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Credit spread determinants: An 85 year perspective

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Abstract

This paper estimates a set of credit spread forecasting models using an 85 year history for AAA and BAA corporate bond yield data for the US. Credit spreads are defined as the corporate bond yield less the 20 year yield on US government bonds and are explained by a set of intuitively appealing financial and economic variables. Initial results relate to the application of cointegration techniques to provide long and short run estimates of the key determinants of credit spreads. The analysis is then extended to allow for an unobservable latent variable Markov Switching specification across two separate states. Finally a deterministic regime model based upon an inflation threshold is estimated demonstrating that key causal relationships exist independently across different inflationary environments.

JEL classification: G11; G12

Keywords: Credit spreads; Cointegration; Markov switching; SETAR model.

1. Introduction

This paper explains credit spread behavior using a set of intuitively appealing economic variables with a data set that spans a sample period from January 1921 to December 2004 at a monthly frequency. Using Moodys US AAA and BAA interest rate data, I estimate a set of econometric models that seek to explain credit spread movements over the yield of equivalent duration government bonds. This paper is the first in the credit spread literature to consider a data sample that covers such a broad range of business cycle conditions. The sample period covers the depression of the 1930s together with the inflationary cycles

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experienced during the 1970s and early 1980s. In using such an expansive data history I am able to uncover significantly different causal relationships in the key credit spread determinants using recently developed regime switching time series techniques. In doing so the analysis builds upon previous empirical work such as Morris, Neale, and Rolph (1998), Bevan and Garzarelli (2000) and Davies (2004) by conditioning upon alternative inflationary and volatility environments during a significantly extended 85 year data sample.

A key feature of the credit spread literature is the role played by the risk free rate in explaining credit spread behavior. Theoretical credit spread models, as in the spirit of Merton (1974), Longstaff and Schwartz (1995) and Duffee (1998), postulate an inverse relation across the risk free rate and the credit spread. Theoretical models therefore argue that as the risk free rate increases, the corporate rate increases less than proportionately and the credit spread tightens. The empirical literature, such as Morris, Neale, and Rolph (1998) and Bevan and Garzarelli (2000), finds the opposite to be true, with increases in the risk free rate inducing a widening of credit spread rates. One key aim of this paper is to shed further light from an empirical perspective on the role of the risk free rate using the extended 85 year data sample and conditioning upon the prevailing inflationary or volatility environment.

Results presented later show that credit spreads are indeed inversely related to the risk free rate, both in the long and short run. The finding of an inverse long run relation is in contrast to earlier findings of Davies (2004) who uses a shorter data history but supports the empirical work of Morris, Neale, and Rolph (1998) and Bevan and Garzarelli (2000). Furthermore, results demonstrate that the lower credit spread model for BAA bonds is more sensitive to changes in the risk free rate. This finding contradicts the theoretical models of Chance (1990) and Longstaff and Schwartz (1995) who argue that higher grade debt should be more sensitive to changes in the risk free rate. However by isolating a deflationary regime for lower grade debt, I find that BAA spreads are 10 times more sensitive to changes in the risk free rate as compared to a normal or inflationary regime. This result is presumably due to a lack of pricing power on the part of firms during periods of deflation. Such a situation clearly increases the risk of default on lower grade corporate debt and hence induces a greater sensitivity to changes in the risk free rate. By conditioning on the deflationary environment, I find that the remaining normal environment accords with theoretical priors. The credit spread appears to be as sensitive to the risk free rate in the BAA case as it is for higher grade AAA debt.

Other results show that the extension to a two regime latent variable model significantly enhances the explanatory power of the variables considered here. The level and return of the S&P 500 equity index is found to play a significant explanatory role as is the estimated long run equilibrium obtained from a cointegration model across the levels series. The key finding, though, is that conditioning upon the inflationary regime generates meaningful and significant power in explaining subsequent credit spread changes. Furthermore, the inflation threshold differs across high and low grade debt. High grade inflation regimes are triggered at an inflation rate of 4% whereas low grade regimes are triggered at an inflation rate of -1%. This seems reasonable given that the main concern for high grade debt investors is inflation risk, since the risk of default is reasonably low. Alternatively lower grade bond investors, while also concerned with inflation, will primarily be concerned with the risk of default. A deflationary environment is of particular concern to lower grade investors since it implies the absence of pricing power within the economy. That lack of pricing power clearly places higher risk firms at an increased risk of default. Given that deflationary episodes are typically periods in which the economic outlook is relatively poor it seems reasonable to expect deflationary environments to be particularly distinct for lower grade debt.

2. Theoretical credit spread models

The first theoretical model that attempted to model bonds subject to default was Merton (1974) who applied insights from options pricing theory to model default risk. The Merton (1974) model argues that the purchase of a risky corporate bond is equivalent to being long an equivalent risk free bond and simultaneously short a put option on the value of the underlying firm where the strike price is equal to the face value of the risk free bond.

In the Merton framework the risk free rate has an impact upon the value of the corporate bond for two reasons. First, an increase in the risk free rate implies that the price of the put option will decrease because the discounted present value of expected future cash flows will have decreased. The corporate bond investor, in being short the put option, experiences a net increase in the value of his long corporate bond position. The price of the corporate bond increases and the spread over an equivalent riskless bond tightens. The second effect arises from the structural assumption that the firms-risk neutral growth path is a positive function of the risk free rate. As the risk free rate increases firm value increases, again lowering the price of a put option on the firm. The overall effect of an increase in the risk free rate is to decrease the effective costs of insurance against default on the firm's debt. The price of a put option to protect against that default has fallen as the risk free rate has increased. Increases in the risk free rate, by reducing the price of the put option, imply that the corporate bond will increase in value, the corporate yield will fall and the spread over an equivalent risk free bond will tighten.

Future changes in the short interest rates are known to be signalled by the slope of the yield curve. Given that the risk free rate is modelled as the three month treasury bill an increase in the slope could signal future increases in the risk free rate. The yield curve slope can therefore be thought of as a proxy for the expected future risk free rate. Hence, in the Merton framework, a steep slope should induce a tightening of credit spreads via an expected future increase in the risk free rate. Alternatively, a shallow yield curve slope is generally found to predict a deterioration in the general economic outlook. A shallow slope, in implying weaker economic activity, implies diminished firm growth prospects and an increased risk of default. A shallow yield curve slope would therefore imply a higher yield on corporate debt and a widening of the corporate spread.

Structural models also emphasize the role played by leverage. Defining leverage as the ratio of a firm's outstanding debt relative to its asset value, it seems reasonable to model asset value within an aggregate model by the overall equity market. Hence, when equity markets increase, asset values correspondingly rise and firm leverage falls. As leverage declines, corporate bonds become less likely to default and the corporate spread should tighten. At the same time equity markets also reflect expectations of the future economic climate. Ignoring any improved leverage position, increases in the equity market signal more favorable economic conditions. Should default actually occur, any potential recovery rate would be expected to be higher with a more favorable economic environment. Hence, increases in the equity market could be expected to induce credit spread tightening.

The final variable included within the core specification models economic conditions directly using observed industrial production. Again the idea here is to gauge the overall degree of firm leverage and potential recovery rates in the event of default. Increases in industrial production tend to increase asset values and at the same time lead to higher recovery rates. Both effects would tend to increase the price of corporate debt, reduce the corporate yield and lead to a tightening in the credit spread.

One final consideration in the model is to consider the role played by the inflation rate upon credit spread movements. The data set considered here covers periods of both significant inflation and deflation and it seems reasonable to expect different inflationary regimes to yield differing causal relationships across differing credit qualities. Low grade bonds are by definition subject to default risk, hence low grade investors will be primarily concerned with the risk of default. Deflationary episodes pose particular problems for low grade firms since there is a lack of pricing power in the broader macro economy. Hence, higher risk firms are particularly vulnerable to the economic environment within a deflationary environment. High grade bonds are alternatively the subject of a very low level of default risk. The primary concern for investors in high grade debt is the risk of inflation, since bonds generally perform poorly under inflationary conditions. Overall then, we might expect different inflationary environments to have differing impacts upon different credit quality models.

3. Data

Corporate bond data are obtained from Moody's Investor Services and are available from the Federal Reserve Bank of St. Louis Data archive for Aaa and Baa yields (index codes: AAA and BAA) beginning in January 1919. Observed data are averages of daily data for each month and relate to non-financial seasoned bonds with a maturity of at least 20 years. Bonds are dropped from the index if their remaining life falls below 20 years, if they become redeemable or if their ratings change. Aaa bonds are deemed to be of the highest credit quality and carry the lowest level of investment risk. Baa are considered to be of moderate risk and lack investment grade characteristics.

The corporate bond series deserve further discussion for a number of reasons. The Moody's interest rate series are based upon the yields of many different bonds contained within a specific rating basket. As such they represent an aggregate yield based upon a broad well-diversified portfolio of individual bonds. The analysis therefore relates to a benchmark yield spread and does not represent the spread of specific individual bonds over the government rate. Other studies such as Duffee (1998) and Collin-Dufresne, Goldstein, and Martin (2001) focus upon individual corporate bond issues and therefore possess a much richer cross sectional dimension in comparison to this analysis. This study, in focusing upon widely followed benchmark yields does, however, benefit from a richer time series dimension in that the Moody's data have an 85 year data history. Given that one of the key aims of the analysis is to consider the influence of several different business cycles upon credit spread behavior it would seem that the aggregate Moody's yield data are well suited to this purpose.

A second issue in using Moody's data relates to the fact that Moody's yields are not constant maturity yields whereas the benchmark government maturity used here is constant at 20 years. Given that corporate yields have a maturity of at least 20 years, this implies a slight maturity mismatch. However, given that corporate bonds are subject to default risk, the actual duration of those bonds is likely to approximate the duration of a 20 year constant maturity government bond. Since one of the key aims of this paper is to consider the role of the short term risk free rate in explaining credit spread behavior it would seem that duration concerns are more important than precise maturity matching. The 20 year constant maturity government yield therefore seems to be the appropriate choice over the nearest alternative of either the 10 or 30 year yields.

The 20 year constant maturity treasury yield (index code GS20) is also sourced from the Federal Reserve data archive and comprises the average yield over the month for business day observations. Data are available from January 1954 from the Federal Reserve and earlier long bond yield data are derived from the NBER Macrohistory data archive from 1919 onwards. Again, monthly observations are constructed as daily averages over the prior month.

Other data are also collected from the Federal Reserve data archive with the exception of the S&P 500 index which is from Bloomberg on a monthly basis. The risk free rate is the monthly 3 month treasury bill rate (code TB3MS) available from January 1934 with earlier data obtained again from the NBER Macrohistory archive. The yield curve slope is then taken as the difference between the 20 year yield and the 3 month treasury bill rate. Industrial production (code INDPRO) is available from January 1921 and it is this series that ultimately restricts the sample size used in the analysis. Finally, the consumer price series (code: cpiaucsl) begins in January 1947, with earlier data obtained again from the NBER Macrohistory archive. Annual inflation rates are constructed by taking the 12th difference in the natural logs of the index series.

4. Econometric estimation

Given that several series used in the analysis are known to be nonstationary $I(1)$ series the first estimator used in the analysis is the Johansen (1988) and Johansen and Juselius (1994) system based procedure. The estimator takes the following form:

$$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \ldots + \Gamma_k \Delta z_{t-k} + \alpha\beta' z_{t-k} + \varepsilon_t, \tag{1}$$

where the β matrix of estimated coefficients contains estimates of the long run cointegrating coefficients of the model and the short run dynamic components of the system as contained within the Γ_i matrices. The z_t matrix in this application will therefore contain the levels series for the spread, treasury bill, equity and industrial production variables. The $\Delta z_{t-1\ldots k}$ matrices will contain the first difference analogues of those variables.

The estimator proceeds in two steps with the initial step involving a search for combinations of the levels $I(1)$ series in z_{t-k} that have high correlations with the $I(0)$ first difference series contained in Δz_t. The strength of those correlations provides an indication of the magnitude of cointegration across the $I(1)$ levels data. Having obtained a matrix of long run cointegrating relationships in $\beta' z_{t-k}$ the remaining dynamic coefficients contained in the Γ_i and α matrices can be obtained by an application of ordinary least squares (OLS). Further details regarding the Johansen procedure can be found in Harris and Sollis (2003) or Johansen (1995).

The second estimator used in the analysis focuses upon the credit spread equation obtained from the Johansen analysis and generalizes that equation to allow it to assume one of two regimes. The procedure used follows the Markov Switching (MS) methodology developed by Hamilton (1990) by allowing the coefficients and residual variance to adopt distinct values according to a specific regime. The estimator is therefore allowed to partition coefficient estimates, and the residual variance, into two distinct regimes in such a way as to maximise the equation's explanatory power. In adopting the MS approach the estimator is seeking to maximise explanatory power by assuming the existence of an unobservable latent variable that is responsible for the regime generating process.

The general model based upon two regimes takes the following form:

$$\Delta z_t = \begin{cases} \Gamma_{1,1}\Delta z_{t-1} + \ldots + \Gamma_{k,1}\Delta z_{t-k} + \alpha_1\beta' z_{t-k} + \varepsilon_t & \text{if } s_t = 1, \\ \Gamma_{1,2}\Delta z_{t-1} + \ldots + \Gamma_{k,2}\Delta z_{t-k} + \alpha_2\beta' z_{t-k} + \varepsilon_t & \text{if } s_t = 2. \end{cases} \tag{2}$$

Notice that the long run cointegrating coefficients obtained from the Johansen estimator contained in β' are assumed to remain constant across the two regimes. For the corporate spread equation the MS model therefore takes the following form:

$$\Delta\text{Spread}_t = \begin{cases} \gamma_{1,1} \cdot \Delta\text{Spread}_{t-1} + \gamma_{2,1} \cdot \Delta T\ \text{Bill}_{t-1} + \gamma_{3,1} \cdot \Delta\text{Log S\&P } 500_{t-1} & \\ \quad +\gamma_{4,1} \cdot \Delta\text{Log Ind P}_{t-1} + \gamma_{5,1} \cdot \text{Slope}_{t-1} & \\ \quad +\alpha_1 \cdot \text{Error Correction Term}_{t-1} + \varepsilon_t & \text{if } s_t = 1, \\ \gamma_{1,2} \cdot \Delta\text{Spread}_{t-1} + \gamma_{2,2} \cdot \Delta T\ \text{Bill}_{t-1} + \gamma_{3,2} \cdot \Delta\text{Log S \&P } 500_{t-1} & \\ \quad +\gamma_{4,2} \cdot \Delta\text{Log Ind P}_{t-1} + \gamma_{5,2} \cdot \text{Slope}_{t-1} & \\ \quad +\alpha_2 \cdot \text{Error Correction Term}_{t-1} + \varepsilon_t & \text{if } s_t = 2. \end{cases} \tag{3}$$

The Error Correction Term in Eq. (3) simply refers to the long run cointegrating equilibrium relationship obtained from the first step of the Johansen technique.

In terms of estimating the separate $\gamma_{i,j}$ and α_j coefficients for regimes $j = 1,\ 2$ the estimator employs a version of the Expectation Maximization (EM) algorithm originally developed by Dempster, Laird and Rubin (1977) and extended by Hamilton (1990) for the MS estimator. Further details can be found in Hamilton (1990) and Franses and van Dijk (2000).

The final estimator used in this paper seeks to extend the latent variable Markov switching model by employing an estimator that distinguishes regimes based upon a particular explanatory variable. The approach therefore attempts to uncover the latent variable that is responsible for generating the separate regimes obtained from the previous estimator. The specific estimator used in this paper adopts the Self Extracting Threshold (SETAR) model where regimes are differentiated according to a specific value of a particular variable. The analysis uses annual inflation rates as the threshold variable so that regimes are obtained by searching over a grid of inflation rates so as to maximize the overall explanatory power of the spread equation.

In the case of the SETAR model the spread equation takes the following form:

$$\Delta\text{Spread}_t = \begin{cases} \gamma_{1,1} \cdot \Delta\text{Spread}_{t-1} + \gamma_{2,1} \cdot \Delta T\ \text{Bill}_{t-1} + \gamma_{3,1} \cdot \Delta\text{Log S\&P } 500_{t-1} \\ \quad +\gamma_{4,1} \cdot \Delta\text{Log Ind P}_{t-1} + \gamma_{5,1} \cdot \text{Slope}_{t-1} \\ \quad +\alpha_1 \cdot \text{Error Correction Term}_{t-1} + \varepsilon_t \\ \qquad\qquad \text{if Annual CPI Inflation}_{t-1} \leqslant \text{Threshold}, \\ \gamma_{1,2} \cdot \Delta\text{Spread}_{t-1} + \gamma_{2,2} \cdot \Delta T\ \text{Bill}_{t-1} + \gamma_{3,2} \cdot \Delta\text{Log S\&P } 500_{t-1} \\ \quad +\gamma_{4,2} \cdot \Delta\text{Log Ind P}_{t-1} + \gamma_{5,2} \cdot \text{Slope}_{t-1} \\ \quad +\alpha_2 \cdot \text{Error Correction Term}_{t-1} + \varepsilon_t \\ \qquad\qquad \text{if Annual CPI Inflation}_{t-1} > \text{Threshold}. \end{cases} \tag{4}$$

The SETAR estimator therefore searches over specific values of the inflation variable and determines the threshold inflation rate at that level which maximizes explanatory power. Further details regarding estimation of the SETAR model can be found in Franses and van Dijk (2000).

5. Results

Table 1 presents preliminary results for a series of unit root tests applied to the levels and first difference transformations of the series using the Augmented Dickey Fuller (ADF) approach. The procedure involves testing the null hypothesis that $\gamma = 0$ using a table of asymptotic ADF critical test statistics:

$$\Delta y_t = \alpha + \beta \cdot \text{Trend} + \gamma \cdot y_{t-1} + \delta_1 \cdot \Delta y_{t-1} + \ldots + \delta_{p-1} \cdot \Delta y_{t-p+1} + \varepsilon_t. \tag{5}$$

Overall the series appear to be non-stationary in levels but stationary $I(0)$ series in first differences. The one exception is the yield curve slope which appears to be stationary without a first difference transformation.

Having described the time series properties for each data series I proceed by adopting the Johansen (1988) system modeling approach estimating the following specification:

$$\begin{bmatrix} \Delta\text{Spread}_t \\ \Delta T\ \text{Bill}_t \\ \Delta\text{S\&P}_t \\ \Delta\text{Ind Prod}_t \end{bmatrix} = \Gamma_i \cdot \begin{bmatrix} \Delta\text{Spread}_{t-1} \\ \Delta T\ \text{Bill}_{t-1} \\ \Delta\text{S\&P}_{t-1} \\ \Delta\text{Ind Prod}_{t-1} \\ \text{Slope}_{t-1} \end{bmatrix} + \alpha\beta' \cdot \begin{bmatrix} \text{Spread}_{t-1} \\ T\ \text{Bill}_{t-1} \\ \text{S\&P}_{t-1} \\ \text{Ind Prod}_{t-1}. \end{bmatrix}. \tag{6}$$

Here, the spread variable can take one of three forms: AAA, BAA yield differentials over the 20 year yield and a quality specification defined as the BAA less AAA yield. Since the slope variable is stationary, I include the yield curve slope as an exogenous variable with a

Table 1
Augmented dickey fuller tests

$$\Delta y_t = \alpha + \beta \cdot \text{Trend} + \gamma \cdot y_{t-1} + \delta_1 \cdot \Delta y_{t-1} + \ldots + \delta_{p-1} \cdot \Delta y_{t-p+1} + \varepsilon_t.$$

	Level		First difference	
	Constant	Trend	Constant	Trend
AAA	−2.460	−2.369	**−9.295****	**−9.307****
BAA	−2.859	−2.852	**−8.776****	**−8.774****
Quality	**−3.405***	**−3.659***	**−7.930****	**−7.924****
T Bill	−1.957	−2.207	**−7.894****	**−7.896****
S&P	0.179	−2.329	**−7.322****	**−7.366****
Ind Prod	−0.766	−2.766	**−6.826****	**−6.817****
Slope	**−3.864****	**−3.928****	**−9.079****	**−9.074****

Note: Asymptotic ADF critical test statistics are −2.88 (−3.43) for the constant test and −3.41 (−3.96) for the trend test at the 5% and 1% levels of significance respectively. Statistical significance is highlighted in bold.

Table 2
Johansen cointegration analysis

$$\text{Credit Spread}_t = \alpha \cdot T\ \text{Bill}_t + \beta \cdot \text{S\&P 500 Index}_t + \gamma \cdot \text{Ind Prod}_t + \varepsilon_t,$$
$$\lambda_{\text{trace}} = -T\sum_{i=r+1}^{n} log(1-\hat{\lambda}_i),$$
$$\lambda_{\max} = -Tlog(1-\hat{\lambda}_{r+1}).$$

Eigenv	$\lambda - \max$	$\lambda - \max_{0.95}$	$\lambda - \max_{0.99}$	Trace	$\text{Trace}_{0.95}$	$\text{Trace}_{0.99}$
AAA System						
0.051	**53.30****	27.07	28.98	**67.38****	47.21	50.35
0.008	7.72	20.97	23.09	14.08	29.68	32.56
0.005	5.24	14.07	16.05	6.36	15.41	17.52
0.001	1.13	3.76	4.95	1.13	3.76	4.95
BAA System						
0.066	**69.38****	27.07	28.98	**82.31****	47.21	50.35
0.007	7.44	20.97	23.09	12.93	29.68	32.56
0.005	4.61	14.07	16.05	5.49	15.41	17.52
0.001	0.88	3.76	4.95	0.88	3.76	4.95
BAA - AAA (Quality Spread) System						
0.061	**63.14****	27.07	28.98	**74.44****	47.21	50.35
0.007	7.12	20.97	23.09	11.30	29.68	32.56
0.004	3.66	14.07	16.05	4.18	15.41	17.52
0.001	0.52	3.76	4.95	0.52	3.76	4.95

Note: Statistical significance is highlighted in bold and is denoted by * and ** at the 5% and 1% levels, respectively.

one month lag. All other variables are modeled endogenously entering both the long run levels relationship and the short term dynamic first difference terms.

Table 2 presents details of the Johansen reduced rank regression for each of the three versions of the model. The first thing to notice is the uniform finding that each system possesses a single significant cointegrating long run vector. For example in the AAA system the largest eigenvalue of 0.051 yields $\lambda_{\max}$ and λ_{trace} statistics of 53.30 and 67.38, respectively. Since these statistics exceed critical values, as tabulated for example by Osterwald-Lenum (1992), I conclude that there is at least one significant cointegrating vector in the AAA system. However, all subsequent eigenvalues are insignificant, leading to the further conclusion that there is at most a single significant cointegrating long run relationship for the AAA system. The same finding applies for both the BAA and quality spread specifications.

Table 3 reports the long run coefficients contained in each cointegrating vector for each system. All estimated coefficients enter significantly as demonstrated by the size of the estimated standard errors in relation to the coefficients themselves. Furthermore, the level of the corporate spread is positively related to the level of the risk free rate. This implies that in the long run increases in the risk free rate induce a widening of the credit spread variable. This finding is opposed to the theoretical framework of Merton (1974), Longstaff and Schwartz (1995) and Leland and Toft (1996) but supports previous empirical work as reported by Morris, Neale, and Rolph (1998). In fact, the estimated coefficients of 0.038

Table 3
Long run cointegration coefficients

$$\text{Credit Spread}_t = \alpha \cdot T \text{ Bill}_t + \beta \cdot \text{S\&P 500 Index}_t + \gamma \cdot \text{Ind Prod}_t + \varepsilon_t.$$

	Unrestricted cointegration analysis		
	AAA System	BAA System	Quality System
T Bill_t	0.038	0.205	0.162
	[0.020]	[0.036]	[0.026]
$\text{S\&P}_t$	0.607	0.855	0.284
	[0.082]	[0.148]	[0.107]
Ind P_t	−0.937	−2.005	−1.077
	[0.142]	[0.257]	[0.186]

Note: Standard errors in brackets [...].

and 0.205 on the Treasury bill variable compare very closely to the equivalent coefficients obtained by Morris, Neale, and Rolph (1998) of 0.028 and 0.178, respectively over their much shorter sample period.

The lower credit quality BAA vector also appears to be more sensitive to changes in the risk free rate, a finding that opposes the theoretical suggestions made by Chance (1990) and Longstaff and Schwartz (1995). Increased credit risk appears to imply an increased sensitivity to interest rate changes, as opposed to a decrease as suggested by theory. This may be due to the enhanced sample period considered which considers an 85 year data history. The sample period covers several business cycles that are atypical with respect to contemporary experience. In particular the analysis includes periods of deflation as well as inflation and the severe recession of the 1930s. Given that deflation implies a lack of pricing power it seems reasonable to expect lower credit firms to be more sensitive to changes in the risk free rate. I will return to this point later when discussing the short run estimation results.

One further result from Table 3 is the consistent finding that the coefficient on the S&P 500 enters with a significantly positive sign. This implies that as the S&P 500 index increases the credit spread widens. While it might be expected that higher stock market levels might imply a lower probability of default and therefore a tightening of spreads, one possible explanation here revolves around an asset allocation argument. Over the long term equities and corporate bonds are closer substitutes than equities and government bonds. Increasingly higher equity index levels might therefore induce investors to re-allocate wealth away from close substitutes such as corporate bonds. As those bonds are sold, the corporate yield will increase relative to the treasury yield. The corporate spread will therefore be positively related to the level of the equity index in the long run. Since portfolio adjustments of this type can be expected to manifest themselves gradually over time a positive corporate spread to equity index relation could be expected to manifest itself in the long run cointegrating equilibrium.

One final point to note in Table 3 is the finding that the coefficient on industrial production accords with theoretical expectations. Increases in industrial production induce credit spread tightening, capturing a lower perceived risk of default, and decreased leverage, the more buoyant the wider economic outlook. Furthermore, the impact of

Table 4
Short run johansen coefficients

$$\Delta\text{Spread}_{t+1,t} = \gamma_1 \cdot \Delta\ \text{Spread}_{t,t-1} + \gamma_2 \cdot \Delta T\ \text{Bill}_{t,t-1} + \gamma_3 \cdot \Delta\text{S\&P } 500_{t,t-1} + \gamma_4 \cdot \Delta\text{Ind P}_{t,t-1} + \gamma_5 \cdot \Delta\text{Slope}_{t,t-1} + \gamma_6 \cdot \text{ECT}_{t-1} + \varepsilon_t.$$

	AAA	BAA	Quality
Constant	**0.082****	**0.259****	**0.194****
	[6.368]	**[7.430]**	**[7.321]**
Δ Spread$_{t,t-1}$	**0.107****	**0.173****	**0.208****
	[3.281]	**[4.985]**	**[5.974]**
ΔT Bill$_{t,t-1}$	0.005	**0.036****	**0.027****
	[0.575]	**[2.149]**	**[2.188]**
Δ S&P 500$_{t,t-1}$	**−0.333****	**−0.795****	**−0.444****
	[4.273]	**[5.077]**	**[3.733]**
Δ Ind P$_{t,t-1}$	**−0.352***	**−0.985****	**−0.615****
	[1.972]	**[2.967]**	**[2.451]**
Slope $_{t-1}$	−0.003	**0.022****	**0.020****
	[0.897]	**[3.023]**	**[3.574]**
ECT$_{t,t-1}$	**−0.066****	**−0.065****	**−0.072****
	[6.294]	**[7.170]**	**[7.175]**
Diagnostics			
$\hat{R}^2$	0.075	0.132	0.125
F-Test	13.085**	31.528**	29.745**
Durbin Watson	1.981	1.943	1.932
Log Like^h	814.80	216.11	504.91

Note: Heteroscedastic t statistics are in [...]. Log Like^h refers to the regression log likelihood value. *F*-test refers to the joint test that all estimated coefficients are zero. Statistical significance is highlighted in bold and is denoted by * and ** at the 5% and 1% levels, respectively.

industrial production appears to be larger for the higher risk BAA spread, again a result that would seem to accord with theory. Riskier debt is more likely to default as the overall economic environment deteriorates.

Table 4 completes the Johansen analysis by reporting short run coefficient estimates, i.e., the Γ and α coefficients from Eq. (1). The lagged change in the credit spread enters significantly across all three specifications indicating a significant degree of persistence. The lagged S&P return also enters significantly for all three models, this time with the anticipated negative sign. Increases in equity returns therefore induce credit spread tightening in the short run. The same relation holds for industrial production growth which also enters significantly for all three credit qualities. Lower quality spreads also appear to be determined by both the change in the risk free rate and the yield curve slope. In both cases the relation is a positive one implying that increases in the risk free rate and yield curve slope induce credit spread widening. The error correction terms obtained from the long run equilibria presented in Table 3 all enter with the anticipated negative sign. Deviations away from the equilibrium level of the corporate spread can therefore be expected to reverse over time. Overall, given that the sample period covers nearly 85 years of data, the explanatory power of the model for each sector is reasonably high. The $\bar{R}^2$

statistics vary from 0.075 for the AAA model to 0.132 for the BAA specification. Finally, all the regression F-statistics are found to be highly significant.

Having identified a reasonable single regime specification for the last 85 years, the analysis continues with the generalization of that single regime treatment to allow for a broader analysis. Initially I adopt a MS approach in which the model is allowed to adopt one of two regimes where the regime generation variable is assumed to be an unobservable latent variable. Table 5 presents coefficient estimates for the 2 regime MS model together with some additional diagnostics detailing the characteristics of the regimes themselves.

Table 5
Short run markov switching coefficients

$$\Delta\text{Spread}_t = \begin{cases} \gamma_{1,1}\cdot\Delta\text{ Spread}_{t-1}+\gamma_{2,1}\cdot\Delta T\text{ Bill}_{t-1}+\gamma_{3,1}\cdot\Delta\text{ Log S\&P 500}_{t-1} & \\ \quad +\gamma_{4,1}\cdot\Delta\text{ Log Ind P}_{t-1}+\gamma_{5,1}\cdot\text{ Slope}_{t-1} & \\ \quad +\alpha_1\cdot\text{ Error Correction Term}_{t-1}+\varepsilon_t & \text{if } s_t=1, \\ \gamma_{1,2}\cdot\Delta\text{ Spread}_{t-1}+\gamma_{2,2}\cdot\Delta T\text{ Bill}_{t-1}+\gamma_{3,2}\cdot\Delta\text{ Log S\&P 500}_{t-1} & \\ \quad +\gamma_{4,2}\cdot\Delta\text{ Log Ind P}_{t-1}+\gamma_{5,2}\cdot\text{ Slope}_{t-1} & \\ \quad +\alpha_2\cdot\text{ Error Correction Term}_{t-1}+\varepsilon_t & \text{if } s_t=2. \end{cases}$$

	AAA		BAA		Quality	
	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2
Constant	**0.02****	**0.10****	**0.13****	**0.58****	**0.05****	**0.50****
	[2.32]	**[5.18]**	**[5.31]**	**[5.30]**	**[3.40]**	**[5.23]**
Δ Spread$_{t,t-1}$	**0.30****	0.07	**0.18****	**0.14***	**0.20****	**0.19****
	[6.11]	[1.49]	**[4.03]**	**[1.86]**	**[6.01]**	**[2.17]**
ΔT Bill$_{t,t-1}$	−0.02	0.00	−0.02	0.03	**0.02***	0.03
	[1.24]	[0.07]	[1.16]	[0.79]	**[1.96]**	[0.90]
Δ S&P 500$_{t,t-1}$	**0.08***	**−0.62****	**−0.30****	**−1.08****	**−0.27****	−0.64
	[1.80]	**[4.29]**	**[2.96]**	**[2.54]**	**[5.56]**	[1.56]
Δ Ind P$_{t,t-1}$	−0.09	**−0.72***	0.15	**−2.19****	0.06	**−1.42***
	[1.06]	**[1.79]**	[0.80]	**[2.41]**	[0.51]	**[1.91]**
Slope $_{t-1}$	0.00	0.01	0.01	**0.05****	−0.01	**0.04****
	[0.95]	[0.07]	[1.13]	**[2.47]**	[0.58]	**[2.39]**
ECT$_{t,t-1}$	**−0.02****	**−0.09****	**−0.04****	**−0.13****	**−0.02****	**−0.16****
	[2.41]	**[5.21]**	**[5.12]**	**[5.18]**	**[2.93]**	**[5.29]**
Std Err	0.041	0.142	0.078	0.338	0.044	0.291
Observn	509	497	733	273	789	217
Prob	0.50	0.50	0.73	0.27	0.79	0.21
Duration	54.89	51.50	28.07	10.24	35.61	9.55
$\hat{R}^2$	0.105		0.198		0.190	
F-Test	11.72		23.52		22.46	
Durbin Watson	1.995		1.951		1.935	
Log Like^h	1118		626		1187	
Lin Test	574.84		817.32		1365.70	

Note: Observn refers to the number of observations in each regime. Prob is the probability of being in each regime. Lin Test refers to the Davies (1987) test that the log likelihood value for the regime model is the same as that for the single regime. The test statistic is distributed as a $\chi^2_{(2)}$ variate. Statistical significance is highlighted in bold and is denoted by * and ** at the 5% and 1% levels, respectively.

The first result that stands out from the MS analysis is the finding that the regime generation process appears to be focusing upon a volatility argument in that the two separate regimes appear to have significantly different regression standard errors. Regime 1 therefore applies to a low volatility regime while the second regime applies to a higher volatility regime.

In so far as specific variables are concerned it is clear that the lagged spread, S&P return and the error correction term all enter significantly regardless of volatility regime. Regime specific results indicate that the tightening effect of industrial production on the corporate spread appears to be a high volatility phenomenon. Furthermore, the slope variable for the lower credit specifications enters positively for the higher volatility regime. It would therefore seem that during more volatile episodes several variables appear to become important in explaining spreads. In more tranquil times the persistence of the spread itself together with equity market performance and the long run equilibrium appear to capture corporate spread behavior.

Overall the results presented in Table 5 demonstrate the potential in allowing for a regime treatment. Explanatory power is enhanced and regime contingent relationships are found to exist over and above those found for a single regime treatment. The MS approach is, however, based on the assumption that an unobservable latent variable drives the switching process. Results presented in Table 6 extend the analysis by employing a Self-Extracting Threshold (SETAR) model where the previous 12 month inflation rate is used as a regime differentiating variable.

The motivation for using inflation lies in the conjecture that differing inflationary environments could be expected to generate significantly different credit spread relationships. For example, it is well known that equities are a natural hedge against inflation, implying that equities tend to outperform bonds during inflationary periods. An inflationary treatment is also interesting from the perspective of this specific data set given that it covers the last 85 years of US inflationary experience. Not only does the data sample encompass the large spikes in inflation experienced during the early 1970s and 1980s but it also covers the 1930s depression where annual deflation rates were as low as 10%/annum. An analysis based upon an inflation/deflation regime generating process also has some contemporary relevance given recent deflationary concerns in the US and the experience of the Japanese economy over the last 15 years.

The first result that becomes apparent from Table 6 is the finding that the inflation threshold differs across alternative credit models. For the AAA specification the critical threshold is located at an inflation rate of 4%/annum. For the lower quality model the inflation threshold differentiates regimes at an inflation rate of -1%, that is, an annual deflation rate of 1%. The AAA analysis therefore isolates an inflationary regime whereas the BAA model isolates a deflationary regime. This finding seems reasonable since investors in lower grade debt are primarily concerned with the risk of default. Deflation implies a lack of pricing power on the part of companies and given that higher risk debt is more vulnerable to the general economic outlook it seems reasonable to expect the lower grade model to differentiate across deflationary and more normal environments. Alternatively, investors in higher grade debt are less concerned with the risk of default, given that it is unlikely, and are instead more concerned with the risk of inflation. This is because bonds generally under-perform in relation to equities when prices increase rapidly. Hence for higher grade debt it seems reasonable to differentiate across very high inflation and more typical inflationary episodes.

Table 6
Short run SETAR

Inflation regime contingent coefficients

$$\Delta \text{Spread}_t = \begin{cases} \gamma_{1,1} \cdot \Delta \text{ Spread}_{t-1} + \gamma_{2,1} \cdot \Delta T \text{ Bill}_{t-1} + \gamma_{3,1} \cdot \Delta \text{ Log S\&P } 500_{t-1} \\ \quad + \gamma_{4,1} \cdot \Delta \text{ Log Ind P}_{t-1} + \gamma_{5,1} \cdot \text{ Slope}_{t-1} \\ \quad + \alpha_1 \cdot \text{ Error Correction Term}_{t-1} + \varepsilon_t \\ \qquad \qquad \text{if Annual CPI Inflation}_{t-1} \leqslant \text{Threshold}, \\ \gamma_{1,2} \cdot \Delta \text{ Spread}_{t-1} + \gamma_{2,2} \cdot \Delta T \text{ Bill}_{t-1} + \gamma_{3,2} \cdot \Delta \text{ Log S\&P } 500_{t-1} \\ \quad + \gamma_{4,2} \cdot \Delta \text{ Log Ind P}_{t-1} + \gamma_{5,2} \cdot \text{ Slope}_{t-1} \\ \quad + \alpha_2 \cdot \text{ Error Correction Term}_{t-1} + \varepsilon_t \\ \qquad \qquad \text{if Annual CPI Inflation}_{t-1} > \text{Threshold}. \end{cases}$$

	AAA		BAA		Quality	
	Low	High	Low	High	Low	High
Constant	**0.07****	**0.18****	**0.55****	**0.18****	**0.40****	**0.11****
	[5.25]	**[3.83]**	**[3.29]**	**[5.86]**	**[3.30]**	**[5.13]**
Δ Spread$_{t,t-1}$	**0.17****	0.26	0.09	**0.26****	0.19	**0.27****
	[4.46]	[1.04]	[0.57]	**[7.60]**	[1.15]	**[8.29]**
ΔT Bill$_{t,t-1}$	0.01	0.01	**0.10****	**0.01****	**0.11****	**0.01***
	[0.35]	[1.36]	**[2.03]**	**[2.11]**	**[2.41]**	**[1.95]**
Δ S&P 500$_{t,t-1}$	−0.25**	−0.79**	−1.10	−0.79**	−0.50	−0.44**
	[3.30]	**[2.53]**	[1.09]	**[6.25]**	[0.60]	**[5.62]**
Δ Ind P$_{t,t-1}$	−0.23	−0.76**	−1.87	−0.76**	−1.56	−0.36**
	[1.47]	[2.11]	[1.31]	**[2.62]**	[1.29]	**[1.99]**
Slope $_{t-1}$	0.00	0.07	−0.05	**0.07****	−0.04	**0.04****
	[0.52]	[0.35]	[0.45]	**[4.84]**	[0.43]	**[5.24]**
ECT$_{t,t-1}$	−0.05**	−0.04**	−0.15**	−0.04**	−0.16**	−0.04**
	[5.07]	**[3.87]**	**[3.53]**	**[5.48]**	**[3.64]**	**[4.79]**
Std Err	0.09	0.14	0.43	0.14	0.37	0.09
Observn	678	328	100	906	100	906
Prob	0.67	0.33	0.10	0.90	0.10	0.90
Thresh	0.04		−0.01		−0.01	
$\hat{R}^2$	0.090		0.160		0.170	
F-Test	**8.53****		**18.56****		**19.02****	
Durbin Watson	1.98		1.93		1.93	
Log Like^h	887.45		432.31		872.31	
Lin Test	**113.65****		**428.23****		**734.78****	

Note: Thresh refers to the inflation rate that distinguishes the inflationary regime. Statistical significance is highlighted in bold and is denoted by * and ** at the 5% and 1% levels, respectively.

For the AAA specification the inflationary environment applies for one third of the data history during which time increases in both the stock market and industrial production all induce a tightening in credit spreads. With firms possessing considerable pricing power during such periods its seems reasonable to find that economic growth prospects together with the strength of the equity market will have explanatory power over AAA spreads.

For the first regime, covering both deflationary and more normal price behavior, the previous change in the spread itself enters significantly together with the equity market return. Notice, though, that the size of the equity return coefficient is one third the size of the coefficient for the inflationary regime. Overall, explanatory power for the inflationary regime model shows some improvement from the single regime treatment but fails to match that obtained from the latent variable (MS) model presented in Table 5. This last finding is not surprising given that the SETAR approach relies on the use of a single descriptive variable to distinguish between regimes. Alternatively, the MS approach relies upon an unobservable latent variable that is potentially capturing the impact of several variables simultaneously.

For the lower quality BAA specification the inflationary threshold distinguishes a deflationary relation within the sample history. The deflationary episode applies when inflation is less than −1% and also applies for roughly 10% of the time. The key result here is that under the deflationary regime very little enters significantly with the exception of the equilibrium error correction term and the risk free interest rate. Changes in the risk free rate induce a positive change in the BAA spread, widening in the case of an increase in the Treasury bill rate. Furthermore, the coefficient on the risk free rate is ten times the size of the equivalent coefficient in the second regime. Changes in the risk free rate therefore have an increased impact in the deflationary environment upon lower grade corporate debt. Again, this seems intuitive since deflation implies a lack of pricing power on the part of companies. Changes in the risk free rate under deflationary conditions are therefore more

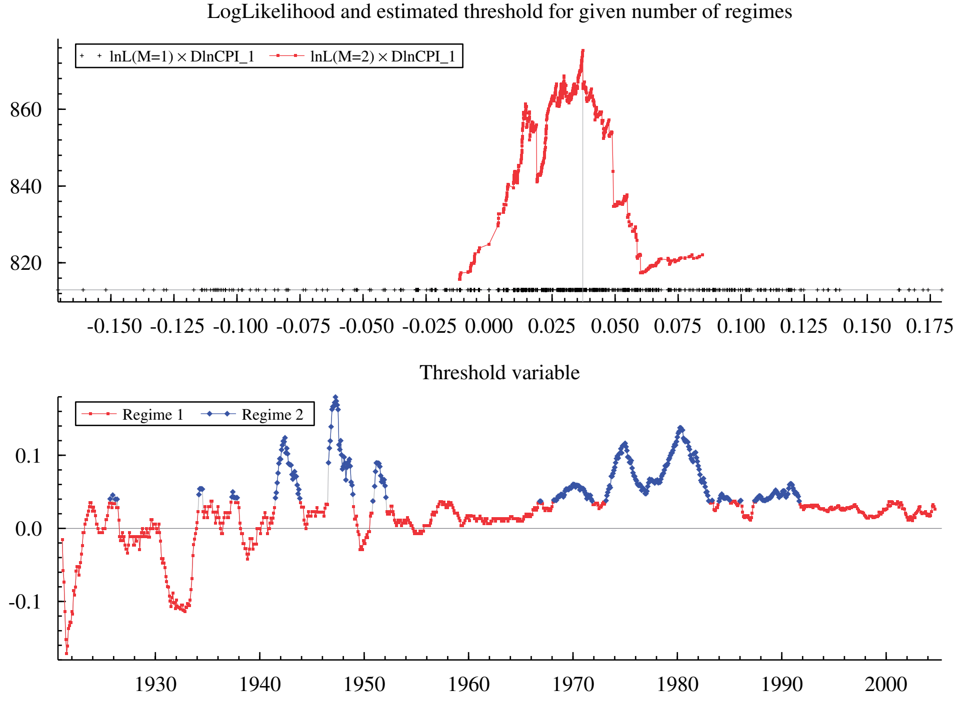

Fig. 1. AAA spread SETAR regime characteristics.

likely to impact the likelihood of default and hence the magnified impact of changes in the risk free rate.

Outside the deflationary regime it appears that the impact of the risk free rate is much reduced although still significant. Notice also that the coefficient on the risk free rate for the BAA model in the second regime is the same size as the coefficient on the risk free rate for the AAA model in the non-inflationary regime. This finding therefore highlights the need to abstract the impact of the deflationary environment on the lower credit model. Having allowed for the deflationary regime, the model now broadly ties in with the theoretical suggestion made by Chance (1990) and Longstaff and Schwartz (1995) who argue that BAA spreads should be less sensitive to changes in the risk free rate. This appears to be almost the case here once we explicitly model for a separate deflationary regime.

In terms of the remaining results for the BAA model in the non-deflationary regime, every other variable included in the specification now enters significantly. This is particularly the case for the previous change in the spread, the equity market return and the yield curve slope. Once again the error correction term enters significantly. Explanatory power is once again enhanced by the regime treatment in relation to the single regime result from Table 4. The linearity test at the base of the table clearly rejects the single regime model in favor of the two regime inflation contingent specification.

Results for the quality spread model mirror those for the BAA specification. The inflation threshold is again located at an inflation rate of -1% and the same magnified impact of the risk free rate is found for the deflationary environment. Given the similarity of the results across the quality and BAA specifications it seems reasonable to conclude

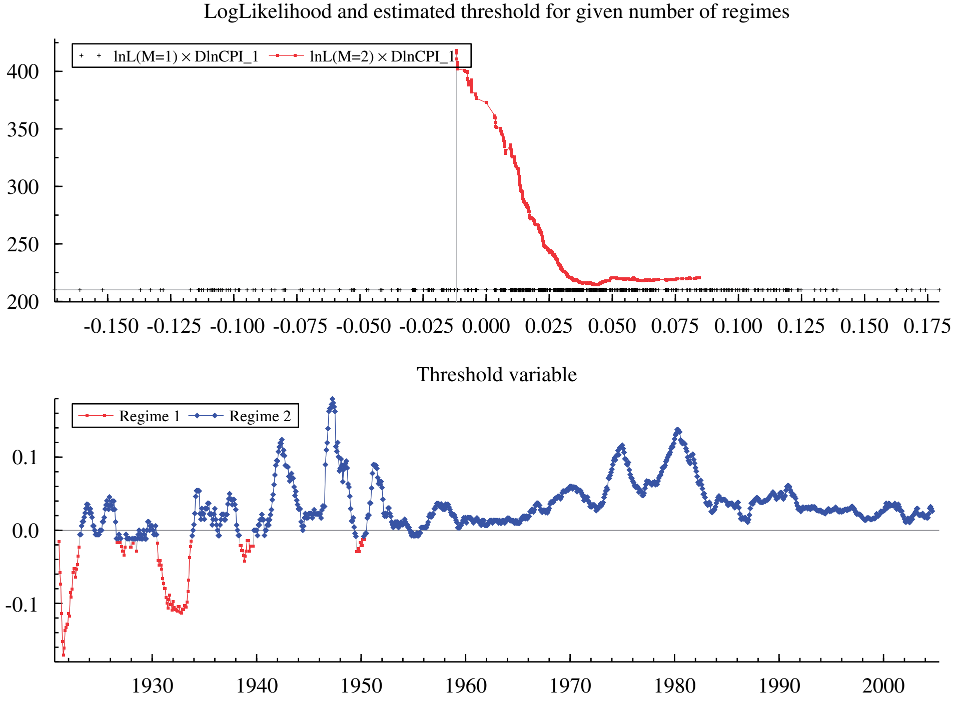

Fig. 2. BAA spread SETAR regime characteristics.

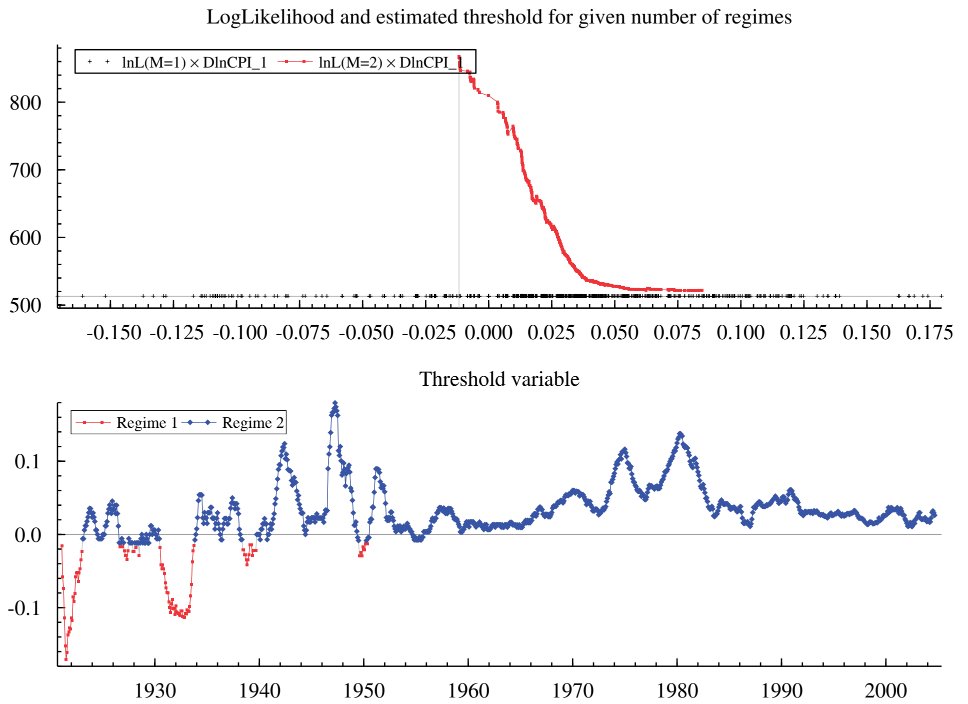

Fig. 3. Quality spread SETAR regime characteristics.

that AAA and government bonds appear to be very close substitutes indeed. This could partly explain the relatively low explanatory power contained in the AAA specification. Clearly the set of factors that drives high quality yields is different from those factors that are important in describing riskier debt. An interesting avenue for further research will be to consider those factors that capture the behavior of high grade AAA debt.

A final set of results, presented in Figs. 1–3, provides a graphical representation of the SETAR results presented in Table 6. For each figure, the top diagram plots the log likelihood function for different values of the inflation threshold variable. In every case the threshold is located at an obvious maximum indicating that the threshold for each model appears to be relatively robust. For the BAA and quality models in Figs. 2 and 3, the plots show a sharp decline in the log likelihood value as the threshold increases above -1%. The lower diagram for each figure shows the inflation rate highlighting the temporal dispersion of the inflation regimes themselves. Here the analysis demonstrates that the regimes are long lived and exhibit significant persistence, a feature that lends further credibility to the results. For the AAA model the inflationary environment applies for roughly one third of the data sample. For the lower grade BAA model the deflationary regime applies for around one tenth of the sample period.

6. Conclusion

This paper analyzes the determinants of US credit spreads over an extensive 85 year data history. The sample period covers several distinct business cycles, some of which could be considered atypical in relation to more recent economic history. Overall the analysis demonstrates that econometric models are capable of explaining up to one fifth of the movement in the various credit aggregates considered. Furthermore, this explanatory power is based upon a lagged forecasting relationship. The change in the credit spread is described by a relatively small group of explanatory variables that have been included with a one month lag.

One of the key findings of this paper is that regime switching econometric techniques are found to enhance explanatory power considerably. Given that regime time series techniques were initially applied to model the business cycle, the application to credit spread models seems a natural application. Markov switching models, based upon an unobservable latent variable, and SETAR models, using an inflation threshold, both generate insights into the behavior of credit markets across different regimes.

High grade credit spreads appear to differentiate regimes at a relatively high rate of inflation. During inflationary periods, industrial production growth, equity returns and the long run equilibrium all appear to be important in explaining changes in the credit spread. During more normal periods industrial production is no longer significant and equity markets returns, while significant, have one third the effect they do in the high inflation state.

Low grade credit spreads are more dependent upon the prevailing economic environment than higher grade spreads. The inflation threshold for low grade debt differentiates a deflationary environment where the change in the risk free rate has ten times the effect on the credit spread when compared to the other regime. Conditioning on deflationary regimes leaves the non-deflation regime explained by all 4 explanatory variables. Overall, explanatory power is considerably enhanced in allowing for an inflationary regime threshold model.

In terms of more general findings it seems that the theoretical conjecture that increases in the risk free rate should induce credit spread tightening does not apply for this data set. Instead changes in the risk free rate induce changes in credit spreads of the same direction. This result applies for both the long and short run, a finding that contradicts the theoretical models of Merton (1974), and Longstaff and Schwartz (1995) and the long run empirical result of Davies (2004) over a much more recent data set. Equity market behavior in both the long and short run appears to be a key determinant of credit spread movements. The finding that in the long run increases in the S&P 500 index induce a widening of spreads warrants further investigation. The suggestion that this may be the result of an asset allocation process as investors switch from debt to equities as the equity market rallies is left for future research. Other avenues to extend the analysis include a search for potential variables that might better capture the evolution of high grade AAA debt. Finally, the SETAR econometric technique applied here is but one of a family of such regime switching models. Other more sophisticated models such as PSTAR/LSTAR models offer the potential to yield further insights.

References

Bevan, A., Garzarelli, F., 2000. Corporate bond spreads and the business cycle. Journal of Fixed Income 9 (4), 8–18.

Chance, D., 1990. Default risk and the Duration of Zero Coupon Bonds. Journal of Finance 45, 265–274.

Collin-Dufresne, P., Goldstein, R.S., Martin, J.S., 2001. The determinants of credit spread changes. Journal of Finance 56, 2177–2207.

Dempster, A.P., Laird, N.M., Rubin, D.B., 1977. Maximum likelihood from incomplete data using the EM algorithm. Journal of the Royal Statistical Society B 39, 1–38.

Davies, A., 2004. Credit spread modelling with regime switching techniques. Journal of Fixed Income.

Davies, R.B., 1987. Hypothesis testing when a nuisance parameter is present only under the alternative. Biometrika 74 (1), 33–43.

Duffee, G.R., 1998. The relation between treasury yields and corporate bond yield spreads. Journal of Finance 53, 2225–2241.

Franses, P.H., van Dijk, D., 2000. Non-linear Time Series Models in Empirical Finance. Cambridge University Press.

Hamilton, J.D., 1990. Analysis of time series subject to changes in regime. Journal Of Econometrics 45, 39–70.

Harris, R., Sollis, R., 2003. Applied Time Series Modelling and Forecasting. Wiley, New York.

Johansen, S., 1988. Statistical analysis of cointegrating vectors. Journal of Economic Dynamics and Control 12, 231–254.

Johansen, S., 1995. Likelihood Based Inference in Cointegrated Vector Autoregressive Models. Oxford University Press, Oxford.

Johansen, S., Juselius, K., 1994. Identification of the long-run and short-run structure: an application to the IS-LM model. Journal of Econometrics 63, 7–37.

Longstaff, F., Schwartz, E., 1995. A simple approach to valuing risky fixed and floating rate debt. Journal of Finance 50, 789–820.

Leland, H., Toft, K., 1996. Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. Journal of Finance 51, 987–1020.

Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance 29, 449–470.

Morris, C., Neale, R., Rolph, D., 1998. Credit spreads and interest rates: a cointegration approach. Working Paper, Federal Reserve Bank of Kansas City.

Osterwald-Lenum, M., 1992. A note with quantiles of the asymmetric distribution of the maximum likelihood cointegration rank test statistics. Oxford Bulletin of Economics and Statistics 54, 461–472.