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The impact of stock market volatility on corporate bond credit spreads

Ronald Bewley [a,*], David Rees [b], Paul Berg [b]

[a] *School of Economics, UNSW, Sydney 2052, Australia*
[b] *Commonwealth Bank of Australia, 120 Pitt Street, Sydney 1155, Australia*

Abstract

There has been a rapid increase in the number of corporate bonds issued in Australia since the middle of 1998. This increase has stimulated interest in characterising the yield curves and the factors that determine changes in these spreads. The focus of this paper is on measuring any impact of stock market volatility on spreads using two different measures. One measure is based on volatility implied from options prices while the other is derived from a conditional heteroscedastic volatility model of changes in a stock market index. It is found that the former has no significant impact on spreads but the latter is both significant and stable over time. This impact is estimated to be negative implying that an increase in volatility cause a decrease in corporate bond spreads.

Keywords: Forecasting; GARCH; Implied volatility; VAR

1. Introduction

It is only since the middle of 1998 that the number of corporate bonds on issue has been sufficiently large to enable an econometric characterisation of credit spreads to be undertaken across a broad range of credit ratings and industries. In a previous line of research [1], fitted yield curves to daily data on spreads to Commonwealth Government Securities for nine (Standard and Poor's) credit ratings categories (AAA–BBB) and five industry categories.

The model constructed was published under the name CBASpectrum, and was estimated separately for each day in an ongoing basis so that the time series of estimated spreads that flow from this model can reasonably be used as data input for this research. Appropriate time series methods can then be used to gain insight into how spreads evolve over time and, in particular, into how they react to market forces external to the corporate bond market.

Since the family of estimated yield curves is characterised by 12 parameters, one strategy is to model the evolution of the estimated parameters. Indeed, such an approach implies that the full system could be

* Corresponding author. Tel.: +61-29385-3398; fax: +61-29385-3930.
E-mail address: r.bewley@unsw.edu.au (R. Bewley).

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modelled by a finite number of equations, whereas the direct modelling of spreads, as is done in this paper, requires that an arbitrary finite subset of an infinite number of ratings/duration combinations be considered. In the first instance, the direct modelling approach has been followed as it has far greater intuitive appeal and can reasonably limited to modelling a smaller number of ratings/duration combinations than the number of parameters in the system.

While credit spreads can be constructed from actual data, such an approach would suffer from the consequent evolution in duration of the selected bonds over time and any particular changes in the characteristics of these bonds. These problems are removed by implying a credit spread for a generic bond of fixed duration and rating over time. The 'bonds' chosen for this study are AAA, AA, A and BBB, each of a constant 5-year duration, and the spreads are measured as deviations from the estimated Commonwealth Government Securities yield curves using CBASpectrum.

Two possible external influences on the corporate bond market are considered in this paper: the stock market, as measured by the ASX Large Capitalisation Index, and implied volatility. While 425 daily observations are used in the analysis of bond spreads: 1 July 1998 to 16 March 2001, 800 daily observations are used to measure volatility so as to remove any end-point effects due to the estimation procedure.

2. Stock market volatility

It is now commonplace to measure volatility in financial time series using ARCH or GARCH models; see [4,6]. These models are based on the notion that the innovations of a time series process unconditionally have a fixed variance, but that volatility clustering occurs in the sense that the conditional variance of a process varies over time.

A GARCH(p, q) model can be expressed as:

$$h_t = \alpha_0 + \sum \alpha_i \varepsilon + \sum \beta_j h_{t-j} + \sum \psi_l g_{lt} \quad (1)$$

where ε_t is the innovations in the levels model, h_t the conditional variance, and g_{lt} are m other factors that determine changes in conditional volatility.

Autoregressions were considered for the log first-difference of the index but no such terms were significant. Indeed, a constant term was not significant and, therefore, was excluded. Thus, ε_t is the change in the log of the index. The preferred model is a GARCH(1, 1). The estimated parameters, with t-ratios, are presented in Table 1.

The implied conditional standard deviations h, from this model are depicted in Fig. 1. It shows some possible initial value problem due to having to estimate h. The impact of an outlier at 18 April 2000 (Day 573) can also be noted. Owing to the scale of this figure, it is difficult to note that the conditional standard

Table 1
Estimated GARCH(1, 1) model

Parameter	Estimate
α_0	0.0588 (2.78)
α_1	0.1034 (3.46)
β_1	0.7999 (14.76)