our graphical analysis and the segmented markets explanation proposed.

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(23) There may also be other issues, such as the potential bias associated with a mismatch between the term of the bond and that of the default probability (as noted earlier in this section), and the fact that our principal variable of interest, the Merton default probability, is a constructed measure.
(24) This is indeed generally the case. For example, in our sample, the median implied default probability for the highest rated credits (AAA to AA-) was 0.3%; that for A+ to A- credits was 3.5%; and that for BBB+ to BBB- credits was 5.7%.
(25) Where Standard and Poor's ratings are unavailable, Moody's ratings have been used. Where an issuer is not rated by either agency, we apply the first available rating from the start of the sample period.
(26) Ratings transitions during the period under review were almost exclusively downwards, with four issuers descending from the AAA to AA- group to the A+ to A- group, and 15 descending from the latter to the BBB+ to BBB- group.

Table C(i): Regression results - ratings subgroups

	AAA/AA-rated issuers		A-rated issuers		BBB-rated issuers	
	(1)[(a)]	(2)[(a)]	(3)	(4)[(b)]	(5)	(6)
$ASWAP_{t-1,i}$	-0.155	-0.192	-0.055	-0.085	-0. 130	-0.125
	(-5.39)***	(-5.29)***	(-3.43)***	(-4.12)***	(-4.24)***	(-4.17)***
$5IPD_{t-1,i}$	0.299	0.296	0.137	0.143	0.467	0.353
	(2.24)**	(2.55)**	(3.61)***	(4.00)***	(2.82)***	(2.31)***
$\Delta 5IPD_{t,i}$	0.307	0.268	0.738	0.438	3.031	1.874
	(1.93)**	(1.78)*	(8.66)***	(5.57)***	(9.00)***	(5.87)***
$\Delta 5IPD_{t-1,i}$	0.052	0.115	0.259	0.104	1.958	1.180
	(0.32)	(0.73)	(2.98)***	(1.28)	(6.19)***	(3.94)***
Issue dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	No	Yes	No	Yes	No	Yes
R^2	**0.080**	**0.605**	**0.114**	**0.478**	**0.321**	**0.474**
Long-run effect	**1.927**	**1.543**	**2.477**	**1. 689**	**3.595**	**2.818**
Observations	593	593	1,560	1,336	918	918
Issues	17	17	56	52	36	36
Av. obs. per issue	34.9	34.9	27.9	25.7	25.5	25.5
Durbin test (p-value)	0.107	0.228	0.212	0.205	0.328	0.536

The dependent variable in our error-correction specification is the change in the asset swap spread. The estimation methodology is least squares, with panel-corrected standard errors. The long-run relationship reported in the table is calculated as $-\beta_2/\beta_1$ in specification **(12)**. t-statistics are reported in brackets, where * = coefficient statistically significant at the 10% level; **=coefficient statistically significant at the 5% level; and *** = coefficient statistically significant at the 1% level. In the final row of Table C(i), we report the results of a test of autocorrelation in the residuals. The residuals from each regression have been regressed against two lags of themselves and all of the regressors in the original regression. A Wald test of joint significance of the two lagged residual terms has then been carried out, with the p-value reported in the table.

(a) Three issues, by BT and GlaxoSmithkline, have been dropped from the regression with both issue and time dummies, due to evidence of autocorrelation in the residuals when included.

(b) Four issues, by BAE Systems and BT, have been dropped from the regression with both issue and time dummies, due to evidence of autocorrelation in the residuals when included.

Including time dummies, we find that explanatory power increases dramatically for the higher-rated groups – for the AAA/AA sample, explanatory power rises to more than 60%, while for the A-rated group, R^2 approaches 0.50. This suggests that systematic factors dominate spread changes for higher investment-grade bond issues.

We also re-estimate the ‘all issues’ regression in Table B, column (1), interacting each right-hand side variable with a ratings dummy, to investigate how much additional explanatory power is afforded us by allowing coefficients to vary by ratings group. Using this approach, we are also able to test formally whether statistically significant differences exist in the estimated coefficients for each group. First, we find that explanatory power rises from 17% to 27% – a significant increment. In Table C(ii), we find that statistically significant differences in coefficients exist between the BBB group and each of the higher ratings groups. The only significant difference between coefficients in the AAA/AA group and the single-A group, is in the short run.

Particularly given the relatively small size of the AAA/AA sample, this result argues in favour of working with just two ratings groups: (i) AAA to A-; and (ii) BBB+ to BBB-. Re-estimating **(12)** for the broader AAA to A- sample, explanatory power is approximately 10%.

Table C(ii): Wald tests of coefficient equality across issuer rating groups

	$\Delta SWAP_{t-1,r,i}$	$5IPD_{t-1,r,i}$	$\Delta 5IPD_{t,r,i}$	$\Delta 5IPD_{t-1,r,i}$
AAA/AA=A (p-value)	0.97	0.55	0.00***	0.12
A=BBB (p-value)	0.07*	0.00***	0.00***	0.00***
AAA/AA = BBB (p-value)	0.12	0.06*	0.00***	0.00***

For each independent variable included on the right-hand side of equation **(12)**, we present the p-value from a joint Wald test of coefficient equality across ratings groups.

4.6 Robustness tests

(i) Composition over time

It should be noted that most of the few issues for which data are available in the early part of the period under review are in the AAA-A sub-sample. Indeed only 10% of the observations in the BBB sample occur prior to June 2000, while in the AAA-A sample, a third of observations occur in this period. This suggests that any results for the BBB sample will be driven by observations in the latter half of the sample period. We therefore wish to examine the extent to which these compositional issues influence our results. In Table D, we present summary results from a re-estimation of **(12)** for the two ratings sub-samples, covering only the period June 2000 – November 2003. The basic tenor of our results remains unchanged, although explanatory power rises slightly for the AAA-A group – from 10% to 15%.

Table D: Summary regression results - ratings subgroups, sample period June 2000 – November 2003

	AAA - A-rated issuers		BBB-rated issuers	
	(1)	(2)[(a)]	(3)	(4)
	Issue dummies only	Issue and time dummies	Issue dummies only	Issue and time dummies
R^2	**0.153**	**0.459**	**0.332**	**0.479**
Long-run effect	**1.031**	**0.293**	**3.211**	**2.582**
Observations	1,568	1,502	824	824
Issues	57	55	36	36
Av. obs. per issue	27.5	27.3	22.9	22.9
Durbin test (p-value)	0.274	0.371	0.294	0.491

The dependent variable in our error-correction specification is the change in the asset swap spread. The estimation methodology is least squares, with panel-corrected standard errors. The long-run relationship reported in the table is calculated as $-\beta_2/\beta_1$ in specification **(12)**. In the final row of Table D, we report the results of a test of autocorrelation in the residuals. The residuals from each regression have been regressed against two lags of themselves and all of the regressors in the original regression. A Wald test of joint significance of the two lagged residual terms has then been carried out, with the p-value reported in the table.
(a) Two issues, by BAE Systems, have been dropped from the regression with both issue and time dummies, due to evidence of autocorrelation in the residuals when included.

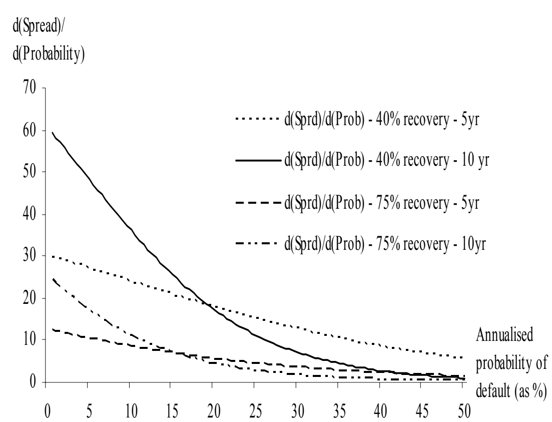
(ii) The spread of maturities

We noted earlier that our data set includes bonds with a rather broad spread of maturities (see footnote 21). According to the theory, this may have an effect on our coefficient estimates. Drawing on the theory presented in Section 2, Charts 3(i) and (ii) plot the theoretical short and long-run responses associated with notional zero-coupon bonds of five and ten-year maturity, assuming first 40% recovery, and then 75% recovery.

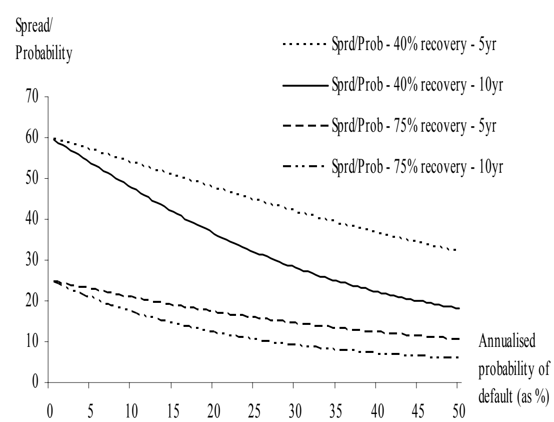
First, in panel (i), we see that at low probabilities, the short-run response is higher for long-maturity bonds, with the difference larger, the lower the recovery rate. At higher probabilities, the short-run response is greater for short-maturity bonds, although at higher recovery rates the difference between the two is modest. In panel (ii), we find that the long-run response is always higher for short-maturity bonds, with the difference increasing in the probability of default. Again, the difference is smaller at higher recovery rates.

Chart 3: Maturity differences

(i) The short-term response



(ii) The long-term response



To examine the extent to which this affects our results, we re-estimate **(12)** and **(13)** for the full sample, and the two ratings sub-samples, but this time interact each regressor with a dummy variable denoting whether a bond is long (maturity is greater than ten years), or short (maturity is less than (or equal to) ten years). We then test whether our coefficients are equal across maturities. The results of these tests are presented in Table E below.

Table E: Wald tests of coefficient equality across maturities

	$\Delta SWAP_{t-1,r,i}$	$5IPD_{t-1,r,i}$	$\Delta 5IPD_{t,r,i}$	$\Delta 5IPD_{t-1,r,i}$
Full sample (p-value)	0.05^{**}	0.04^{**}	0.31	0.13
AAA - A (p-value)	0.06^{*}	0.08^{*}	0.01^{***}	0.79
BBB (p-value)	0.05^{*}	0.97	0.69	0.57

For each independent variable included on the right-hand side of **(12)**, we present the p-value from a joint Wald test of coefficient equality across ratings groups.

Interestingly, coefficient differences across maturities are relatively small. In the BBB sample, short-run differences are not statistically significant, which is consistent with the modest differences at higher default probabilities (for high recovery rates) observed in Chart 3, panel (i).[27] If we consider these test results alongside the full results from separate regressions by rating and maturity, reported in Annex B, we find a slightly lower long-run coefficient in the BBB long-maturity sample. Once again, this is consistent with the profile in panel (ii).

There are more statistically significant differences in the higher-quality sub-sample, both for short-run and long-run coefficients, although the magnitudes are relatively modest. Again consistent with the theory, the short-run response is higher at longer maturities (given low default probabilities in the higher-quality sub-sample), and the long-run response is slightly higher. Nevertheless, the observed differences are insufficient to alter the broad thrust of our results.

4.7 Comparison with Collin-Dufresne et al (C-DGM)

The results presented above are more supportive of the structural model than those of Collin-Dufresne *et al* (2001) for lower investment-grade issues. It is therefore natural to ask whether this reflects the data employed or the estimation methodology.

We examine this question by applying C-DGM's linear methodology to our UK data set and then comparing the explanatory power with that obtained above for each ratings subgroup, using specification **(12)**. The specification we estimate is similar to that in **(8)**.[28] There are some subtle differences in the measures employed, though in essence we take suitable UK equivalents of the US measures adopted by C-DGM. The most notable difference is in the measure of leverage employed, for which we take the default ratio employed in the Bank's Merton model.[29] The results are presented in Table F below.

R^2s in Table F of 0.12 and 0.21,[30] for AAA-A and BBB samples respectively, compare with 0.10 and 0.32 using the direct Merton approach in specification **(12)** (as reported in Section 4.5). Thus, the two approaches yield similar results for higher-quality credit spreads, while our direct Merton approach does much better as we move down the credit scale.

This outcome is broadly intuitive, for the advantage of the Merton approach is that it exploits the non-linearity inherent in the structural model, which only begins to have an effect as a company's

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(27) It should be noted, however, that the long-maturity sample for BBB issuers is relatively small (just 11 issues, and 267 observations in total).
(28) This is taken from C-DGM's equation (1), page 2,184.
(29) For firm leverage, C-DGM employ the book value of debt, divided by the sum of the book value of debt and the market value of equity. In their regressions by ratings group (the authors' Table III, page 2,188), the authors include a measure of individual stock returns instead of leverage.
(30) This compares with 0.23 and 0.19 in C-DGM's US study, for the authors' single-A and BBB sub-samples respectively. Interestingly, therefore, explanatory power in the sterling market appears to be somewhat lower for the highest quality issues. This may reflect lower liquidity in the sterling market and the narrower investor base.

asset value approaches the default point. Given that highly-rated companies tend to be some distance from default, capturing the non-linearity in the structural model would not be expected to add much value.

Table F: Regression results – including determinants of the structural model in a linear specification

	All issuers	AAA - A-rated issuers	BBB-rated issuers
	(1)	(2)	(3)
Δ DEFAULT RATIO$_{t,i}$	-3.711	-2.571	-10.607
	(-3.60)***	(-3.16)***	(-2.59)***
Δ R10$_t$	-10.071	-3.874	-22.654
	(-4.68)***	(-2.83)***	(-3.51)***
(Δ R10)^2_t	1.303	-10.628	51.707
	(0.19)	(-2.35)**	(2.81)***
ΔSPR 2-10$_t$	14.697	6.754	31.395
	(5.78)***	(3.95)***	(4.29)***
Δ FTSE 100-VOL$_t$	-0.143	-0.259	0.004
	(-1.26)	(-3.39)***	(0.01)
Δ JUMP$_t$	1.024	1.129	1.150
	(4.22)***	(7.12)***	(1.58)
Δ LN(FTSE 100)$_t$	-72.024	-48.628	-112.867
	(-5.40)***	(-5.57)***	(-3.09)
Issue dummies	Yes	Yes	Yes
Time dummies	No	No	No
R^2	**0.103**	**0.121**	**0.213**
Observations	3,220	2,301	919
Issues	78	61	36
Av. obs. per issue	41.3	37.7	25.5
Durbin test (p-value)	0.166	0.185	0.400

The dependent variable in our error-correction specification is the change in the asset swap spread. The estimation methodology is least squares, with panel-corrected standard errors. Regressors are: ΔDEFAULT RATIO – change in the ratio of a company's asset value to its 'default point', as included in the Merton model, where 'default point' is defined as all of a company's short-term and half of its long-term liabilities; ΔR10 – change in the 10-year gilt yield; $(\Delta R10)^2$ – squared change in the 10-year gilt yield; ΔSPR 2-10 – change in the spread between 10 and 2-year gilt yields; ΔFTSE 100-VOL – change in the implied volatility of the option on the FTSE 100 index futures contract; ΔJUMP- probability of a 20% decline in the FTSE 100 index, calculated from option prices; ΔLN(FSTE 100) – the change in the natural log of the FTSE 100 price index. t-statistics are reported in brackets, where * = coefficient statistically significant at the 10% level; **=coefficient statistically significant at the 5% level; and *** = coefficient statistically significant at the 1% level. In the final row of Table F, we report the results of a test of autocorrelation in the residuals. The residuals from each regression have been regressed against two lags of themselves and all of the regressors in the original regression. A Wald test of joint significance of the two lagged residual terms has then been carried out, with the p-value reported in the table.

The signs and significance of our estimated coefficients in Table F are, by and large, consistent with the priors set out in C-DGM – in particular, the default ratio, the real interest rate, the FTSE 100 return and the ‘jump’ each carry the correct sign and are statistically significant across ratings groups.(31) Among the other factors, the spread factor takes the wrong sign, as does the volatility measure (where significant). The former may reflect distortions in the UK gilt market during the late 1990s/early 2000s, while the latter is likely to be due to collinearity with the change in the FTSE 100 index, with which the sample correlation is -0.71.

5. Extensions to the basic model

5.1 Heterogeneous responses

We suggested above that there may be heterogeneous responses even at the level of the individual issue, perhaps reflecting idiosyncratic liquidity factors. In particular, thin-trade effects, discussed briefly in Section 2, may significantly influence the observed response to changes in default probability. Allowing heterogeneous responses also in part addresses the maturity differences identified in Section 4.6.

In light of this, we perform a further round of tests, allowing both the long-run and short-run slope coefficients to change for each issue in the panel (though time dummies, where included, remain common to the whole sample). In order to ensure sufficient degrees of freedom at the issue level, we reduce the data set to include only those issues with at least 25 observations over the sample period. Unfortunately, this leads to a marked decline in the size of the ratings sub-samples – particularly the BBB sample. The specification we adopt is presented in **(14)** below.

$$\Delta ASWAP_{t,i} = \beta_{0i} + \beta_{1i} ASWAP_{t-1,i} + \beta_{2i} 5IPD_{t-1,i} + \beta_{3i} \Delta 5IPD_{t,i} + \beta_{4i} \Delta 5IPD_{t-1,i} + \varepsilon_{t,i} \qquad \textbf{(14)}$$

In Table G, columns (1) and (3), we present the results from our estimation of **(14)**. We calculate coefficient estimates and standard errors using the Mean Group Estimator methodology described in Matyas and Sevestre (1996). The coefficient shown is thus the mean of the estimates across panel members, $\overline{\beta}$, with the standard error calculated by:

$$se(\overline{\beta}) = \sqrt{\frac{\sum^{N}(\hat{\beta} - \overline{\beta})}{N(N-1)}} \qquad \textbf{(15)}$$

where N is the number of issues in the panel.

In columns (2) and (4), we add time dummies to the specification in **(14)**. We continue to work with ratings sub-samples, so as to be able to investigate explanatory power. Mean group estimates of the coefficients in regressions excluding time dummies continue to carry the expected sign (columns (1) and (3) of Table G), and remain statistically significant at conventional levels. Explanatory power increases markedly, to more than a quarter for the AAA-A sample, and to almost a half for the BBB

(31) The ‘jump’ variable actually has a p-value of 0.11.

sample. For the full sample (not reported), explanatory power rises to 41%, which is significantly higher than has been found in other empirical studies.

Table G: Regression results – exploring heterogeneous responses: Mean Group Estimator

	AAA - A-rated issuers		BBB-rated issuers	
	(1)	(2)	(3)	(4)
$ASWAP_{t-1,i}$	-0.272	-0.218	-0.246	-0.436
	(-6.55)***	(-8.17)***	(-8.94)***	(-10.61)***
$5IPD_{t-1,i}$	0.404	0.247	1.049	1.161
	(3.57)***	(2.98)***	(2.19)**	(2.47)**
$\Delta 5IPD_{t,i}$	0.845	0.213	2.914	1.401
	(4.18)***	(1.24)	(4.65)***	(2.05)**
$\Delta 5IPD_{t-1}$	0.358	0.209	1.104	-0.181
	(1.77)*	(1.09)	(2.55)***	(-0.46)
Issue dummies	Yes	Yes	Yes	Yes
Time dummies	No	Yes	No	Yes
R^2	**0.278**	**0.578**	**0.481**	**0.654**
Long-run effect	**1.486**	**1.134**	**4.271**	**2.663**
Observations	1,886	1,886	590	590
Issues	36	36	14	14
Av. Obs. per issue	52.4	52.4	42.1	42.1
Durbin test (p-value)	0.291	0. 378	0.393	0.294

The dependent variable in our error-correction specification is the change in the asset swap spread. The estimation methodology is least squares, with panel-corrected standard errors. Mean group estimates of each coefficient are reported, with t-statistics based upon standard errors calculated by **(15)**. The long-run relationship reported in the table is calculated as $-\beta_{2i}/\beta_{1i}$ in specification **(14)**. t-statistics are reported in brackets, where * = coefficient statistically significant at the 10% level; **=coefficient statistically significant at the 5% level; and *** = coefficient statistically significant at the 1% level. In the final row of Table G, we report the results of a test of autocorrelation in the residuals. The residuals from each regression have been regressed against two lags of themselves and all of the regressors in the original regression. A Wald test of joint significance of the two lagged residual terms has then been carried out, with the p-value reported in the table.

Once time dummies are included, however, the sizes of the coefficients on implied default probability diminish in absolute magnitude and the short-run coefficients in the higher-quality sub-sample lose their statistical significance. Nevertheless, explanatory power increases further, rising to more than a half for the high-grade sample, and to almost two thirds for the BBB group. This analysis suggests that heterogeneity at the level of the individual issue is indeed an important feature of the data set, and that recognition of this, as well as a more direct application of the Merton model, generates increased empirical support for structural models – at least in the case of lower-rated credits. Nevertheless, a larger data set would be required to strengthen our results using this methodology.

5.2 One-year implied probabilities of default

A further possibility is that investors respond more readily to changes in near-term default expectations. If bondholders have short investment horizons (or holding periods),(32) one might argue that they will place greater weight on near-term expectations than on those spanning the life of a bond. Thus, for each of the AAA-A and BBB sub-samples, we replace the five-year annualised probability in our pooled specifications **(12)** and **(13)** with the one year ahead probability. Results are presented in Table H.

Table H: Regression results – one-year implied probability of default

	AAA - A-rated issuers		BBB-rated issuers	
	(1)	(2)[(a)]	(5)	(6)
$ASWAP_{t-1}$	-0.075	-0.100	-0.151	-0.184
	$(-5.83)^{***}$	$(-6.05)^{***}$	$(-5.13)^{***}$	$(-5.80)^{***}$
$1IPD_{t-1}$	0.188	0.228	0.905	1.137
	$(4.27)^{***}$	$(4.72)^{***}$	$(2.98)^{***}$	$(3.95)^{***}$
$\Delta 1IPD_t$	1.033	0.837	4.039	3.358
	$(8.88)^{***}$	$(7.23)^{***}$	$(10.33)^{***}$	$(9.21)^{***}$
$\Delta 1IPD_{t-1}$	0.281	0.080	2.049	1.340
	$(2.31)^{**}$	(0.65)	$(5.55)^{***}$	$(3.87)^{***}$
Issue dummies	Yes	Yes	Yes	Yes
Time dummies	No	Yes	No	Yes
R^2	**0.128**	**0.474**	**0.439**	**0.577**
Long-run effect	**2.514**	**2.275**	**5.977**	**6.188**
Observations	2,289	2,010	918	918
Issues	61	57	36	36
Av. obs. per issue	37.5	35.3	25.5	25.5
Durbin test (p-value)	0.130	0.199	0.183	0.303

The dependent variable in our error-correction specification is the change in the asset swap spread. The estimation methodology is least squares, with panel-corrected standard errors. The long-run relationship reported in the table is calculated as $-\beta_2/\beta_1$ in the one-year probability equivalent of specification **(12)**. t-statistics are reported in brackets, where * = coefficient statistically significant at the 10% level; **=coefficient statistically significant at the 5% level; and *** = coefficient statistically significant at the 1% level. In the final row of Table H, we report the results of a test of autocorrelation in the residuals. The residuals from each regression have been regressed against two lags of themselves and all of the regressors in the original regression. A Wald test of joint significance of the two lagged residual terms has then been carried out, with the p-value reported in the table.
(a) Two issues, by BAE Systems and BT, have been dropped from the regression with both issue and time dummies, due to evidence of autocorrelation in the residuals when included.

One might expect this effect to be strongest at higher default probabilities, where investors' sensitivity to downside risk is likely to be heightened. These results suggest that this is indeed the case. For this group (column (3)), the long-run coefficient rises to approximately 6, and explanatory

(32) A full treatment of this hypothesis is beyond the scope of this paper.

power increases to 44%, from 32% in Table C(i). The R^2 rises further, to 0.58, with the addition of time dummies.

For the AAA-A sample, on the other hand, the results are not markedly different from those for the AAA-AA and single-A samples in Table C(i), with explanatory power still only 13%.

Although these results carry some intuitive appeal and provide some initial evidence in favour of the hypothesis that credit spreads respond more readily to changes in near-term default expectations, more work needs to be done to both tie down the theory behind such behaviour, and to firmly establish the robustness of the results.

6. Concluding remarks

The foregoing analysis yields some interesting results on the relationship between credit spreads and implied probabilities of default generated by a structural model. In a pooled least-squares regression, we find that only 17% of the variability in asset swap spreads is explained by variation in the five-year annualised implied default probability. We consider several explanations for such low explanatory power, noting that heterogeneity among panel members in factors such as liquidity conditions and recovery rates might undermine a pooled estimation technique.

We first consider heterogeneity at the level of the issuer's credit rating, estimating a separate pooled specification for each ratings subgroup. We find that our specification explains just 10% of the variation in credit spreads for high-quality bond issues, rising to a third for lower-quality investment-grade credits. Adding time dummies to the specification, to capture time-varying systematic market factors, such as liquidity premia, explanatory power rises to almost a half for both sub-samples. This reveals that such factors are particularly important for higher-grade issues.

The explanatory power obtained for lower investment-grade credits is higher than in other empirical studies. Comparison with a broadly equivalent specification to that in Collin-Dufresne *et al* (2001) suggests that this is a reflection of the more direct application of the Merton approach; in particular, capturing the non-linearity inherent in the structural model, which is most important for companies that are closer to the default point.

In a further round of tests, we allow for heterogeneity in responses across individual issues in the ratings subgroups. Heterogeneity does indeed appear to be an important feature of the data set, with explanatory power increasing to 28% for high-quality issues, and almost 50% for BBB issues.

Together, these results suggest that the principal innovations of this paper – the direct application of the Merton model and the investigation of heterogeneity in responses at the issue level – lead to a stronger empirical result for the structural model; at least for lower investment-grade credits.

Finally, we consider whether we are losing valuable information in the annualisation process for our implied default probabilities. If investors have short horizons, they may place greater weight on near-term default probabilities, and this will perhaps be more important for lower-grade bond issues. This hypothesis is supported by the data. Returning to a pooled specification with common coefficients, but retaining differences across ratings, we find once again that almost half of the variability in BBB credit spreads is explained by the regression specification. Explanatory power remains at just 12% for high-quality issues.

Many of these results would appear to have an intuitive interpretation. It has been established elsewhere in the literature that the theoretical relationship between credit spreads and default expectations does not hold fully in practice, and this paper concurs. Spreads would appear to be influenced by market factors, such as liquidity premia, and these are likely to be time varying. Thus, it is intuitive that, for high-quality issuers, where both the level and variability of the probability of default is likely to be lower, the relative contribution of default expectations is likely to be much smaller.

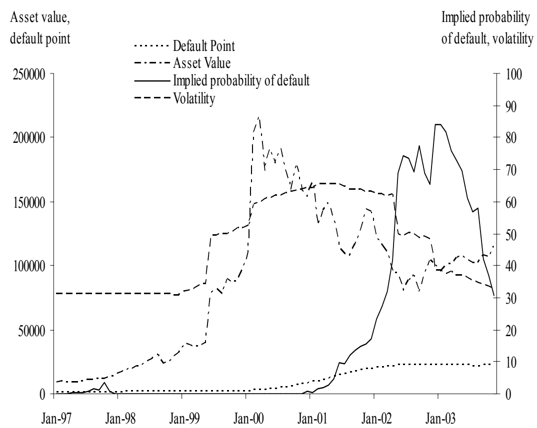
The apparent greater sensitivity of lower-grade spreads to near-term default expectations is an interesting result, which may warrant further attention. This finding is suggestive of short-termism on the part of market participants, but a full treatment of this issue is beyond the scope of this analysis. We would also agree with previous researchers that more work needs to be done to identify omitted common market factors related to supply/demand conditions in the corporate bond market and liquidity. There may also be other idiosyncratic factors, perhaps related to recovery rates that have not been fully captured in our specification. A further potential avenue for future research might be to examine whether one might systematically adjust spreads for non-credit factors in order to yield a cleaner indicator of loss expectations.

Annex A

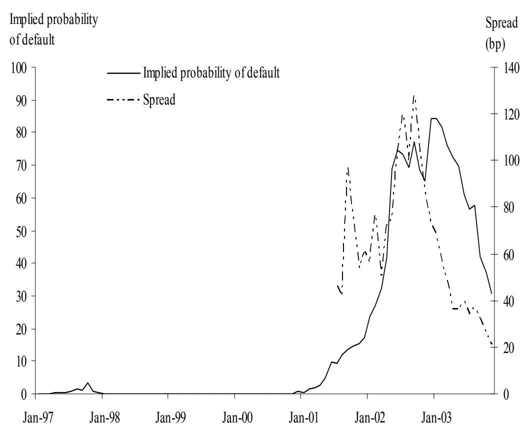
Chart A1: Examples from the telecommunications sector

A1(a) Vodafone

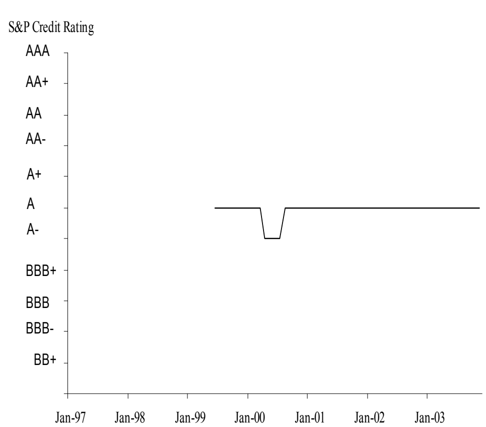
(i) Structural model inputs



(ii) IPD and asset swap spread

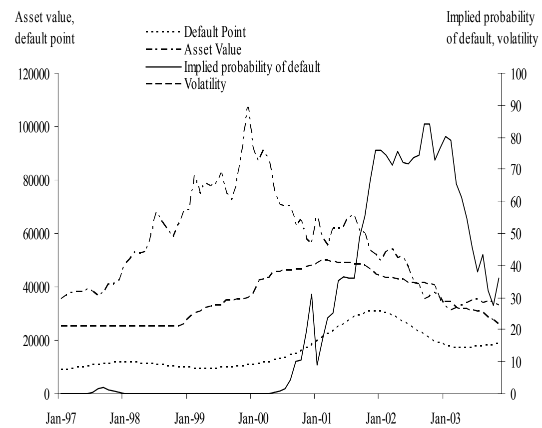


(iii) S&P credit rating

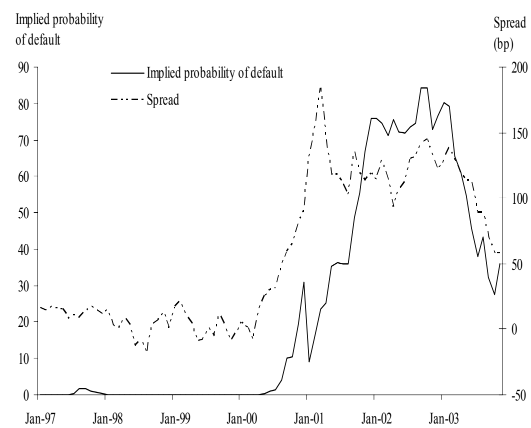


A1(b) British Telecom

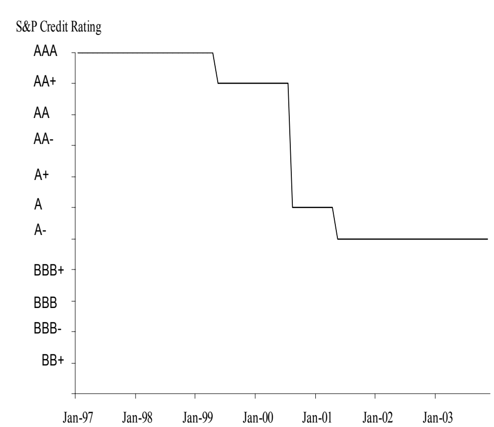
(i) Structural model inputs



(ii) IPD and asset swap spread



(iii) S&P credit rating



Annex B

Maturity differences

	AAA - A-rated issuers		BBB-rated issuers	
	> 10 years	≤ 10 years	> 10 years	≤ 10 years
	(1)	(2)	(5)	(6)
$ASWAP_{t-1,i}$	-0.045	-0.122	-0.372	-0.107
	(-2.47)**	(-6.87)***	(-5.85)***	(-3.29)***
$5IPD_{t-1,i}$	0.065	0.196	1.267	0.438
	(1.32)	(5.52)***	(3.80)***	(2.28)**
$\Delta 5IPD_{t,i}$	1.000	0.521	2.932	3.087
	(6.17)***	(6.90)***	(6.05)***	(7.46)***
$\Delta 5IPD_{t-1}$	0.212	0.249	2.049	1.886
	(1.35)	(3.12)***	(4.32)***	(4.93)***
Issue dummies	Yes	Yes	Yes	Yes
Time dummies	No	No	No	No
R^2	**0.087**	**0.142**	**0.455**	**0.312**
Long-run effect	**1. 434**	**1.606**	**3.410**	**4.091**
Observations	915	1,374	267	651
Issues	27	42	11	29
Av. obs. per issue	33.9	32.7	24.3	22.4
Durbin test (p-value)	0.616	0. 276	0.514	0.346

The dependent variable in our error-correction specification is the change in the asset swap spread. The estimation methodology is least squares, with panel-corrected standard errors. The long-run relationship reported in the table is calculated as $-\beta_{2i}/\beta_{1i}$ in specification **(12)**. t-statistics are reported in brackets, where * = coefficient statistically significant at the 10% level; **=coefficient statistically significant at the 5% level; and *** = coefficient statistically significant at the 1% level. In the final row of the table, we report the results of a test of autocorrelation in the residuals. The residuals from each regression have been regressed against two lags of themselves and all of the regressors in the original regression. A Wald test of joint significance of the two lagged residual terms has then been carried out, with the p-value reported in the table.

Annex C

Bond issues included in the econometric analysis

Data from Merrill Lynch as at 30 November 2003 unless otherwise stated.

Issuer	Maturity Date	S&P Rating	Sector	Par value (£m)	Market Cap'n (£m)	Asset Swap Spread
BOC	29/04/2009	A+	Basic Industry	200	208	47
BOC	29/01/2016	A+	Basic Industry	200	219	67
Corus Group[(a)]	20/05/2008	BBB-	Basic Industry	200	168	640
ICI	15/04/2005	BBB	Basic Industry	100	111	96
			Basic Industry Total		**706**	
British Aerospace	29/12/2008	BBB	Capital Goods	150	196	88
British Aerospace	24/11/2014	BBB	Capital Goods	100	135	111
GKN	14/05/2012	BBB	Capital Goods	325	352	93
GKN	28/10/2019	BBB	Capital Goods	350	366	102
Rexam	27/03/2009	BBB	Capital Goods	370	406	72
Rolls Royce	14/06/2016	BBB	Capital Goods	200	223	112
Smiths Industries	30/06/2016	A-	Capital Goods	150	172	57
Smiths Industries	12/07/2010	A-	Capital Goods	150	172	35
Tomkins	20/12/2011	BBB	Capital Goods	150	177	95
			Capital Goods Total		**2,200**	
Boots	26/05/2009	A+	Consumer Cyclical	300	308	18
Dixons	15/11/2012	Baa1(Moody's)	Consumer Cyclical	300	300	79
GUS	16/07/2009	BBB+	Consumer Cyclical	350	368	45
GUS	12/12/2013	BBB+	Consumer Cyclical	350	356	62
Kingfisher	23/03/2010	BBB+	Consumer Cyclical	150	165	48
M&S	23/01/2007	A	Consumer Cyclical	150	162	23
M&S	07/11/2011	A	Consumer Cyclical	375	389	49
			Consumer Cyclical Total		**2,048**	
Allied Domecq	18/04/2011	BBB+	Consumer Non-Cyclical	450	469	76
Allied Domecq	12/06/2014	BBB+	Consumer Non-Cyclical	250	266	86
Cadbury Schweppes	30/11/2006	BBB	Consumer Non-Cyclical	250	252	26
Gallaher	21/05/2009	BBB	Consumer Non-Cyclical	300	318	74
Gallaher	06/02/2013	BBB	Consumer Non-Cyclical	250	253	86
Glaxosmithkline	01/12/2005	AA	Consumer Non-Cyclical	500	579	-4
Glaxosmithkline	02/10/2008	AA	Consumer Non-Cyclical	500	497	-6
Glaxosmithkline	19/12/2033	AA	Consumer Non-Cyclical	1000	1,004	31
Diageo	31/05/2005	A	Consumer Non-Cyclical	200	220	15
Imperial Tobacco	13/06/2012	BBB	Consumer Non-Cyclical	350	374	95
Sainsbury	27/04/2005	A-	Consumer Non-Cyclical	100	106	41
Sainsbury	11/07/2012	A-	Consumer Non-Cyclical	300	315	76
Sainsbury	05/04/2017	A-	Consumer Non-Cyclical	250	258	84
Sainsbury	05/04/2032	A-	Consumer Non-Cyclical	350	358	95
Scottish & Newcastle	04/12/2006	BBB	Consumer Non-Cyclical	150	159	34
Tate & Lyle	28/06/2012	BBB	Consumer Non-Cyclical	200	210	78
Tesco	30/11/2006	A+	Consumer Non-Cyclical	150	157	16
Tesco	30/07/2007	A+	Consumer Non-Cyclical	325	354	29
Tesco	13/06/2008	A+	Consumer Non-Cyclical	250	262	25
Tesco	18/12/2009	A+	Consumer Non-Cyclical	350	360	20
Tesco	12/10/2010	A+	Consumer Non-Cyclical	150	160	24
Tesco	13/12/2019	A+	Consumer Non-Cyclical	350	360	40

Tesco	14/12/2029	A+	Consumer Non-Cyclical	200	221	50
Tesco	13/01/2033	A+	Consumer Non-Cyclical	200	207	46
			Consumer Non-Cyclical Total		**7,720**	
BG Energy	20/06/2008	A-	Energy	200	212	29
BG Energy	13/11/2012	A-	Energy	250	253	38
BP	30/06/2004	AA+	Energy	150	153	5
Centrica	14/12/2005	A	Energy	125	132	15
Centrica	02/11/2012	A	Energy	400	407	34
Shell	30/01/2006	AAA	Energy	375	385	-37
			Energy Total		**1,543**	
Carlton Comms	06/06/2007	BBB-	Media	200	218	70
Carlton Comms	02/03/2009	BBB-	Media	250	256	66
Daily Mail	29/03/2013	BBB	Media	300	336	115
Daily Mail	09/04/2021	BBB	Media	165	233	152
Pearson	13/06/2008	BBB+	Media	100	124	49
Pearson	27/10/2014	BBB+	Media	250	270	71
Reuters	26/11/2004	A	Media	200	208	123
			Media Total		**1,646**	
BAA	10/02/2007	A+	Services Cyclical	200	226	37
BAA	29/03/2021	A+	Services Cyclical	250	327	66
BAA	04/08/2028	A+	Services Cyclical	200	221	63
BAA	10/12/2031	A+	Services Cyclical	900	928	64
BAA	31/03/2016	A+	Services Cyclical	300	460	75
Six Continents	21/12/2007	BBB	Services Cyclical	250	262	25
British Airways[(b)]	15/06/2008	BBB-	Services Cyclical	100	106	511
British Airways[(b)]	23/08/2016	BBB-	Services Cyclical	250	247	436
FirstGroup	15/04/2013	BBB	Services Cyclical	300	326	92
Hilton	29/07/2008	BBB	Services Cyclical	175	188	79
Hilton	11/07/2012	BBB	Services Cyclical	250	269	101
P&O Princess	25/06/2012	A-	Services Cyclical	200	218	85
			Services Cyclical Total		**3,779**	
Rentokil	19/11/2008	BBB+	Services Non-Cyclical	250	254	46
			Services Non-Cyclical Total		**254**	
BT Group	31/03/2006	A-	Telecommunications	229	267	58
BT Group	07/12/2006	A-	Telecommunications	400	450	35
BT Group	07/12/2016	A-	Telecommunications	700	847	93
BT Group	26/03/2020	A-	Telecommunications	300	398	78
BT Group	07/12/2028	A-	Telecommunications	600	617	76
Cable & Wireless[(c)]	06/08/2012	BBB+	Telecommunications	200	187	717
Vodafone	10/07/2008	A	Telecommunications	400	422	21
Vodafone	26/11/2032	A	Telecommunications	450	458	63
			Telecommunications Total		**3,646**	
			Grand Total		**23,542**	

(a) Standard and Poor's downgraded Corus Group to sub-investment grade in November 2002. Our analysis therefore includes data for Corus Group only up to this time and the rating shown in this table is the last recorded investment-grade rating for the company.
(b) Standard and Poor's downgraded British Airways to sub-investment grade in July 2003. Our analysis therefore includes data for British Airways only up to this time and the rating shown in this table is the last recorded investment-grade rating for the company.
(c) Standard and Poor's downgraded Cable and Wireless to sub-investment grade in January 2003. Our analysis therefore includes data for Cable and Wireless only up to this time and the rating shown in this table is the last recorded investment-grade rating for the company.

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