Interest Rates, Stock Returns and Credit Spreads: Evidence from German Eurobonds

NIKLAS WAGNER* – WARREN HOGAN† – JONATHAN BATTEN‡

We investigate daily variations in credit spreads on investment-grade Deutschemark-denominated Eurobonds during the challenging 1994–1998 period. Empirical results from a Longstaff and Schwartz (1995) two-factor regression, extended for correlated spread changes and heteroskedasticity, indicate strong persistence in spread changes. Consistent with theory and previous findings, changes in spreads are significantly negatively related to the term-structure level while, contrary to theory, the proxy for asset value does not yield a significant negative contribution. We even find a significant positive relation for Eurobonds with long maturity. Tentative interpretations are portfolio-rebalancing activities or differing risk factor sensitivities on short- vs. long-maturity bonds.

(J.E.L.: G14, G15).

1. Introduction

The 1990s were a critical period for Western Europe both politically and economically. In the case of the third largest issuer in the international bond market, Germany, in addition to concerns arising from the implementation of the euro, there were issues associated with its reunification and large impacts from events such as the 1998 Russian debt crisis. Largely...
driven by the former, government spending in Germany increased significantly, there was deterioration in its external position and large volumes of bonds were issued to finance the resulting budget deficits. The private sector also undertook massive spending initiatives with a new infrastructure also funded by bond issues, in both local and external markets. External measures of risk, such as the country risk measures of Euromoney, showed a decline in overall credit quality, even though Germany’s AAA rating on its sovereign bonds was never seriously challenged. Last but not least, equities experienced an exceptional worldwide boom period. Under these circumstances, it would be insightful to determine the extent to which the theoretical models for the pricing of risky bonds, proposed, for example, by Longstaff and Schwartz (1995) and Das and Tufano (1996) provide any explanation for the changes in the yield premium of German bonds issued in external markets. These models predict a negative correlation between changes in default-free interest rates, the returns on risky assets and changes in credit spreads. An empirical test of these implications is crucial for predicting credit spread changes and for the application of pricing models.

The objective of this study is to examine the short-term credit spread dynamics of investment-grade Deutschemark (DEM)-denominated Eurobonds within an econometric extension of the Longstaff and Schwartz (1995) two-factor regression model. As we suspect that the implementation of the third stage of the European Monetary Union, which took place in January 1999, had a potential disturbing structural impact on the credit spread dynamics under examination, we utilize a unique set of daily zero-coupon yield data during the years 1994 to 1998. Using data covering the second half of the 1990s, including the 1998 Russian debt crisis, the present investigation is conducted in a setting comparable with that of Campbell and Taksler (2003) who also study this striking period of – on average – increasing stock market levels accompanied by increasing corporate bond spreads. Campbell and Taksler show that the idiosyncratic firm-level volatility helps explain spreads; the same holds for firm-level implied volatility; see Cremers et al. (2004). Apart from unsystematic risk factors, systematic risk factors may help explain credit spread variations. Related papers include, for example, Collin-Dufresne et al. (2001), Delianedis and Geske (2001) and Elton et al. (2001).

Given the above-mentioned comprehensive explanations of credit spread changes, we would like to determine in the present study whether short-term variations in credit spreads may still accord with the basic predictions of a parsimonious Longstaff and Schwartz model. In an extension of the original methodology, our regression framework allows for correlated as well as autoregressive conditional heteroskedastic (ARCH) innovations (for an early documentation of ARCH effects in credit spread

changes, see Pedrosa and Roll, 1998). Following studies such as Longstaff and Schwartz (1995), Duffee (1998) and Barnhill et al. (2000), we utilize (i) returns on a well-diversified market index as a proxy for the asset-value factor and (ii) changes in a government bond rate with short maturity as the proxy for changes in the default-free interest-rate level.

Previous empirical evidence on the explanation of international credit spread changes appears mixed. Originally, in US bond markets, Longstaff and Schwartz (1995) found evidence of a negative relation for both changes in the short-term interest rate and changes in corporate asset value. A weaker but significant negative relation between changes in credit spreads and interest rates was also found by Duffee (1998) and Collin-Dufresne et al. (2001), while Neal et al. (2000) identified a negative relationship only for the short term and a reversal to a positive relationship for the long run.

Pointing out potential deficiencies of previous regression methodologies, we apply the extended framework to our dataset of Eurobond credit spread changes. Our results indicate time-varying variability and strong persistence in spread changes. Allowing for these features improves the performance of the model and reduces a tendency to otherwise overestimate the impact of interest-rate changes on credit spread changes. The finding of strong persistence indicates that relevant pricing information is not fully captured by our state variables. It also shows that information in general is not immediately incorporated in bond prices, which is due to a secondary market for corporate bonds, which is relatively illiquid. While consistent with theory and previous empirical findings, changes in the short rate in fact turn out to be significantly negatively related to daily changes in credit spreads, though the latter are not found to be significantly negatively related to equity index returns. However, we even find a significant positive relation for bonds with long maturity. As potential explanations for such positive short-term correlation, we suggest portfolio-rebalancing activities where long-maturity bonds are sold for stocks or differing risk factor sensitivities on short- vs. long-maturity corporate bonds. The methodology and the findings of this paper can, for example, support credit spread traders, sellers of credit spread derivatives and corporate borrowers, because these market participants must judge the impact of possible changes in stock market conditions on the prices of their securities in the secondary market.

The remainder of this paper is structured as follows. Section 2 outlines the methodological framework of our study as well as the theoretical model. Section 3 introduces the dataset and discusses the empirical results that add to the work on European yield spreads by Annaert and DeCeuster (1999), Dühlmann et al. (2000) and Boss and Scheicher (2002), for example. Section 4 provides a discussion of our findings.
2. The Methodological Framework

2.1. The Model

Following Merton (1974), assuming frictionless markets in which securities are traded in continuous time, Longstaff and Schwartz (1995) develop a valuation framework for risky bonds, which allows for both default and interest-rate risk. Default is modelled based on a given constant threshold value $K$ and firm value $V$ that follows a geometric Brownian motion. When default is triggered, i.e. firm value $V$ falls below the threshold $K$ during the bond’s time to maturity $(0; T]$, corporate debt holders receive a fraction $(1 - W)$ of the face value at maturity while, of course, otherwise the full proceeds are paid back at maturity. Interest-rate risk is modelled as a Vasicek-type mean-reverting process with Brownian noise for the short-term riskless rate $r$. In summary, the model has a two-factor structure with firm value and the interest-rate level representing the risk factors.\footnote{This framework offers a number of points for discussion. For example, credit spreads often rise with increasing maturity, rather than fall. While other approaches – such as the alternative reduced-form models of Jarrow et al. (1997), Duffie and Singleton (1999) and Madan and Unal (2000) – better match empirical evidence, the problem is that they lack an underlying theory to explain changes in corporate bond prices. Also, credit ratings are commonly used to proxy default risk while empirical evidence suggests that they are neither forward-looking nor accurate risk proxies, which is largely due to the effects of aggregation (Helwege and Turner, 1999). For recent discussions on the different features of credit risk models, see Altman et al. (2004) and Batten and Hogan (2003).}

Given the above-mentioned assumptions, and defining the solvency ratio $X = V/K$, the present value of a risky discount bond may be expressed as a function of $X$, $r$ and $T$, $P(X, r, T)$, which has a pay-off of 1 if default does not occur and of $(1 - W)$ if default occurs. A credit spread is then defined as the difference in the yield between a risky bond $P(X, r, T)$ and riskless bond $D(r, T)$ of equivalent maturity and coupon rate. Thus, to express credit spreads in terms of the Longstaff and Schwartz (1995) model, begin with the price of a pure-discount risky bond, $P(X, r, T) = D(r, T) \{1 - WQ(X, r, T)\}$, where $Q(X, r, T)$ is the risk-neutral probability of default. Note that price of the pure-discount risky bond is defined as $P(C, T) = e^{-CT}$, where $C$ is the risky bond’s yield to maturity. Hence, it follows for the yield of a risky bond

$$-\frac{\ln[P(X, r, T)]}{T} = -\frac{\ln[D(r, T)]}{T} - \frac{\ln[1 - WQ(X, r, T)]}{T}$$

where $-\ln[D(r, T)]/T$ is the yield $r$ on a corresponding default-free bond. The credit spread, $S \equiv C - r$, is the difference between the risky and the default-free yield.
\[
S = -\frac{\ln[1 - WQ(X, r, T)]}{T}
\]

It then follows that the first difference of \( S \) given as

\[
\Delta S = \Delta \left[ -\frac{\ln[1 - WQ(X, r, T)]}{T} \right]
\]

will be a function of \( \Delta X, \Delta r \) and \( \Delta T \). Hence, in this model, apart from a reduction in maturity \( T \), changes in asset value \( V \), which drive the solvency ratio \( X \), and changes in the short rate \( r \) are the main factors that determine changes in credit spreads.

### 2.2. Econometric Specification

Longstaff and Schwartz (1995) perform tests of a regression equation to explain changes in credit spreads. Given corporate yields \( C_{i,j,t} \) and government yields \( G_{j,t} \) for several different rating classes \( i \) and maturities \( j \), we define \( S_{i,j,t} = \ln C_{i,j,t} - \ln G_{j,t} \) as the logarithmic relative credit spread at time \( t = 1, \ldots, \tau \). Changes in relative credit spreads are regressed against changes in logarithmic government yields \( G_{k,t} \) with fixed maturity \( k \), which proxy changes in the short rate \( r \). Returns, \( R_t = \ln I_t - \ln I_{t-1} \), of a market index \( I \) are used as a proxy for changes in aggregate firm value. Dropping superscripts \( i \) and \( j \) for the spread variable for readability reasons, the regression models for relative credit spread changes are then of the form

\[
\Delta S_t = \beta_0 + \beta_1 \Delta \ln G_{k,t} + \beta_2 R_t + \varepsilon_t
\]

There are at least three points worth mentioning with this econometric approach to modelling credit spread changes.

1. **Time-series dependence in spread changes** \( \Delta S_{i,j} \) will typically result in autocorrelated innovations \( \varepsilon_t \). Note that dependence in spread changes may result from a low liquidity in the bond markets in general as well as in a relatively illiquid corporate bond market as compared with the government bond market. Illiquidity would indicate that asynchronous

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\(^2\) The definition of logarithmic spreads was introduced due to an improvement in the econometric specification. As credit spreads have a lower theoretical boundary, which equals zero, the distribution of standard credit spread changes has bounded left support (which is given by \(-1\) times the prevailing spread). Logarithmic spread changes are not subject to such a boundary. Results not reported here show that all of our basic empirical results remain unchanged, once standard spread changes (as defined in section 2.1) are used.

trading is a potential source of spurious dependence. This point is critical particularly for daily and weekly data.

2 As financial time-series typically exhibit volatility clustering, a time-varying variance of the innovations, i.e. heteroskedasticity in the $\varepsilon_t$s, may reduce estimation efficiency.

3 When $j = k$, $\ln G^k_t$ (as well as $\Delta \ln G^k_t$) appears on the left- as well as on the right-hand side of the regression equation (1). This has a disturbing effect on the estimation of the regression coefficient; more precisely, this will violate the orthogonality condition given by $\text{cov}(\Delta \ln G^k_t; \varepsilon_t) = 0$ and will cause potentially biased estimates of $\beta_1$; note that this also holds for the weighting approach in Longstaff and Schwartz (1995). To overcome the problem, one may choose $k \neq j$.

To overcome these issues, the regression model (1) may be respecified within a modified regression model to explain changes in the spreads $\Delta S_{i,j}^t$ by the interest-rate changes $\Delta \ln G^k_t$, $k \neq j$, and the index returns $R_t$. Each single model has the form

$$\Delta S_t = \rho \Delta S_{t-1} + \lambda \varepsilon_{t-1} + \beta_0 + \beta_1 \Delta \ln G^k_t + \beta_2 R_t + \varepsilon_t$$

The spread changes $\Delta S_{i,j}^t$ follow an autoregressive moving average process, ARMAX(1, 1), with two exogenous variables. The innovations and their conditional variance are given by the autoregressive conditional heteroskedastic, GARCH(1, 1), specification

$$\varepsilon_t = Z_t \sigma_t$$

$$\sigma_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2, \quad \omega_0 > 0; \omega_1, \omega_2 \geq 0$$

which is based on given start random variables ($\sigma_0^2$, $Z_0$) and standardized independent identically distributed (i.i.d.) random variables $Z_t$; for more details on the econometrics, see for example Mills (1999).

3. Empirical Investigation of Credit Spread Changes

3.1. The Dataset

Our empirical investigation of credit spread changes is based on daily DEM-denominated Eurobond credit spreads. The spreads are obtained from the credit spread pages of Reuters Information Services and span $\tau = 1,165$ observations during the period from February 25, 1994 to October 21, 1998. Note that at the end of 1998, DEM Eurobond issues accounted for USD369.4 billion in volume which, following the US-Dollar...
with USD1,673.4 billion and the Japanese-Yen with USD407.1 billion, made it the third largest currency of issue; see BIS (1998). Claes et al. (2002) provide a detailed survey of the Eurobond market.

We investigate the yields of AAA- (highest credit quality) and A-rated Eurobonds with maturities fixed at 5, 10 and 30 years. The calculation of the Eurobond yields is performed along the following line. First, Eurobond prices are obtained from European over-the-counter price quotes, of all available bonds within the specified credit class. Then, the calculated zero-coupon yields are the basis for the benchmark yields. Reuters provides these to the financial community on a daily basis. Specifically, the yields of the benchmark maturities for the different bond ratings are calculated from bond yields with various maturities along the yield curve and are then interpolated to from a benchmark set of yields at the maturity intervals using cubic spline techniques. These techniques are commonly used, as they produce a zero curve, which is smooth both in its first- and in its second-order derivatives. More details on the calculation are given in the Appendix.

The credit spreads $S_{ij}t = \ln C_{ij}t - \ln G_{jt}$ for the rating classes $i \in \{\text{AAA, A}\}$ and maturities $j \in \{5, 10, 30\}$ contain the benchmark yields $C_{ij}t$ and the zero-coupon yields $G_{jt}$ of German government bonds with the same maturity. These spreads represent the difference in logarithmic yields between two zero-coupon securities. To illustrate the yields and spreads in the sample period, Figure 1 presents time-series plots of the yields for five-year maturity bonds as well as the AAA and A credit spreads. The spread of the A-rated bonds at any point in time exceeds that of the AAA-rated bonds, where the deviation becomes larger (smaller) during periods of increasing (decreasing) spreads. Note that, in response to the 1998 Russian debt crisis, credit spreads widen quickly at the end of the sample period.

The summary statistics for our spread data are summarized in Table 1. While the lower credit-rating class implies higher average spreads, the results indicate a non-monotonous relation between average spreads and maturity. All spread distributions are positively skewed.

As additional variable, we use the logarithmic yield on the two-year government bond $\ln G_{2t}$ as a proxy for the interest-rate factor. The proxy for the change in the asset-value factor is the return on the CDAX equity index.

Note that while the Reuters’ data do not allow us to give a detailed industry-group analysis of the Eurobond issuers in our sample, Eurobond issues by banks and insurance companies clearly play a dominant role; a Reuters bond system search reveals only six non-financial corporate issuers for the given period. This is a typical situation for Europe and Germany, in particular, where financial corporations rather than non-financial corporations issue securities. Non-financials tend to raise debt via bank loans.
Figure 1: Yields and Spreads for Eurobonds with Five-year Maturity
Top: Government bond yields as well as benchmark yields on AAA- and A-rated Eurobonds.
Bottom: Logarithmic relative spreads, $S_{AA,5}^A$ and $S_{A,5}^A$.

index. This broad index represents the overall market capitalization of publicly traded German stock issues.4

3.2. Estimation Results

A summary of the estimation results for our models is provided in Table 2. Because our dataset contains daily data, which are particularly prone to the modelling issues discussed in section 2.2, we estimate the regression model under an ARMAX(1, 1) specification incorporating GARCH(1, 1) innovations. In Table 2, we report both OLS results for model (2.1) and the results from a Gaussian quasi-ML (QML) estimation for specification (2.2).

The results from Table 2 allow for the following conclusions. A main result is that the significance of the parameters allows us to reject the hypothesis \( \beta_1 > 0 \) for all rating classes and maturities in our sample (assuming a 95 per cent confidence level here and in the following), no matter whether we assume model (2.1) or (2.2). In contrast, the hypothesis \( \beta_2 > 0 \) cannot be rejected for any of the given combinations. Hence, while interest rates are significantly negatively related to changes in credit spreads, there is no evidence for a negative relation with equity index returns. Index returns turn out not to play a significant role in the determination of most of the daily spread changes in the sample. Moreover, there is evidence of a significant positive relation considering the 30-year maturities, i.e. an insignificant negative relation reverts to a significant positive relation for long maturities. One interpretation of this result is due to portfolio-rebalancing actions of fund managers in our sample period.

Table 1: Time-series Summary Statistics for the Eurobond Credit Spreads, \( S_{ij,t} \).

<table>
<thead>
<tr>
<th>( i )</th>
<th>( j )</th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA 5</td>
<td>5</td>
<td>0.0147</td>
<td>0.0140</td>
<td>0.0160</td>
<td>0.380</td>
</tr>
<tr>
<td>10</td>
<td>0.0365</td>
<td>0.0329</td>
<td>0.0235</td>
<td>2.88</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>0.0220</td>
<td>0.0175</td>
<td>0.0171</td>
<td>0.561</td>
<td></td>
</tr>
<tr>
<td>A 5</td>
<td>0.0729</td>
<td>0.0724</td>
<td>0.0192</td>
<td>0.691</td>
<td></td>
</tr>
<tr>
<td>10</td>
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<td>0.0704</td>
<td>0.0347</td>
<td>2.05</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>0.0689</td>
<td>0.0523</td>
<td>0.0424</td>
<td>1.09</td>
<td></td>
</tr>
</tbody>
</table>


4 Note that our Eurobond sample and the German stock market – as represented for example by the CDAX – are both dominated by financials. The CDAX returns are highly correlated with DAX returns (financials amount to an index weight of around 30 per cent of the DAX during the 1994–1998 period) as well as with CDAX banking industry index returns. CDAX and DAX returns reveal a correlation coefficient of 0.99; CDAX and CDAX banking returns reveal a correlation coefficient of 0.84 for the given sample period. Our main findings as obtained for the broadest equity proxy CDAX are not substantially affected by such alternative index choices.
While such a relation for long-maturity quality bonds may be puzzling from a theoretical standpoint, it indicates that spread prediction based on equity proxies may need to be treated with care. Section 4 provides a further discussion of tentative explanations of this finding.

Turning to the different model specifications, we observe substantial evidence of persistence in spread changes. Significant positive estimates of the AR term $\rho$ and negative estimates of the MA term $\lambda$ for model (2.2) are found for five of our six regressions where the exception of uncorrelated spread changes is given for A-rated bonds with 30-year maturity. This implies that spread changes tend to be followed by changes of equal sign and that large-model innovations tend to be dampened during the succeeding trading days. The significance of both the AR and the MA coefficients also indicates strong linear time-series persistence which cannot be captured by a simple AR(1) specification.

All GARCH coefficients are significant which is consistent with the observable clustering of volatility in the pattern of spread changes plotted over time. The extended specification improves model fit as measured by the coefficients of determination adjusted for the number of model

Table 2: Estimation Results with $t$-values in parenthesis

<table>
<thead>
<tr>
<th>$i$</th>
<th>$j$</th>
<th>$\beta_1^{(i,j)}$</th>
<th>$\beta_2^{(i,j)}$</th>
<th>$\rho^{(i,j)}$</th>
<th>$\lambda^{(i,j)}$</th>
<th>$\omega_1^{(i,j)}$</th>
<th>$\omega_2^{(i,j)}$</th>
<th>$R^2_{\text{adjusted}}$</th>
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<td>AAA</td>
<td>5 (2.1)</td>
<td>-0.53</td>
<td>-0.047</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.31</td>
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<td></td>
<td></td>
<td>(-10.56)</td>
<td>(1.94)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>(2.2)</td>
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<td>-0.015</td>
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<td>0.051</td>
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<td>(3.33)</td>
<td>(1.39)</td>
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</table>

parameters. Interestingly, the ARMAX-GARCH model reveals a reduced absolute magnitude of the estimated $\beta_1$ coefficients. Hence, the results in Table 2 indicate that model (2.1) would, on average, tend to overestimate the impact of changes in the interest rate on credit spreads.

Figures 2 and 3 give a graphical illustration of improved model fit based on residual and quantile/quantile (QQ) plots. For the modelled AAA 10-year maturity spread changes, $\Delta S_{t}^{AAA}$, Figure 2 compares the OLS residuals from model (2.1) with those of the standardized QML residuals from model (2.2). The OLS-residual plot clearly indicates heteroskedasticity, which is reduced in the QML residuals. Also, when model (2.2) is fitted, the corresponding QQ plots in Figure 3 demonstrate graphically that the model yields a substantial reduction in excess kurtosis as measured against the normal distribution.

Overall, our results indicate that empirical studies of credit spread changes are not easy to interpret. The problem of potential model misspecification, which may result in biases in the estimated sensitivities of spread changes, should therefore be considered in any empirical investigation. Problems with the econometric specification (such as orthogonality condition violations as well as linear time-series dependence and volatility clustering) play a role in model estimation. The proposed time-series specification can help improve estimation and yields improved validity of the results.

4. Discussion

This study extends the empirical research on the behaviour of credit spreads to the market of DEM-denominated Eurobonds by investigating

Figure 2: Residual Analysis of Modelled Spread Changes for AAA-rated Eurobonds with 10-year Maturity, $\Delta S_{t}^{AAA,10}$
the implications of the two-factor structural Longstaff and Schwartz (1995) model of credit spreads. The model predicts that credit spread changes are negatively correlated with both interest-rate and asset-value factors. We use a dataset based on daily variations in credit spreads on investment-grade DEM-denominated Eurobonds during the 1994–1998 period. This is a unique period in German and European history which predates the introduction of the euro and was characterized by an equity market boom. Utilizing an extended time-series regression specification, we find changes in spreads to be significantly negatively related to the term-structure level. As it turns out, the broad stock market proxy for aggregate asset value does not explain variations in credit spreads consistently. We even find a puzzling significant positive relationship between credit spread changes on long-maturity Eurobonds and the returns on the asset-value proxy. The positive relation appears strongest for the longest maturity and the lowest rating class within our sample.

Our findings of an insignificant relation between spread and asset-value changes and a significant positive relation for bonds with long maturity clearly contrast previous evidence. As we focus on investment-grade DEM-denominated Eurobonds, there is reason to believe that a credit risk-based asset-value mechanism may not play a dominant role in the determination of spreads. Thus, as pointed out, for example, in Elton et al. (2001), a large part of the variations in credit spreads may not be related to credit risk. Using unexplained (i.e. credit risk and tax unrelated) credit spreads, Elton et al. document a positive relation between negatively
signed changes in monthly spreads and classic risk factors including the equity market return. Hence, conditional on considering credit risk, the authors still document a negative relation between spread changes and aggregate asset value. Hence, the question arises where such difference in the results may come from. Although a detailed analysis is beyond the scope of this paper, we may offer some tentative thoughts. Three possible points of discussion are as follows.

The first point considers the role of the different data frequencies. Long-run monthly behaviour does not necessarily match the short-term dynamics on higher frequency data as given by our daily measurement period. A future analysis of spreads on a common set of bonds measured over different horizons may shed more light on this issue.

The second point considers different sensitivities with respect to systematic risk factors. As Elton et al. point out, the well-documented time-varying premium for bearing risk in capital markets may yield systematic risk factor premiums on corporate bonds, where the sensitivity of credit spreads to risk factors should tend to increase for longer maturities and lower credit quality. Given that the factor loadings for bonds vs. stocks potentially differ in a joint-factor model, credit spreads may move in response to changes in the factor levels. In the given second-half 1990s scenario, decreasing risk-free rates supported a bullish bond market together with a bullish stock market. This pushed up spreads given that the yields of long-maturity bonds showed low variation in anticipation of a long-run reversal in capital markets. On the other hand, prices of shorter term investment-grade Eurobonds increased via the asset-value transmission mechanism yielding the predicted negative relation. An explanation of the positive relationship for long-maturity Eurobonds would then be given by different risk factor sensitivities for short- vs. long-maturity bonds. In the case of bonds with long maturity, the joint-factor sensitivities may dominate the asset-value transmission mechanism and hence default risk considerations.

Finally, we point out that the positive relationship for long-maturity Eurobonds may be attributed to potential portfolio-rebalancing activities. Portfolio rebalancing because of variations in risk tolerance may induce fund managers to swap long-dated Eurobonds for stocks and vice versa. An increased risk tolerance can induce fund managers to sell bond for stocks, thereby driving up credit spreads. As such, the bullish stock market of the 1990s pushed up equity valuations while investors were tempted to trade long-term risky bonds for equity.

It remains an issue for future research to reconcile our findings with those of, for example, Elton et al. (2001). It appears that multi-factor models of asset returns may play an important future role in modelling and predicting credit spreads as measured over different time horizons.
REFERENCES


The approach used by Reuters is to calculate the benchmark yields from all available bonds in one credit class as follows. Consider a zero-coupon rate \( Z_i \) on a zero-coupon curve \( Z(t_i), i = 1, 2, 3, \ldots, n \). For \( t \in (t_i; t_{i+1}) \), assume a cubic representation of the form \( Z(t) = \alpha + \beta t + \gamma t^2 + \delta t^3 \), where the equalities \( Z(t_i) = Z_i \) and \( Z(t_{i+1}) = Z_{i+1} \) hold and the second derivatives satisfy the conditions \( Z''(t_i) = Z''_i \) and \( Z''(t_{i+1}) = Z''_{i+1} \). Then, the zero-coupon yield for maturity \( t \), \( Z(t) \), is expressed as follows:

\[
Z(t) = a Z_i + b Z(t_{i+1}) + c Z''_i + d Z''(t_{i+1})
\]

where \( a = (t_{i+1} - t)/h; b = (t - t_i)/h; c = 1/6(a^3 - a)h^2; d = 1/6(b^3 - b)h^2 \) and \( h = t_{i+1} - t_i \). The values of the second derivatives can be solved using a set of equations that allow for the calculation of any interpolated yield with maturity \( t \in (t_i; t_{i+1}) \).

**Non-technical Summary**

This paper investigates daily variations in credit spreads on investment-grade DEM-denominated Eurobonds during the challenging 1994–1998 period. The 1990s were a critical period for Western Europe both politically and economically. In the case of the third largest issuer in the

international bond market, Germany, in addition to concerns arising from the implementation of the euro, there were issues associated with its reunification as well as large impacts from events such as the 1998 Russian debt crisis. Under such circumstances, it would be insightful to determine the extent that theoretical models for the pricing of risky bonds provide any explanation for the changes in the yield premium of German bonds issued in external markets. These models predict a negative correlation between changes in default-free interest rates, the returns on risky assets and changes in credit spreads. An empirical test of these implications is crucial for predicting credit spread changes and for the application of pricing models.

Utilizing an extended time-series regression specification, we find that daily variations in credit spreads are highly persistent while significantly negatively related to the term-structure level. As it turns out, the broad stock market proxy for aggregate asset value does not explain variations in credit spreads consistently. We even find a puzzling significant positive relationship between credit spread changes on long-maturity Eurobonds and the returns on the asset-value proxy. The positive relation appears strongest for the longest maturity and the lowest rating class within our sample. Our finding of an insignificant relation between spread and asset-value changes and a significant positive relation for bonds with long maturity clearly contrasts previous evidence. As we focus on investment-grade DEM-denominated Eurobonds, there is reason to believe that a credit risk-based asset-value mechanism may not play a dominant role in the determination of spreads. However, results in the literature point out that even conditional on credit risk, a negative relation between spread changes and aggregate asset value should prevail.

Hence, the question arises where such difference in the results may come from. We offer three tentative points of discussion. The first point considers the role of the different data frequencies. The second point considers different sensitivities with respect to systematic risk factors. In the given second-half 1990s scenario, decreasing risk-free rates supported a bullish bond market together with a bullish stock market. This pushed up spreads given that the yields of long maturity bonds showed low variation in anticipation of a long-run reversal in capital markets. Finally, we point out that the positive relationship for long maturity Eurobonds may be attributed to potential portfolio rebalancing activities where long maturity bonds are sold for stocks.