On Credit Spread Slopes and Predicting Bank Risk

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Abstract

We examine whether bank credit-spread curves, engendered by a mandatory subordinated-debt requirement, would help predict bank risk. We extract credit-spread curves for each bank each quarter, and analyze the predictive properties of credit-spread slopes. We find that credit-spread slopes are significant predictors of future credit spreads. We also find that credit-spread slopes provide significant additional information on future bank risk variables, especially for small banking firms and highly levered banking firms, over and above other bank-specific and market-wide information.

(*Constructing Credit-Spread Curves; Credit-Spread Slopes; Predicting Credit Spreads and Bank Risk*)

1 Introduction

Economists have extensively analyzed the information content of the term structure of riskless interest rates. Numerous studies, for example, have been undertaken to establish whether the rational expectations theory of the riskless term structure holds. The tests examine whether the slope of the yield curve is capable of predicting future changes in the short rate. Shiller, Campbell and Schoenholtz (1983) conclude that the simple version of the theory, which says the slope of the term structure could be used to forecast the direction of future changes in the interest rate, is "worthless." However, later studies by Fama (1984), Mishkin (1988), and Hardouvelis (1988), among others, have found predictability at the very short end of the term-structure curve. Fama and Bliss (1987) find that current period long rates contained useful information for predicting short-rate movements.[1]

In contrast, very few studies have investigated the information content of the term structure of credit spreads. What is known is that credit spread curves for individual firms can be upward, downward or humped shaped and that over time the shapes of credit spread curves for different firms can move in similar or in different ways. Further, it is now well recognized that the behavior of short-term credit spreads are negatively correlated with short term riskless interest rates. Surprisingly, however, to the best of our knowledge, no studies have been conducted to establish whether the shape of the term structure of credit spreads conveys any information about the future direction of forward credit spreads. In particular, no studies have been conducted to evaluate whether the slope of the credit spread curve for an individual firm can be used to assist in predicting future credit spreads. Therefore, the first objective of our study is to establish whether the rational expectations theory, that has been well-examined for the term structure of riskless interest rates, carries over to credit spreads.

Of course, the ability to predict future credit spreads, based on credit-spread slope information, does not necessarily imply that future default probabilities or expected loss given default can be better predicted. The reason for this is that a significant component of credit spreads contain information on liquidity, taxes, and other market-wide factors. Huang and Huang (2002), for example, use structural models of bond prices to examine credit spreads and conclude that credit risk only accounts for around $20\% - 30\%$ of the observed spreads. Collin-Dufresne, Goldstein and Martin (2001) conclude that the majority of changes in credit spreads arise from factors that are not firm specific or related to equity-market performance or interest rates. Krishnan, Ritchken and Thomson (2003) conclude that the primary drivers of changes in credit-spread levels for banks are common market variables, although firm-specific factors become more important for

[1] For excellent reviews of this literature, see Rudebusch (1995), and Backus, Foresi, Muzumdar and Wu (2001).

certain subsets of banking firms - for low rated banking firms, for banks rather than for bank holding companies, and around times when banks issue new debt. Elton, Gruber, Agrawal and Mann (2001) estimate a state tax premium of the order of 40 basis points, as a component of credit spreads. Perraudin and Taylor (2003), and Houweling, Mentink and Vorst (2003) use different methods to estimate liquidity premium of the order of 20 basis points. Yu (2002) investigates a transparency premium in credit spreads, based on the clarity and timeliness of a firm's accounting numbers disclosures. Since changes in credit spreads reflect events other than default and recovery assessments, it is unclear whether improving forecasting of credit spreads necessarily translates into improved forecasts of firm risk variables. For example, a positive sloped credit spread curve may indicate that future credit spreads are more likely to increase, but may not necessarily indicate that firm specific risk will increase. Our second goal in this paper is, therefore, to assess whether credit-spread slopes convey information on future firm-specific accounting-risk variables.

Our study differs from the above-mentioned articles in three fundamental ways. First, with the exception of Krishnan, Ritchken and Thomson (2003), none of the above studies computed the slopes of credit-spread curves since the term structure of credit spreads was never computed. Indeed, in most studies, no direct effort was made to differentiate among credit spreads of differing maturities. Implicit in these studies is therefore the assumption that shocks to the credit-spread curve are parallel, or at least perfectly correlated, along the maturity spectrum. However, our data reveals that this assumption is not true. Indeed, in about 10% of cases, the short term credit spread and the long term credit spread moves in different directions. Second, none of the above studies were concerned about *forecasting* future credit spreads. For the most part, these studies investigated contemporaneous changes in credit spreads with changes in firm specific, market, liquidity and other common risk factor variables. Third, unlike most studies, we confine ourselves to investigating banking firms. We choose to do this because the information content of banking debentures has policy-specific implications.[2] Further, banks are more homogeneous than non-banking firms, and regulation provides researchers with better data. Finally, the banking literature to date has used relatively crude measures of expected default risk, based on "averaging" credit spreads over maturities. By separating out credit spreads across the maturity spectrum, we have the potential to more accurately estimate the

[2] Policymakers are actively considering the use of subordinated debt (SND) as a regulatory tool. A consultative paper issued by the Basel Committee on Banking Supervision (1999) proposes new risk-based capital standards with a view to increased granularity in risk measurement and improved supervision. The U.S Shadow Regulatory Committee has come out strongly in favor of mandatory SND as a mechanism for realizing enhanced market discipline of banks. Moreover, the Gramm-Leach-Bliley Act of 1999 requires all large banking firms to have at least one SND issue outstanding at all times.

default propensity of a bank.

What do we know about the shape of credit-spread curves? Theoretical option models, starting with Merton (1974), have shown that credit-spread curves could be increasing, decreasing, or hump-shaped. Low-quality firms have downward-sloping credit spreads reflecting the fact that over the longer term they would have to improve in order to survive. In contrast, high-quality firms may deteriorate over the long run and, hence, their longer-dated credit spreads should widen with maturity. Extensions to the Merton model by Longstaff and Schwartz (1995) and Jarrow, Lando and Turnbull (1997), among others, have basically drawn similar conclusions. Implicit in the explanations for the slope of credit-spread curves is the assumption that the term structure of credit spreads compensates investors for bearing default risk. However, based on the recent studies, which have shown that default risk may account for a small component of credit spreads, it is not too surprising that the empirical evidence has been inconclusive. Fons (1994) and Sarig and Warga (1989) have provided support for the above described "firm-quality-change" theory, while Helwege and Turner (1999) reject this theory by showing that speculative-grade issuers have positively sloped credit spreads. We find that the credit-spread curves of banking firms can be upward or downward sloping, but the average credit-spread slope is negative. Credit spreads of lower-rated banks are typically higher, and their slopes, on average, more steeply downward sloping.

Can information on today's term structure of credit spreads predict be helpful in predicting future credit spread changes of a firm? In particular, are forward credit spreads unbiased predictors of future spot credit spreads, or equivalently, does the expectations hypothesis hold for credit spreads? We find that there is significant information contained in the current period credit-spread curve about future credit spreads. Our findings on the predictability of future credit spreads based on current credit-spread slopes are in line with the findings by Backus, Foresi, Mozumdar and Wu (2001) who investigate predictability of riskless forward rate changes. We find that the degree of predictability of future credit spreads depends on the maturity of the credit spread, with longer-dated credit spreads (greater than 2-year forward credit spreads) being more predictable, and not significantly influenced by economy-wide factors. Firm-specific accounting risk variables add additional power, over and above the credit-spread slope, for predicting forward credit spreads with maturities exceeding two years. Shorter-dated forward credit spreads, with maturities of less than a year are more influenced by market-wide variables. While forward credit spreads of almost all maturities are predictable (the slope helps), the expectations hypothesis is rejected in favor of a time varying risk premia.

Can today's term structure of credit spreads predict future accounting risk variables of a firm? We need to be cognizant of two issues while attempting to determine the answer to this question. First, as discussed above, credit spreads can be contaminated by economy-wide factors, tax and transparency effects and time varying risk premia that prevent them from cleanly reflecting accounting risk variables of a firm. Second, even if credit spreads do reflect risk, they will likely reflect the net effect of all accounting risk variables on firm risk, rather than any one accounting risk variable. Therefore, after partialling out the effects of current firm risk variables, economy-wide factors, as well as spread level effects, we then examine whether there is any relationship between today's forward credit spread slope variables and *linear combinations* of *future* firm-specific accounting risk variables, using the technique of canonical correlations analysis. We find evidence that credit-spread slopes do contain information, over and above other firm specific and market-wide factors, on future collections of bank risk variables. This relationship is especially strong for smaller banking firms and for highly levered firms. Indeed, from a regulatory perspective, these are the banking firms for which it may be more important to estimate the future direction of bank risk variables.

Thus, we conclude that the credit spread slope for banking firms, in conjunction with credit ratings, is not only helpful for predicting future levels of credit spreads, but also provides information on firm risk variables, with the signal being strongest for smaller and more leveraged banks. This evidence suggests that credit-spread curves engendered by a mandatory subordinated debt (SND) requirement for banks may provide regulators with additional information on future credit spreads and bank risk variables, over and above the information they would already possess in the absence of SND.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 describes the model used to construct the credit-spread curves for each firm each quarter, and discusses the fit. Section 4 examines the features of credit-spread slopes. Sections 5 and 6 examine the predictability of future credit spreads and future firm-risk variables respectively using current-period credit-spread slopes. Section 7 concludes.

2 Data

2.1 Risky-Bond Transaction Data

Our first task is to construct credit-spread curves at the end of each quarter for as many different banks as possible, and then to repeat this exercise for a control sample of non-banking firms. The reason we use quarters as our time increment is that we want to relate changes in credit spreads to changes in firm-specific information, and such information is available only over quarterly intervals.

The data for our analysis comes from the Fixed Income Securities Database (FISD) on corporate bond characteristics and the National Association of Security Commissioners (NAIC) database on bond transactions. Data from both databases are matched for the period January 1994 through December 1999. The FISD database contains issue and issuer-specific information for all U.S. corporate bonds maturing in 1990 or later. The NAIC database consists of all transactions in 1994-1999 by life insurance, property and casualty insurance, and health maintenance companies.[3]

For our sample of banking firms, we have 18,776 trades across 185 different firms.[4] The distribution of trades and banking firms across the 24 consecutive quarters is shown in the first two columns of Table 1.

Our first screen eliminates all bonds other than fixed-rate U.S. dollar-denominated bonds that are non-callable, non-puttable, non-convertible, not part of an unit (e.g., sold with warrants) and have no sinking fund. We also exclude bonds with asset-backed and credit-enhancement features. This ensures that our credit spreads relate more directly to the creditworthiness of the issuer rather than the collateral. We use only transaction prices. Further, we eliminate all data that have inconsistent or suspicious issue/dates/maturity/coupon etc., or otherwise do not look reasonable.

Table 1 Here

Columns 3 and 4 of Table 1 show the distribution of trades by quarter that remain after applying this filter. We are left with 14,660 trades over 144 different banking firms. Our second screen eliminates all firm-quarter combinations for which we have fewer than 7 trades for the quarter. This filter ensures that we obtain a reliable credit-spread curve for a firm at the end of each quarter. This leaves us with 9,167 transactions over 81 different banking firms. Columns 5 and 6 of Table 1 show the resulting distribution of transactions using this criterion. Our third and final screen removes firms for which we cannot collect firm-specific risk variables. We need data to compute all our firm-risk measures for all the 24 quarters of our data set plus one quarter before our data begins and one quarter after it ends (the actual risk measures we use are discussed later). This leaves us with our final database of 6,590 transactions from 50 banking firms. The distributions of the trades and firms over each quarter are shown in the final two columns of Table 1.

[3]This database replaces the no longer available Warga (1998) database that was used by Blume, Lim and Mackinlay (1998), Collin-Dufresne, Goldstein and Martin (2001) and Elton, Gruber, Agarwal and Mann (2000, 2001) and is the one used by Campbell and Taksler (2002).

[4]We use the term banking firms to refer to both banks and bank holding companies.

We are, finally, left with a database that contains the transaction prices, trading dates, and the specific terms of SNDs, ordered by firm-quarters. The details on maturity and coupon of SNDs as well as firm ratings of our final sample of banking firms are as follows. 59% of issues have maturities between 1 and 10 years, 12% of issues have maturities of less than an year, and 25% of issues have maturities between 10 and 25 years. 72% of issues have coupon rates between 6% and 8%, and 18% of issues have coupon rates greater than 8%. The credit ratings come from Duff and Phelp, Standard and Poor's, Moody's, and Fitch. Whenever an issue is rated is more than one rating agency, we compute the average credit rating. For 8% of the issues the average credit rating is AA and above, for 62% of the issues the average credit rating is A, for 14% of the issues the average credit rating is BBB, for 3% of the issues the average credit rating is BB or below. We could not find the issue ratings for the remaining 13% of the issues. Thus, the majority of the banking firm SND issues in our final sample have maturities between 1 and 10 years, have coupon rates between 6% and 8%, and have been rated $A-$ or higher.

We use this final sample of banking firms to construct the credit-spread curves for each firm each quarter. The average number of issues (transactions) per firm-quarter used to construct credit-spread curves was 5.01 (13.67). Since 59% of all issues in our final sample have time to maturity between 1 and 10 years, in some of our analyses, we focus on the $10 - 3$ year credit-spread slopes.

2.2 Riskless Yield Data

We need to estimate the zero riskless yield curve for each day. To set this up, for each day we use the weekly 3-month, 6-month, one, two, three, five, seven, ten, twenty and thirty year constant-maturity-treasury rate data from January 1993 to December 2000 obtained from the web site of the Federal Reserve Bank of St. Louis. We use a cubic-smoothing-spline procedure to extract the par rates for 3 and 6-month maturities, and then for all remaining maturities at 6 month intervals. From this par curve, we then extract the zero-coupon rates for $3-$ and 6-month maturities and for all maturities thereafter at intervals of 6 months. The final saved output for each day is the annualized continuously compounded zero coupon yields for the three and six month rates, and for the one, two, three, five, seven, ten, twenty and thirty year maturities.

In addition to the risky and riskless yield data, we use the following firm-specific risk data and economy-wide data in our analyses.

2.3 Firm-Specific Risk Variables

We use the following 5 proxies for risk for banks and bank holding companies (BHCs) in our analysis: (a) Return on Assets (ROA), computed as Net Income Before Taxes and Extraordinary Items divided by Total Assets; (b) Loans to Total Assets, computed as Loan Assets divided by Total Assets; (c) Non Performing Assets computed as (Loans past due 30-89 days + Loans 90 days past due + Non accrual loans) divided by loans and leases net of unearned income; (d) Net charge-offs, computed as (Charge-offs minus recoveries) divided by loan assets; and (e) Leverage, computed as Total Assets divided by Total Equity Capital. As ROA increases, bank risk decreases, while as each of the other 4 ratios increases, bank risk increases. All the bank risk ratios are calculated from the Federal Financial Institutions Examination Council's Reports of Income and Condition (henceforth Call Reports), while all BHC variables are calculated from the Federal Reserve Y-9 statements.

In addition, we use credit-rating information (from Duff and Phelp, Standard and Poor's, Moody's, and Fitch) on issues made by each banking firm. We establish a single numeric credit score for each firm-quarter. First, we translate the letter ratings from each agency for each issue on each firm into numeric scores, with 1 representing the lowest rating and 15 the highest rating. We then take the average values of all the agency ratings over all outstanding issues each firm-quarter, to obtain a single numeric credit-rating score for each firm each quarter. The most common ratings for the banking firms in our sample, using the Standard & Poor's notation, are $BBB+$, $A-$ and A, which correspond to scores of 9, 10 and 11 respectively.

2.4 Market Variables

We use 3 market variables in our analyses. These are (a) the Growth in Industrial Production (GIP), (b) S&P 500 buy and hold return (S&P), and (c) a stock market volatility index - the VIX Index. The data on GIP are taken from the website of the Federal Reserve Bank of St. Louis, the S&P data comes from the Center for Research in Securities Prices database, and the data on VIX index comes from the Chicago Board Options Exchange website.

2.5 Term Structure Variables

We use 2 term structure variables in our analyses. These are (a) 5-year Treasury yield (T5), and (b) the slope of the yield curve defined as the 10-year Treasury yield minus 3-year Treasury yield (TSlope). The data on T5 and TSlope comes from the website of the Federal Reserve Bank of St. Louis.

3 Extracting Credit Spreads

Our goal is to use the price information on all bonds for each firm that traded in a particular quarter together with concurrent riskless term structure, to extract a term structure of credit spreads for each firm at the end of each quarter. Given the abundant daily information on the riskless term structure, we use a 2-factor model to estimate the parameters with the help of the Kalman filtering technique. Given the limited trade data for a firm-quarter, the dynamics for credit spreads are kept relatively simple. Our model allows the short credit-spread process for each firm to be mean reverting and to be correlated with interest rates. In addition, over each quarter, we assume the volatility of the credit spread is constant. Since the parameters are reestimated each quarter, and since at each trade date the riskless term structure is taken as given, the model's primary purpose is to extract spread curves over the quarter that provides extremely close fit of theoretical bond prices to their observed bond counterparts.

3.1 Pricing Risky Bonds

We adopt a reduced form model, in which the default process is modeled directly as surprise stopping times. Let $h(t)$ be the hazard rate process, with $h(t)dt$ representing the risk neutral probability of defaulting in the interval $(t, t+dt)$. We follow Duffie and Singleton (1999) and define recovery, $y_r(\tau)$, at the time of default, τ, to be a fraction, ϕ, say, of the pre-default value of the bond. That is:

$$y_r(\tau) = \phi G(\tau_{-}, T)$$

where $G(t,T)$ is the price of the zero coupon bond that promises to pay \$1 at date T. Duffie and Singleton consolidate the hazard rate with the loss rate and define the instantaneous credit spread, $s(t)$, to be:

$$s(t) = h(t)(1 - \phi(t)).$$

They show that the price of a risky zero coupon bond can be obtained by pretending the bond is riskless and discounting it at a rate higher than the riskless rate. Specifically,

$$G(t,T) = E_t^Q\left[e^{-\int_t^T (r(v)+s(v))dv}\right] \quad (1)$$

$$P(t,T) = E_t^Q\left[e^{-\int_t^T r(v)dv}\right] \quad (2)$$

where $P(t,T)$ is the date-t price of a riskless bond that pays \$1 at date T. We define the date-t credit spread for the time interval $[t, t+m]$ to be $s_p(t;m)$, where:

$$s_p(t;m) = -\frac{1}{m} log\left[\frac{G(t,t+m)}{P(t,t+m)}\right]$$

and $s(t;0) = s(t)$.

In order to establish a model for the credit-spread curve at any date, $s_p(t;\cdot)$, then, requires the specification of the dynamics for the interest rate process, $r(t)$ and the instantaneous spread, $s(t)$.

Some authors have parameterized the instantaneous credit spread as a function, usually affine, of candidate economic and firm-specific state variables and then directly estimated the effects of these variables. Examples of this approach include Jarrow and Yildirim (2002), Bakshi, Madan and Zhang (2001), and Driessen (2002). Unfortunately, the number of trades that survived our rigorous screening process at the individual firm level is rather limited. So, from a practical perspective, it is not possible to include many state variables into the dynamics of the instantaneous credit spread. Indeed, even those papers that parameterize credit spreads as a function of candidate state variables limit themselves to considering only a few state variables. Jarrow and Yildirim (2002) use only interest rates as the state variable; Bakshi, Madan and Zhang (2001) consider a variety of models with no more than two state variables and Driessen (2002), using weekly mid-point prices of corporate bonds, allows for two common factors and one firm specific variable.

Given the data constraint, we adopt an approach that is similar to Collin-Dufresne, Goldstein and Martin (2001). We first extract a term structure of credit spreads for a firm at the end of each quarter in a way such that the fit of observed transaction prices in the quarter is very precise. Then we relate the fitted credit spreads to a host of possible explanatory variables. The advantage of this approach is that it allows us to consider a large set of potential explanatory variables for credit spreads, without being limited by the number of eligible transactions per firm-quarter.

As described next, we use a 3-factor model as a calibrating device to construct quarterly credit-spread curves for each firm. The resulting credit spread curve for each firm-quarter, has the property that among all our possible credit spread curves, it best fits the actual set of traded bond prices in that quarter. The model is rich enough to produce upward, downward and hump shaped curves.

The full dynamics of the state variables under the data generating measure is given by:

$$dr(t) = [\theta(t) + u(t) - \overline{a}r(t)]dt + \sigma_r dw_r(t) \quad (3)$$

$$du(t) = -bu(t)dt + \sigma_u dw_u(t) \quad (4)$$

$$ds(t) = [\alpha_0 - \overline{\alpha}_1 s(t)]dt + \sigma_s dw_s(t) \quad (5)$$

where $E_t^P[dw_r(t)dw_u(t)] = \rho_{ur}dt$, $E_t^P[dw_u(t)dw_s(t)] = \rho_{us}dt$, $E_t^P[dw_r(t)dw_s(t)] = \rho_{rs}dt$, $\overline{a} =$

$a + \lambda_r \sigma_r$, and $\overline{\alpha}_1 = \alpha_1 + \lambda_s \sigma_s$.

Here, the interest rate evolves according to a two-factor double mean-reverting model. The value of $\theta(t)$ is chosen to make the model consistent with the prices of all zero coupon bond prices. $u(t)$ is a component of the long-run average mean of the short rate. It is stochastic and mean reverts to zero at rate b. The parameters a, b, σ_r, and σ_u, are constants and $dw_r(t)$ and $dw_u(t)$ are standard Wiener processes, with correlation $\rho_{ru} dt$. The market price of interest rate risk, $\lambda_r(t)$, is proportional to $r(t)$, and the market price of central tendency risk, $\lambda_u(t)$, is zero. This latter assumption is consistent with the empirical findings of Jegadeesh and Pennacchi (1996). Finally, we assume that the credit spread process has constant volatility, σ_s, mean reverts, and its innovations are correlated with the innovations of the interest rate process. The market price of credit-spread risk, $\lambda_s(t)$, is assumed to be proportional to $s(t)$.

Under these assumptions, the no arbitrage conditions lead to:

$$G(t,T) = P(t,T) e^{-D(m)s(t) - K(t,T)} \tag{6}$$

where

$$\begin{aligned} K(t,T) &= \alpha_0 \int_t^T D(v,T) dv - \frac{1}{2}\sigma_s^2 \int_t^T D^2(v,T) dv \\ &\quad - \sigma_r \sigma_s \rho_{rs} \int_t^T B(v,T) D(v,T) dv - \sigma_u \sigma_s \rho_{us} \int_t^T C(v,T) D(v,T) dv \end{aligned}$$

and

$$\begin{aligned} B(v,T) &= \frac{1}{a}[1 - e^{-a(T-v)}] \\ C(v,T) &= \frac{1}{(a-b)}[\frac{1}{a} e^{-a(T-v)} - \frac{1}{b} e^{-b(T-v)}] + \frac{1}{ab} \\ D(v,T) &= \frac{1}{\alpha_1}[1 - e^{-\alpha_1 (T-v)}] \end{aligned}$$

Equivalently, the date-t credit spread over $[t, t+m]$ is $s_p(t;m)$, where:

$$s_p(t;m) = \overline{D}(m) s(t) + \overline{K}(m) \tag{7}$$

and

$$\begin{aligned} \overline{D}(m) &= \frac{D(t, t+m)}{m} \\ \overline{K}(m) &= \frac{K(t, t+m)}{m}. \end{aligned}$$

3.2 Estimation Technique

Our state variables (r_t, u_t, s_t) are not directly observable. However, we do have a rich set of riskless term-structure data that allows us to measure, with error, functions of (r_t, u_t).

To facilitate estimation using discretely observed data, we separate the estimation problem into two phases. In the first phase, we estimate the riskless term-structure parameters using a time series of cross-sectional riskless bond prices. We impose both cross-sectional model restrictions and conditional time series restrictions. We accomplish this using the Kalman filter approach, which is a recursive, unbiased least squares estimator of a Gaussian random signal.

While, in principle, the Kalman filter approach could be used for the entire system of riskless and risky bonds, the availability of data on risky-bond trade prices data is comparatively smaller. Therefore, the resulting credit spread parameter estimates each quarter would depend too heavily on the initial priors that need to be specified. To avoid this possible bias, we adopt an empirical Bayes estimation procedure used in non-linear mixed effects models. This approach produces consistent estimators and is very close in intent to the Kalman filtering approach.

3.2.1 Estimating Parameters from Riskless Prices

To facilitate estimation using discretely observed data, we rewrite the riskless bond model as a discrete time state space system. Notice that in order to do this we need to specify the dynamics of the state variables under the data-generating measure. This requires specification of the market prices of risk. Under this process, the joint distribution of the riskless interest rate state variables $\{r(t), u(t)\}$ is bivariate normal when viewed from any earlier date. With discretely observed data, we can write:

$$S_{t+h} = \gamma_0(h) + \gamma_1(h) S_t + \epsilon_{t+h} \tag{8}$$

where $S_t' = (r(t), u(t))$, $\gamma_0(h)' = (\frac{\theta}{\overline{a}}(1 - e^{-\overline{a}h}), 0)$ and

$$\gamma_1(h) = \begin{pmatrix} e^{-\overline{a}h} & \frac{1}{(\overline{a}-b)}(e^{-bh} - e^{-\overline{a}h}) \\ 0 & e^{-bh} \end{pmatrix}$$

and $\epsilon_{t+h} \sim N(0, Q(h))$, where

$$Q(h) = \begin{pmatrix} \sigma_{rr}(h) & \sigma_{ru}(h) \\ \sigma_{ru}(h) & \sigma_{uu}(h) \end{pmatrix}$$

and

$$\begin{aligned}
\sigma_{rr}(h) &= \frac{\sigma_r^2}{2\overline{a}}(1-e^{-2\overline{a}h}) + \frac{\sigma_u^2}{(\overline{a}-b)^2}\left[\frac{1}{2b}(1-e^{-2bh}) + \frac{1}{2\overline{a}}(1-e^{-2\overline{a}h}) - \frac{2}{(\overline{a}+b)}(1-e^{-(\overline{a}+b)h}\right] \\
&\quad + \frac{\rho\sigma_u\sigma_r}{(\overline{a}-b)}\left[\frac{1}{(\overline{a}+b)}(1-e^{-(\overline{a}+b)h}) - \frac{1}{2\overline{a}}(1-e^{-2\overline{a}h})\right] \\
\sigma_{uu}(h) &= \frac{\sigma_u^2}{2b}(1-e^{-2bh}) \\
\sigma_{ru}(h) &= \frac{\rho\sigma_r\sigma_u}{(\overline{a}+b)}(1-e^{-(\overline{a}+b)h}) + \frac{\sigma_u^2}{(\overline{a}-b)}\left[\frac{1}{2b}(1-e^{-2bh}) - \frac{1}{(\overline{a}+b)}(1-e^{-(\overline{a}+b)h}\right]
\end{aligned}$$

Equation (8) defines the state transition equation. If at date-t, we observe the prices of bonds with maturities m_1, m_2,m_3,...,m_n, then the n yields can be written in matrix form as

$$Y_t = G + HS_t + \Upsilon_t \tag{9}$$

where

$$\begin{aligned}
Y_t' &= (y_t(m_1), y_t(m_2), \ldots, y_t(m_n)) \\
G' &= (A(m_1), A(m_2), \ldots, A(m_n)) \\
H' &= \begin{pmatrix} B(m_1) & B(m_2) & \ldots & B(m_n) \\ C(m_1) & C(m_2) & \ldots & C(m_n) \end{pmatrix}
\end{aligned}$$

and the measurement error in the yields is $\Upsilon_t \sim (0, \sigma_\Upsilon^2 I_n)$.

Equations (8) and (9) constitute a state space system whose parameters can be estimated by maximum likelihood. The likelihood function is estimated recursively using a Kalman filter as follows.

We first need an estimate of the initial state vector, S_0, and its variance-covariance matrix, R_0, say. More generally, assume at date t, S_t and R_t are given. Viewed from date t, our predictions for date $t+h$ are:

$$\begin{aligned}
\hat{S}_{t+h|t} &= \gamma_0(h) + \gamma_1(h)S_t \\
\hat{R}_{t+h|t} &= \gamma_1(h)R_t\gamma_1(h)' + Q(h)
\end{aligned}$$

The innovation vector, η_{t+h}, and its variance, V_{t+h}, are computed as:

$$\begin{aligned}
\eta_{t+h} &= Y_{t+h} - (G + H\hat{S}_{t+h|t}) \\
V_{t+h} &= \sigma_\Upsilon^2 I_n + H\hat{R}_{t+h|t}H'
\end{aligned}$$

The date-t forecasts are then blended with the date $t+h$ innovations, to yield the updated values for S_{t+h} and its variance V_{t+h} as follows.

$$\begin{aligned} S_{t+h} &= \hat{S}_{t+h|t} + \hat{R}_{t+h|t} H' V_{t+h}^{-1} \eta_{t+h} \\ R_{t+h} &= \hat{R}_{t+h|t} - \hat{R}_{t+h|t} H' V_{t+h}^{-1} H \hat{R}_{t+h|t} \end{aligned}$$

After computing the innovation vector η_t, and V_t for each date using this recursive procedure, the log likelihood function is

$$\sum_{t=1}^{n} -\frac{1}{2}\left(|V_{ht}| + \eta'_{ht} V_{th}^{-1} \eta_{th}\right)$$

The optimal parameter set corresponds to the set that maximizes this function. This optimization procedure is solved using numerical methods.

3.2.2 Estimation of the Credit-Spread Parameters

Consider a particular firm and assume that over a quarter there are K observable bond trades. Let $t_1 < t_2 < \ldots < t_K$ represent the trade dates, and let a_i represent the actual bond price at date t_i, $i = 1, 2, \ldots, K$. Notice that the firm may have multiple bonds outstanding so that the coupons and maturity dates at different trade dates might vary. Let $\hat{a}_i$ be our theoretical risky bond price computed at date t_i, conditional on knowledge of the state variables at date t_i. The parameters that remain to be estimated are $\Phi = \{\alpha_0, \alpha_1, \lambda_s, \rho_{rs}, \rho_{us}, \sigma_s\}$.

Let $\mathcal{S}$ represent the path of the state variable over the K trading dates. That is, $\mathcal{S} = \{s(t_1), s(t_2), \ldots, s(t_K)\}$. Further let:

$$\begin{aligned} \hat{A}' &= (\hat{a_1}, \hat{a}_2, \ldots, \hat{a_K}) \\ A' &= (a_1, a_2, \ldots, a_K). \end{aligned}$$

Let $SSE(\Phi, s(0), \mathcal{S})$ represent the sum of squared errors between bond price residuals given the initial spread, $s(0)$, the path, $\mathcal{S}$, and the parameters in Φ. Our goal will be to choose estimates that minimize the *expected* sum of squared errors, where the expectation is taken over all possible paths. Notice that the residuals will be correlated because the time series of state variables is generated by an Ornstein-Uhlenbeck process. Let Σ_K be the $K \times K$ covariance matrix with $(\Sigma_K)_{ij} = Cov_0[(s(t_i), s(t_j))|s(0)]$, and

$$Cov_0[(s(t_i), s(t_j))|s_0] = \frac{\sigma_s^2}{2\overline{\alpha}_1} e^{-\overline{\alpha}_1(\overline{t}_{ij} - \underline{t}_{ij})}(1 - e^{-\overline{\alpha}_1 \underline{t}_{ij}})$$

where $\bar{t}_{ij} = Max[t_i, t_j]$ and $\underline{t}_{ij} = Max[t_i, t_j]$. Consistent least squares estimates are then generated by minimizing the following expected weighted sums of squares:

$$Min_{s_0,\Phi} E[(A - \hat{A})' \Sigma_K^{-1} (A - \hat{A})].$$

We could have conducted the estimation once for each banking firm using the full time series data. Rather, we conducted the estimation separately over each firm-quarter. The reason for this is that we did not want our quarterly term structure curves for each banking firm to be dependent on the model specification. Rather, we wanted to use the model as a calibrating device that came as close as possible to fitting the data. By allowing the parameters to change over each firm-quarter, we added considerable degrees of freedom, and this additional flexibility allowed us to obtain very good fits to the actual raw data for each firm-quarter.

3.3 Empirical Results

Figure 1 shows the basis point errors when our model is used to determine the riskless yield curve. The figure shows histogram plots for all the one-step-ahead prediction errors, by maturity.

Figure 1 Here

On average, the model displays almost no bias in estimating yields, and the majority of predictions fall within 20 basis points of the observed values. The average absolute one week prediction yield errors is 10.44 basis points.

Figure 2 shows the distribution of errors in bond prices produced by our model. The percentage errors are bucketed by the underlying maturity of the bond, and the results are presented in the form of histograms. The five maturity buckets correspond to: shorter than 2 years, $2-5$ years, $5-10$ years, $10-20$ years, and greater than 20 years. All transactions are included in the analysis. In particular, we had over 1000 transactions in each of the five classes, with the modal class being the $5-10$ year group, which contained over 5000 transactions. The histograms reveal that the inter-quartile ranges for percentage errors for banking firms are symmetrically distributed about zero for all maturity contracts. The inter-quartile range extends for about 2.5%. In aggregate, the mean (median) pricing error was 0.22% (0.16%). The mean of the absolute percentage errors was 2.2%, while the median of the absolute percentage errors was 1.2%. These results indicate that the model is fitting actual data remarkably well with no obvious biases along the maturity spectrum.

Figure 2 Here

The average percentage pricing error per banking firm is close to zero, and there are very few observations where the average deviates from 0.5%. This indicates that the estimation of credit-spread curves has indeed effectively incorporated the information on bond prices.

4 Credit-Spread Slopes

Table 2 summarize the average credit spread levels and the average credit-spread slopes for the full sample of banking firms as well as for sub-samples segregated by credit ratings, type, size and leverage. The high credit rating category comprises banking firms with credit ratings of A^- and above. High and low categories based on size (total assets) and leverage are defined in terms of being above and below the sample median respectively.

Table 2 Here

Banks have higher credit spreads than BHCs, perhaps because the holders of subordinated debt issued by BHCs typically have recourse to assets owned by other banks and non-bank subsidiaries in the same holding company. Smaller banking firms have larger credit spreads than the larger ones, but the differences are not significant. Higher leverage banking firms have slightly greater credit spreads than the less levered banking firms, but again, the differences are not statistically significant. The biggest differences are in the credit rating categories. The lower rated banking firms have higher average credit spreads for all maturities. The gap in credit spreads between the low and high ratings groups is typically around 30 basis points for most maturities, reaching a maximum of over 40 basis points for the 5 year maturity.

While the riskless term structure over this period was generally upward sloping, the average credit-spread slope for banking firms is negative. The average $3-1$ year credit spread slopes is -24 basis points, and the average $10-3$ year credit spread slopes almost -18 basis points. Like the average credit spreads, credit-spread slopes for the two credit-ratings groups are also quite distinct. For the lower rated banking firms, the average credit spread curve is more than twice as steeply negative. The average $10-3$ year slope, for example, is -38 basis points. In contrast, for the higher rated firms, the slope is -14 basis points. These results are consistent with the findings of Fons (1994), who claims that low rated firms would be more likely to display downward sloping credit spread curves.

All the credit-spread slopes are highly correlated. The correlation between the $10-3$ and the $3-1$ slopes is 90%; between the $10-3$ and the $7-3$ slopes is 99.3%; and between the $10-3$ and the $10-5$ slopes is 99%.

5 Credit-Spread Slope as a Predictor of Future Forward Credit Spreads

Under the expectations hypothesis for credit spread curves, the n-period forward credit spread is an unbiased estimator of the future one-period spot credit spread. In particular, let g_t^n be the forward credit spread for the quarterly period $[t+n, t+n+1]$, viewed from quarter, t. The spot credit spread for the current quarter is therefore g_t^0. Clearly, the n-quarter credit spread yield is just the average of the forward credit spreads over the period:

$$s_p(t,n) = \frac{1}{n}\sum_{j=0}^{n-1} g_t^j.$$

Following Backus, Foresi, Mozumdar and Wu (2001), we predict future forward credit spreads using the regression:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n(g_t^n - s_t) + \epsilon_{t+1} \tag{10}$$

for maturities n ranging from one quarter to ten years in increments of quarters. If the credit-spread slope can predict the n-quarter forward rates, then β_n should be significantly different from 0. For the expectations hypothesis to hold perfectly, with no time varying risk premia, β_n should be 1. We estimate equation (10) first in a pooled setting over all banking firms, and then separately for each firm in our sample.

The top panel of Figure 3 plots the beta coefficients of the pooled regressions against maturity. All the beta coefficients are significantly different from 1, indicating that the expectations hypothesis for credit spreads does not hold perfectly. However, all coefficients are significantly different from 0, indicating that the credit-spread slope is informative of future forward credit spreads. The beta coefficients are an increasing function of maturity. This plot is very similar to the plot of regression slopes of *riskless forward rate* obtained by Backus, Foresi, Mozumdar and Wu, and suggests that the nature of predictability of credit spreads might follow along lines similar to predictability of riskless forward rates.

Figure 3 Here

The bottom panel shows the normalized beta values in a box-whiskers plot for individual banks across the maturity spectrum. The overall pattern of the beta coefficients plot remains unchanged. Predictability is always there for all future forward credit spreads; and the greatest departures from the expectations hypothesis occur at the short end of the maturity spectrum.

There is significant cross sectional variation over firms, especially for the shorter maturity forward credit spreads. Indeed, the 95% confidence intervals for the short end maturities are much larger than the others. Based on our previous analyses, this could be attributed to firm specific risk differences. To investigate this, we classify all banking firms into quartiles according to their ratings. The slopes of the forward-rate regression are computed for banking firms in the lowest and highest ratings groups, and the results presented in Figure 4.

Figure 4 Here

The beta coefficients for the shorter maturity forward credit spreads are significantly different for the two groups. This indicates that predictability of forward credit spreads in the near future could well depend on firm ratings. To investigate this more rigorously, we consider the following regression specification:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n^{(1)} R + \beta_n^{(2)} R^2 + \epsilon_{t+1}. \tag{11}$$

We incorporate a quadratic effect for ratings, since credit spreads may expand non linearly as ratings deteriorate. We compare the results of this benchmark model with a model that incorporates slope variables. In particular, we consider the additional explanatory power of a 3-vector of the slope and the slope interacted with ratings and the slope interacted with the square of ratings.

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n^{(1)} R + \beta_n^{(2)} R^2 + \delta_n^{(1)} (g_t^n - s_t) + \delta_n^{(2)} (g_t^n - s_t) R + \delta_n^{(3)} (g_t^n - s_t) R^2 + \epsilon_{t+1}. \tag{12}$$

Table 3 examines the explanatory power of the two regression specifications.

Table 3 Here

Table 3 shows that the ratings variables, by themselves, cannot predict forward credit spreads well. The 3-vector of slope variables, however, adds significantly to the explanatory power. This holds true for all maturities, especially the longer maturities. The adjusted R^2 values for the full model range from around 10% at the short end (3 months) to around 90% at the longer end (10 years).

Table 4 shows the normalized beta coefficients of the individual regression equations, together with their p values of the associated t-statistics.

Table 4 Here

Notice that for forward credit spreads maturities beyond a year, the two most important variables are the slope-rating interaction terms. The individual contribution of rating, rating squared, and the slope variable, by themselves, in the full model are, generally, insignificant. Collectively, however, the credit-spread slope variables are very informative of future credit spreads.

We now wish to establish whether credit-spread slope variables add significant explanatory power of future forward credit spreads, over and above that explained by level effects, firm specific variables and market wide factors. Towards this goal, we redefine R_t as a 2- vector consisting of the rating and squared rating terms at date t, and $Slope_t^{(n)}$ as a 3-vector of the n-period forward credit spread slope, $g_t^n - s_t$, together with its interaction effect with ratings and its interaction effect with the square of ratings. Let F_t represent the 5-vector of firm variables at date t, NF_t the 5-vector containing the square of each of these variables, and, following Flannery and Sorescu (1996), IF_t the 4-vector of the interaction effects obtained by multiplying leverage with each of the other firm variables. M_t is the 3-vector of market variables known at date t and T_t is the 2-vector of riskless term structure variables. Actually, the firm accounting variables are not publicly known as on the last day of a quarter. The final Call Report (bank level) data are released to the public around 65 days after the end of the quarter, and the final Y9 (BHC level) data are released to the public around 80 days after the end of the quarter. However, F_{t-1}, the vector of the 5 firm specific variables pertaining to quarter $t-1$ are known precisely to the market at date t. We therefore use a two-stage regression specification to estimate the firm specific variables, their non-linear effects and interaction effects. In particular, the firm variables are estimated as:

$$F_t = \alpha_0 + A_1 F_{t-1} + A_2 M_t + A_3 T_t + e_t,$$

where A_1, A_2 and A_3 are appropriately sized matrices of coefficients and e_t is a vector of mean zero errors, and the future forward credit spreads are predicted using:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_R R_t + \beta_S Slope^{(n)}_t + \beta_F F_t + \beta_{IF} IF_t + \beta_{NF} NF_t + \beta_M M_t + \beta_T T_t + \epsilon_{t+1}. \quad (13)$$

Table 5 reports the sequential contribution of each block of variables in predicting the next quarter's forward credit spreads. We start with the 3-vector of slope variables, then sequentially add the firm credit rating variables, the firm accounting risk variables, the firm interaction variables, the non-linear firm risk variables, the market variables, and finally the riskless term structure variables. The table reports the *incremental* R square values, the sequential partial F-values, and the resulting p values, for the different maturities.

Table 5 Here

The 3-vector of slope variables are statistically and economically significant predictors of forward credit spreads for all maturities. The 3-vector of market variables, consisting of GIP, S&P, and the VIX index, are significant predictors of forward credit spreads of up to 1 year maturity, while the 2-vector of term structure variables, consisting of the five year Treasury rate and the slope of the riskless yield curve, are significant predictors of forward credit spreads up to the 2 year maturity. Thus, economy-wide variables are significant predictors of credit spreads at the shorter end of the maturity spectrum, but perhaps due to mean reversion, have little influence on the longer dated forward credit spreads. In contrast, as the maturity extends beyond 3 years, firm specific information becomes more relevent and the block of firm variables as well as the non linear effects surface as additionally useful predictors. Since the longer maturity forward credit spreads are less buffeted around by economy-wide factors, and therefore, might provide cleaner measures of default risk, we expect and find the balance sheet risk accounting proxies to eventually be significant predictors.

The partial R squared values reported in table 5 clearly depend on the order in which the blocks are inserted. The conclusion is that once the slope variables are in the model, the marginal contribution of the remaining blocks vary, but in general are, economically, fairly small. In Table 6, we examine the marginal contribution of each block in the presence of all other blocks of variables.

Table 6 Here

Even when the slope variable block is the last to enter, it still adds significantly to the explanatory power over future credit spread levels. This holds true for all maturities. The market-wide variables (the stock market and the term structure variables) have significant additional predictive power over credit spreads for shorter maturities of less than 3 years. On the other hand, firm-specific accounting variables have significant predictive capability beyond all other variables only for maturities longer than 3 years.

When we look at the individual regression coefficients, we find that future forward credit spreads of up to a year are determined, to some extent, by the returns and volatility of the stock market (VIX and $S\&P$). Beyond one year, the only market-wide factor is significant is the 5-year Treasury yield. Beyond 3-years, no single market factor has significant influence over future credit spreads, but some firm variables creep in as adding significance.

Table 7 Here

6 Credit-Spread Slope as a Predictor of Bank Risk

The fact that credit-spread slopes can predict future forward credit spreads does not, however, imply that credit-spread slopes contain information about future firm risk variables, over and above other information that is available to the market in terms of firm-specific risk information and market-wide information. Moreover, even if credit-spread slopes contain information about future firm risk variables, there is no reason to believe that any specific firm risk variable can be predicted by the current period credit-spread slope variables. Rather, future credit spreads may be influenced by combinations of some or all of our firm risk variables. In other words, if the credit spread captures the firm's default probability or expected loss given default, it will likely reflect the net effect of all future firm risk variables. Therefore, we conduct a canonical correlation analysis between the next quarter's firm risk variables and the current period's explanatory variables.

Our canonical correlation analysis examines whether there is any linear relationship between current period credit-spread slope variables and next period's firm risk variables, after controlling for market-wide and firm-risk variables as well as credit spread level effects, in the current period. If there is no significant canonical correlation, then slope variables cannot provide any additional information on future firm risk, over and above other information already known to the market. If there are significant correlations, then slope variables may be useful for predicting the direction of the overall set of firm-risk variables. Let

$$\begin{aligned} Y_{t+1} &= (F_{t+1}, NF_{t+1}, IF_{t+1}) \\ C_t &= (F_t,\ NF_t,\ IF_t,\ M_t,\ T_t,\ R_t,\ s_t) \\ X_t &= (Slope^{(0.25)}_t, Slope^{(0.5)}_t, Slope^{(0.75)}_t, Slope^{(1)}_t, Slope^{(2)}_t, Slope^{(3)}_t, Slope^{(5)}_t, Slope^{(10)}_t). \end{aligned}$$

Here Y_{t+1} is a 14-vector of next quarter banking firm-specific risk variables, C_t is a 20-vector consisting of firm (linear, nonlinear and interaction effects), market, term structure, ratings and credit spread level effects, and X_t is a 24-vector of the 3-slope effects for each of our 8 maturities.

Our goal is to partial out the effects of C, on Y, and then evaluate if there is any additional explanatory power (correlation) provided by inear combinations of our slope variables, X, on the set of future firm risk variables.

The first canonical correlation corresponds to the highest possible correlation among all linear combinations of X and Y once the impact of the variables in C have been removed. The second canonical correlation consists of the highest correlations between those linear combinations of X and Y, again with the effects of C partialled out, that are orthogonal to the first canonical covariates, and so on.

Table 8 reports the canonical correlations and redundancy measures, as well as the Bartlett test statistics, for the full model, where the effects of C on Y are not partialled out, and for the reduced model, where, the marginal effects of slope variables, X, above and beyond the effects of C on Y, are assessed.

Table 8 Here

The Bartlett tests reveal that once the effects of C have been removed, the first two canonical correlations are significantly different from 0. Indeed, once the effects of C have been removed, the best linear combination of slope variables with linear combinations of firm risk variables, has a canonical correlation of 0.787, while the next best orthogonal set has a correlation of 0.587. These results reveal that the slope variables might be able to add explanatory power to the prediction of future firm-risk variables, above and beyond the factors controlled for in vector C.

In Table 8 we also report the canonical loadings associated with the firm risk variables, Y. The important loadings are on Return on Assets, ROA Non Performing Assets, NPA, Net Charge Offs, $NETC$, the quadratic effects, NPA^2, $NETC^2$, and on the interaction effect of leverage with nets charge offs, $LEV \times NET$. The coefficients of these terms are all signed correctly, in the sense that variables that increase with risk have positive coefficients, and variables that decrease with risk have negative coefficients. In this regard, the first dependent canononical covariate can be viewed as a measure of risk that can be well predicted by the set of slope variables. Squaring each of these coefficients gives the R^2 values that would be obtained by regressing the specific dependent variable against the covariate. For example, the first covariate explains about 6%, of the variability of ROA, 5% of NPA, 14% of $NETC$, 12% of NPA^2, 43% of NET^2, and almost 6% of $LEV \times NET$. The independent canonical covariate consisting of linear combinations of slope variables accounts for $0.787^2 = 62\%$ of the variability of the first dependent canonical covariate. All the loadings of the first independent canonical variable are positive.

In contrast, the canonical loadings for the second dependent canonical covariate are less concentrated on specific variables. The largest weights are on the nonlinear terms and interaction variables, and their signs are not easily interpreted. As a result, while statistically significant, the second covariate is difficult to interpret as a risk measure.

We therefore conclude that combinations of dependent variables, representing accounting risk variables, can be well predicted from credit spread slope variables, once all other effects have been removed.

Before providing a variety of robustness checks on our result, it is useful to investigate whether the slope variables can provide additional forecasting power to individual firm risk variables. This information is provided by the redundency measures in Table 8. Roughly speaking, the redundency measure for the first canonical function is the equivalent of computing all the R^2 values between the predictor set of slope variables and each variable in the predictor set, and taking their average. In our case, this "average" is about 4.6%. That is, once the information of C on Y is partialled out, the slope variables in the first canonical function, can explain about 4% additional variation for each of our 14 firm risk variables. The additional contribution of the second canonical function of the slope variables adds an average of 1%.[5] As discussed earlier, this result is not surprising since inevitably their are multiple reasons for a banking firm to enter financial distress.

6.1 Additional Robustness Checks

Canonical correlations analysis ia a useful technique for exploring relationships among multiple criterion and predictor variables, but like regression analysis, the results must be interpreted carefully. In this section we will conduct several robustness tests from which a pattern emerges that indicates that slopes are indeed capable of signaling additional information about future firm-risk, above and beyond credit spread levels, current firm risk variable levels (including nonlinear and interaction effects), market information and riskless term structure effects.

Our first analysis repeats the previous analysis, but rather than use slope information over all 8 maturities simultaneously, we conduct the analysis by maturity. Hence, once the effects of C are partialled out, the number of independent variables is reduced to 3, the dimension of X_n where $X_n = (Slope_t^{(n)}$. Table 10 shows the results for each of our 8 maturities. Also shown, is the impact of canonical correlations when the affects of C are not partialled out. In the latter case, the first 5 canonical functions are significant. After partialling out C only the first canonical function is consistently significant for all maturities. In these cases, the canonical variate for the firm-risk variables does indeed have the interpretation of a risk variable, and the most significant firm-risk loadings are generally on the same sets of variables as reported in Table 8.

Table 9 Here

Our final robustness check is to examine the canonical covariates for varois subsamples. The left panel of table 11 reports the canonical correlations, redundancy measures as well as the

[5] We actually regressed each future firm risk variable on X, after partialling out the effects of C, and obtained a rather large range of partial R^2 values, which did average out to about 4%.

Bartlett test statistics for the full sample of banking firms, as well as for various sub samples: banks and BHCs, small and large banking firms, and highly levered and low leverage banking firms. High and Low categories based on size (total assets), and leverage are defined in terms of being above and below the sample median respectively.[6] The right panel reports the same statistics when the effects of firm variables, stock market, riskless term structure and rating variables are partialled out.

Table 10 Here

The left panel, not surprisingly, again shows that the first 5 canonical correlations are all significant for the full sample, as well as for the various sub samples. The redundancy index for the first set is around 0.21 for the full sample, and 0.31 to 0.37 for the various sub samples.

The right panel shows the predictive power of the slope-related variables, given the effects of levels, ratings, firm and market variables, have been partialled out. The best linear combination of the slope variables correlates highly with future bank-risk variables, even after these variables have been partialled out, not only for the full sample, but also for select sub samples, including small banking firms and highly levered banking firms. The canonical correlation between the first (the best) linear combination of future firm risk variables and the slope variables is about 0.80 for the full sample as well as for these 2 sub samples. The Bartlett tests, shown by the chi-squared statistics indicate that the first canonical variates have significant correlation for the full sample and for these sub samples. The redundancy index of the first set of slopes ranges from 0.042 for the full sample to 0.046 and 0.047 for these 2 sub samples. These results indicate that the information content of credit-spread slopes on *individual* future firm risk variables, is small, but the marginal value of the slope information above and beyond other information, for these groups, adds significantly to the explanatory power of future firm risk.

However, for large banking firms, and for banks and BHCs separately, even the first pair of canonical covariates are not significant. This indicates that for these firms, slope information, at the margin, provides no additional information about future firm risk.

Overall, the results indicate that that for smaller and more leveraged banking firms, the slope and slope rating interaction variables collectively are capable of explaining future firm risk variables in the aggregate, above and beyond other information that the market possesses.

[6] We do not segregate the banking firms based on credit ratings because the ratings variables appear as explanatory variables in our canonical regressions.

7 Conclusion

In this paper, we examine two issues. First, we examine whether the shape of the term structure of credit spreads conveys any information about the future direction of credit spreads. Second, we assess whether current period credit-spread slopes convey information on future firm-specific accounting risk variables above and beyond information that the market possesses.

Economists have extensively analyzed the information content of the term structure of riskless interest rates. Surprisingly, however, to the best of our knowledge, no studies have been conducted to analyze the predictive properties of the term structure of credit spreads. We believe that this is the first paper to do so. Moreover, with the exception of Krishnan, Ritchken and Thomson (2003), none of the studies in this literature has extracted the term structure curves for credit spreads, and hence could not have computed the slopes of credit-spread curves. In this paper, we carefully extract the term structure of credit spreads for each firm each quarter. Our study confines itself to investigating banking firms. We choose to do this because the information content of banking subordinated debt has policy-specific implications. By separating out credit spreads across the maturity spectrum, we have the potential to more accurately estimate the default propensity of a bank, and the resulting analyses is more revealing and of interest to bank policymakers.

We find strong evidence that current credit-spread slopes can predict future forward credit spreads. Predictability is always present across all maturities. However, the rational expectations hypothesis is rejected in favor of time varying risk premia. Further, at the short end, market variables improve predictability of forward credit spreads. At the longer end, predictability is less influenced by market variables but more influenced by current period firm variables.

The ability to predict future credit spread levels does not imply that one can predict future levels of pure default and/or recovery risk. We do find evidence however, that once all current firm market and ratings variables have been removed, there is a significant linear association between slope variables and future firm risk variables. Further, this association is strongest for small banks, and for highly leveraged banks. These results indicate that credit slope information is not only informative for predicting future credit spread levels, but it also adds information, beyond other relevant information, for assessing future levels of firm risk variables in the aggregate.

Our results lead us to conclude that credit-spread slopes combined with bond ratings do provide additional signals of future firm risk above and beyond other information. This suggests that credit spread curves engendered by a mandatory SND requirement for banks may provide useful additional information not only about future credit spread levels but also about future bank risk variables, above and beyond the accounting information, market and Treasury rate information and credit ratings information. However, such a conclusion must be tempered with the realization that our sample consists only of firms that voluntarily selected to issue subordinated debt.

References

Bakshi, Gurdip, Dilip Madan and Frank Zhang (2001), "Investigating the Source of Default Risk: Lessons from Empirically Evaluating Credit Risk Models", Working Paper, University of Maryland.

Backus, David, Silverio Foresi, Abon Muzumdar and Liuren Wu (2001), "Predictable Changes in Yields and Forward Rates,"*Journal of Financial Economics*, 59, 281-311.

Bliss, Robert (2001),"Market Discipline and Subordinated Debt: A Review of Some Salient Issues", Federal Reserve Bank of Chicago, *Economic Perspectives*, 25, 24-45.

Blume, Marshall E.; Felix Lim, Craig A. MacKinlay (1998),"The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality?", *Journal of Finance*, 53, 1389-1413.

Campbell, John and Glen B. Taksler (2002), "Equity Volatility and Corporate Bond Yields", Working Paper, Department of Economics, Harvard University.

Collin-Dufresne, Pierre, Robert Goldstein, and Spencer Martin (2001), "The Determinants of Credit Spread Changes", *Journal of Finance*, 56, 2177-2207.

Driessen, Joost (2002)"Is Default Risk Priced in Bonds?", forthcoming, *Review of Financial Studies.*

Duffie, Darrell, and Ken Singleton (1999), "Modeling Term Structures of Defaultable Bonds", *Review of Financial Studies* 12, 687-720.

Elton, Edwin, Martin Gruber, Deepak Agrawal, and Christopher Mann (2000), "Factors Affecting the Valuation of Corporate Bonds", Working Paper, New York University.

Elton, Edwin, Martin Gruber, Deepak Agrawal, and Christopher Mann (2001), "Explaining the Rate Spread on Corporate Bonds", *Journal of Finance* 56, 247-277.

Fama, Eugene F. (1984),"The Information in the Term Structure," *Journal of Financial Economics* 13, 509-28.

Fama, Eugene F.; Robert R. Bliss (1987), "The Information in Long-Maturity Forward Rates", *American Economic Review* 77, 680-92.

Flannery, Mark and Sorin Sorescu 1996, "Evidence of bank market discipline in subordinated debenture yields: 1983-1991", *Journal of Finance*, 1347-1377.

Fons, Jerome S. (1994), "Using Default Rates to Model the Term Structure of Credit Spreads", *Financial Analysts Journal* (September-October), 25-32.

Hardouvelis, Gikas A. (1988);"The Predictive Power of the Term Structure during Recent Monetary Regimes", *Journal of Finance* 43, 339-56.

Huang Jing-zhi, and Ming Huang (2002), "How much of the Corporate -Treasury Yield Spread is Due to Credit Risk", working paper, Stanford University.

Helwege, Jean and Christopher M. Turner (1999), " The Slope of the Credit Yield Curve For Speculative-Grade Issuers ", *Journal of Finance* 54, 1864-1889.

Houweling, Patrick, Albert Mentink, Ton Vorst (2003),"How to Measure Corporate Bond Liquidity", European Finance Association 2003 Annual Conference Paper No. 298.

Jarrow, Robert, David Lando, Stuart Turnbull (1997);"A Markov Model for the Term Structure of Credit Risk Spreads", *Review of Financial Studies* 10, 481-523.

Jarrow, Robert, and Yildiray Yildirim (2002), "Valuing Default Swaps Under Market and Credit Risk Correlation", *Journal of Fixed Income*, 11, 7-19.

Jegadeesh, Narasimhan and George Pennacchi (1996), "The Behavior of Interest Rates Implied by the Term Structure of Eurodollar Futures", *Journal of Money, Credit and Banking* 28, 426-446.

Krishnan, C.N.V, Peter Ritchken and James Thomson (2003), "Monitoring and Controlling Bank Risk: Does Risky Debt Help?", forthcoming, *Journal of Finance.*

Longstaff, Francis and Eduardo Schwartz (1995) "A Simple Approach to Valuing Risky Fixed and Floating Rate Debt", *Journal of Finance* 50, 789-821.

Merton, Robert C (1974), "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", *Journal of Finance* 29, 449-470.

Mishkin, Frederic S. (1988); "The Information in the Term Structure: Some Further Results", *Journal of Applied Econometrics* 3, 307-14.

Morgan, Donald and Kevin Stiroh (2001), "Bond Market Discipline of Banks: The Asset Test", *Journal of Financial Services Research* 20, 195-208.

Perraudin, William and Alex P. Taylor (2003),"Liquidity and Bond Market Spreads", European Finance Association 2003 Annual Conference Paper No. 879.

Rudebusch, Glenn D. (1995),"Federal Reserve Interest Rate Targeting, Rational Expectations, and the Term Structure", *Journal of Monetary Economics* 35, 245-74.

Sarig, Oded, and Arthur Warga (1989),"Some Empirical Estimates of the Risk Structure of Interest Rates", *Journal of Finance* 44, 1351-60.

Shiller, Robert J., John Y. Campbell, and Kermit L. Schoenholtz (1983), "Forward Rates and Future Policy: Interpreting the Term Structure of Interest Rates", *Brookings Papers on Economic Activity* 1, 173-217.

Warga, Arthur (1998), "Fixed Income Database", University of Houston, Houston, Texas.

Yu, Fan (2002), "Accounting Transparency and the Term Structure of Credit Spreads," Working Paper, Graduate School of Management, University of California, Irvine.

Table 1
Descriptive Statistics of Banking Firm Subordinated Debt Trades

Our initial sample contains all banking firm debt transactions data found in the National Association of Security Commissioners (NAIC) database for the period 1994 through 1999. The first screen eliminates all debt other than fixed-rate US dollar denominated debt that is non-callable, non-puttable, non-convertible, not part of an unit (e.g. sold with warrants) and has no sinking fund. We exclude debt with asset-backed and credit enhancement features. We eliminate non-investment grade debt. We use only trade prices. Further, we eliminate all data that have inconsistent or suspicious issue/dates/maturity/coupon etc., or otherwise does not look reasonable. The second screen eliminates all those firm-quarter combinations for which we had less than 7 trades for the quarter, to ensure that we could obtain reliable estimates for the credit spread curve for a firm at the end of each quarter. The third and final screen removes transactions from firms for which bank specific risk measures are not found in the Y-9 and call reports for all the 24 quarters of our data set, one quarter before our data begins and one quarter after it ends.

Quarter	Initial sample		Sample after first screen		Sample after second screen		Sample after third screen	
	# Trades	# Firms	# Trades	# Firms	# Trades	# Firms	# Trades	# Firms
Q11994	207	29	185	28	51	4	0	0
Q21994	257	28	198	28	61	6	35	3
Q31994	194	28	158	28	88	10	41	5
Q41994	263	30	224	29	141	12	100	8
Q11995	560	43	400	42	254	14	220	10
Q21995	599	46	466	45	317	20	257	12
Q31995	624	43	496	42	345	23	289	17
Q41995	701	52	540	50	387	30	313	18
Q11996	767	58	589	56	408	33	300	22
Q21996	516	50	485	50	287	36	243	25
Q31996	613	52	456	50	317	38	278	27
Q41996	887	57	652	56	436	41	365	28
Q11997	873	51	609	50	429	44	296	29
Q21997	719	59	576	58	382	47	285	27
Q31997	753	57	587	55	401	48	276	29
Q41997	737	50	588	49	368	49	263	30
Q11998	1220	76	892	74	517	52	359	30
Q21998	1186	76	851	74	538	55	282	30
Q31998	782	67	654	66	456	59	223	31
Q41998	1095	74	888	73	554	63	382	33
Q11999	1277	92	1082	91	619	67	408	36
Q21999	1448	97	1021	93	607	70	441	40
Q31999	1069	89	941	88	541	73	422	42
Q41999	1429	98	1122	98	663	82	512	41
Total	18776	185	14660	144	9167	81	6590	50

Table 2
Credit Spread Levels and Slopes

The panels report the average credit-spread levels and credit-spread slopes, respectively, for our final sample of 482 credit-spread curves, and by Credit Rating, Firm Type (bank or BHC), Size, and Leverage. The High Credit Rating category comprises banking firms with credit ratings of A- and above, and the Low Credit Rating category the remaining banking firms. High and Low categories based on size (total assets), and leverage are defined in terms of being above and below the sample median respectively. The means are reported in basis points, with the standard errors in parenthesis.

			Credit Ratings		Firm Type		Size		Leverage	
	Maturity (Years)	**All**	**Low**	**High**	**BHC**	**Bank**	**Small**	**Large**	**Low**	**High**
	3	133.7	176.2	157.0	127.8	145.5	135.7	131.6	130.5	136.8
		(3.0)	(12.02)	(22.20)	(2.99)	(6.80)	(5.20)	(3.16)	(5.15)	(3.21)
	5	124.4	156.9	113.9	120.3	132.6	125.9	122.9	122.6	126.1
Levels		(2.9)	(12.01)	(19.11)	(2.82)	(6.69)	(5.09)	(2.89)	(5.04)	(2.96)
	7	119.6	146.7	109.3	116.5	125.9	120.8	118.6	118.6	120.7
		(3.0)	(12.24)	(19.23)	(2.90)	(6.76)	(5.21)	(2.89)	(5.09)	(3.07)
	10	115.8	138.1	105.5	113.5	120.4	116.6	115.0	115.4	116.2
		(3.1)	(12.52)	(20.35)	(3.06)	(6.90)	(5.39)	(2.98)	(5.19)	(3.29)
	Spread (Years)									
	3 - 1	-24.2	-45.3	-25.3	-20.4	-31.9	-24.8	-23.7	-21.8	-26.6
		(2.2)	(5.75)	(2.40)	(2.52)	(3.98)	(3.37)	(2.71)	(2.96)	(3.14)
Slopes	**7- 3**	-14.0	-29.4	-14.1	-11.2	-19.6	-15.0	-13.0	-11.9	-16.1
		(1.5)	(4.26)	(1.51)	(1.73)	(2.60)	(2.35)	(1.71)	(1.92)	(2.18)
	10 - 5	-8.6	-18.8	-8.4	-6.8	-12.3	-9.3	-7.9	-7.2	-10.0
		(1.0)	(2.96)	(1.03)	(1.18)	(1.77)	(1.56)	(1.22)	(1.27)	(1.52)
	10 - 3	-17.9	-38.0	-14.1	-14.2	-25.2	-19.2	-16.6	-15.1	-20.6
		(1.9)	(5.63)	(1.51)	(2.28)	(3.40)	(3.07)	(2.28)	(2.50)	(2.88)

Table 3

Forward Credit Spreads: Predictive Power of Ratings and Slope

The table shows the results for predicting n-period ahead forward credit spreads in the next quarter, The first regression specification uses the firm ratings variables, while the second adds the slope of the forward credit-spread curve and the interaction effects. The two regression specifications used are:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n^{(1)} R + \beta_n^{(2)} R^2 + \varepsilon_{t+1},$$

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n^{(1)} R + \beta_n^{(2)} R^2 + \delta_n^{(1)} (g_t^n - s_t) + \delta_n^{(2)} (g_t^n - s_t) R + \delta_n^{(3)} (g_t^n - s_t) R^2 + \varepsilon_{t+1},$$

where s_t is the current period spot credit spread, g_{t+1}^{n-1} is the n-1 period ahead forward credit spread in the next quarter g_t^n is the n-period ahead forward credit spread in the current quarter, and *R* is the current period firm rating. The predictive power of the ratings variables, and the incremental explanatory power of the slope variables given the ratings variables, measured in terms of the R^2 changes and the *F*-value changes along with their *p*-values, are reported below. The results are reported for different maturities ranging from 3 months to 10 years.

Maturity	Model	R square	R square change	F change	F change p value
3 months	Ratings	0.002	0.002	0.34	0.709
	Slope & Ratings	0.116	0.114	16.54	0.000
6 months	Ratings	0.008	0.008	1.48	0.228
	Slope & Ratings	0.409	0.401	86.89	0.000
9 months	Ratings	0.021	0.021	4.14	0.017
	Slope & Ratings	0.653	0.632	232.81	0.000
1 year	Ratings	0.032	0.032	6.50	0.002
	Slope & Ratings	0.791	0.759	465.35	0.000
2 years	Ratings	0.052	0.052	10.55	0.000
	Slope & Ratings	0.928	0.876	1548.02	0.000
3 years	Ratings	0.056	0.056	11.50	0.000
	Slope & Ratings	0.935	0.879	1735.11	0.000
5 years	Ratings	0.058	0.058	11.93	0.000
	Slope & Ratings	0.926	0.868	1495.07	0.000
10 years	Ratings	0.059	0.059	12.05	0.000
	Slope & Ratings	0.909	0.850	1190.83	0.000

Table 4
Future Changes in Forward Credit Spreads: Ratings and Slope Coefficients

The table shows the regression coefficients, along with the p-values associated with the *t*-statistics, of the following regression specification:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n^{(1)} R + \beta_n^{(2)} R^2 + \delta_n^{(1)} (g_t^n - s_t) + \delta_n^{(2)} (g_t^n - s_t) R + \delta_n^{(3)} (g_t^n - s_t) R^2 + \varepsilon_{t+1},$$

where s_t is the current period spot credit spread, g_{t+1}^{n-1} is the n-1 period ahead forward credit spread in the next quarter g_t^n is the n-period ahead forward credit spread in the current quarter, and *R* is the current period firm rating. The results are reported for different n (maturities) ranging from 3 months ahead to 10 years ahead.

	Maturity							
Variable	**3 months**	**6 months**	**9 months**	**1 year**	**2 years**	**3 years**	**5 years**	**10 years**
ratings	0.141	-0.052	-0.135	-0.173	-0.191	-0.171	-0.139	-0.113
	(0.64)	(0.84)	(0.49)	(0.26)	(0.03)	(0.04)	(0.12)	(0.26)
ratings^2	-0.181	0.008	0.097	0.140	0.171	0.158	0.133	0.112
	(0.55)	(0.97)	(0.61)	(0.35)	(0.05)	(0.06)	(0.14)	(0.26)
slope	0.405	0.743	0.739	0.669	0.414	0.273	0.163	0.122
	(0.72)	(0.43)	(0.29)	(0.20)	(0.12)	(0.22)	(0.43)	(0.55)
slope*ratings	-0.902	-0.928	-0.384	0.105	1.163	1.599	1.908	2.008
	(0.72)	(0.64)	(0.80)	(0.93)	(0.04)	(0.00)	(0.00)	(0.00)
slope*ratings^2	0.845	0.841	0.464	0.119	-0.628	-0.927	-1.137	-1.209
	(0.54)	(0.45)	(0.58)	(0.85)	(0.06)	(0.00)	(0.00)	(0.00)

Table 5
Determinants of Future Forward Credit Spreads: Sequential Predictive Power

This table shows the incremental power (the R^2 change, F-statistic and the p-values). of the sequentially adding blocks of independent variables into the predictive equation:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_R R_t + \beta_S\ Slope_t^{(n)} + \beta_F F_t + \beta_{IF} IF_t + \beta_{NF} NF_t + \beta_M M_t + \beta_T T_t + \varepsilon_{t+1},$$

$$F_t = \alpha_0 + A_1 F_{t-1} + A_2 M_t + e_t,$$

The blocks of variables with statistically significant predictive power over future changes in forward credit spreads are shown in bold font.

Block of Variables	Maturity	R Square Change	F Value	p Value	Maturity	R Square Change	F Value	p Value
		Sequential Contribution of Each Block				Sequential Contribution of Each Block		
slope variables		0.113	12.142	**0.00**		0.926	1204.458	**0.00**
ratings variables		0.001	0.373	0.54		0.001	3.643	**0.06**
firm variables (linear)		0.007	0.633	0.67		0.000	0.424	0.83
firm interaction variables	**3 month**	0.007	0.786	0.53	**2 years**	0.000	0.421	0.79
firm variables (non linear)		0.013	1.095	0.36		0.001	1.015	0.41
market variables		0.034	5.046	**0.00**		0.001	1.291	0.28
term structure variables		0.011	2.403	**0.09**		0.001	2.283	**0.10**
slope variables		0.405	65.207	**0.00**		0.934	1356.820	**0.00**
ratings variables		0.000	0.000	0.98		0.001	3.467	**0.06**
firm variables (linear)		0.002	0.280	0.92		0.001	0.634	0.67
firm interaction variables	**6 month**	0.007	1.044	0.38	**3 years**	0.000	0.550	0.70
firm variables (non linear)		0.007	0.847	0.52		0.002	2.203	**0.05**
market variables		0.024	5.234	**0.00**		0.000	0.918	0.43
term structure variables		0.007	2.264	0.11		0.000	1.193	0.30
slope variables		0.650	177.784	**0.00**		0.925	1177.195	**0.00**
ratings variables		0.000	0.236	0.63		0.000	2.147	0.14
firm variables (linear)		0.001	0.124	0.99		0.001	0.825	0.53
firm interaction variables	**9 month**	0.004	1.216	0.30	**5 years**	0.001	1.636	0.16
firm variables (non linear)		0.003	0.642	0.67		0.004	4.172	**0.00**
market variables		0.013	4.751	**0.00**		0.001	1.096	0.35
term structure variables		0.005	2.524	**0.08**		0.000	0.593	0.55
slope variables		0.789	358.711	**0.00**		0.908	942.078	**0.00**
ratings variables		0.000	0.836	0.36		0.000	1.244	0.27
firm variables (linear)		0.000	0.093	0.99		0.001	0.940	0.45
firm interaction variables	**1 year**	0.003	1.244	0.29	**10 years**	0.003	2.682	**0.03**
firm variables (non linear)		0.001	0.520	0.76		0.007	6.024	**0.00**
market variables		0.007	3.987	**0.01**		0.001	1.028	0.38
term structure variables		0.003	2.834	**0.06**		0.000	0.502	0.61

Table 6
Determinants of Forward Credit Spreads: Predictive Power in Full Model

This table shows the power of each blocks of independent variables in predicting future forward credit spreads, given everything else. The regression model is

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_R R_t + \beta_S\, Slope_t^{(n)} + \beta_F F_t + \beta_{IF} IF_t + \beta_{NF} NF_t + \beta_M M_t + \beta_T T_t + \varepsilon_{t+1},$$

$$F_t = \alpha_0 + A_1 F_{t-1} + A_2 M_t + e_t,$$

The table reports the contribution to the predictive power by each block of explanatory variables (the R^2 change, F-statistic and the p-values) given everything else (in the full model). The analysis is restricted to all firms-quarters with credit rating information. The blocks of variables with statistically significant predictive power over future changes in forward credit spreads are shown in bold font.

Block of Variables	Maturity	Contribution of Each Block in the Full Model			Maturity	Contribution of Each Block in the Full Model		
		R Square Change	Partial F Value	p Value		R Square Change	Partial F Value	p Value
ratings variables		0.000	0.099	0.754		0.001	2.952	0.087
firm variables (linear)		0.012	1.081	0.371		0.001	0.631	0.676
firm interaction variables		0.010	1.149	0.333		0.000	0.715	0.582
firm variables (non linear)		0.005	0.505	0.732		0.001	1.723	0.144
all firm variables	**3 month**	0.025	0.792	0.679	**3 years**	0.002	1.108	0.351
market variables		0.025	3.644	**0.013**		0.000	0.870	0.457
term structure variables		0.011	2.403	**0.092**		0.000	1.225	0.295
slope variables		0.106	15.703	**0.000**		0.805	1577.326	**0.000**
ratings variables		0.000	0.003	0.955		0.000	2.535	0.112
firm variables (linear)		0.008	1.004	0.415		0.001	0.644	0.666
firm interaction variables		0.009	1.417	0.228		0.000	0.627	0.643
firm variables (non linear)		0.002	0.267	0.899		0.002	2.749	**0.028**
all firm variables	**6 month**	0.012	0.609	0.847	**4 years**	0.004	1.789	**0.043**
market variables		0.016	3.555	**0.015**		0.001	1.153	0.327
term structure variables		0.007	0.007	**0.101**		0.000	0.785	0.457
slope variables		0.374	49.420	**0.000**		0.799	1498.263	**0.000**
ratings variables		0.000	0.149	0.700		0.000	2.205	0.138
firm variables (linear)		0.004	0.888	0.489		0.001	0.619	0.685
firm interaction variables		0.006	1.642	0.163		0.000	0.585	0.674
firm variables (non linear)		0.001	0.225	0.924		0.003	3.636	**0.006**
all firm variables	**9 month**	0.007	0.589	0.863	**5 years**	0.006	2.344	**0.005**
market variables		0.009	3.209	**0.023**		0.001	1.322	0.267
term structure variables		0.005	2.578	**0.077**		0.000	0.614	0.541
slope variables		0.573	213.375	**0.000**		0.792	1406.938	**0.000**
ratings variables		0.000	0.526	0.469		0.000	1.633	0.202
firm variables (linear)		0.002	0.758	0.581		0.001	0.500	0.776
firm interaction variables		0.004	1.746	0.139		0.000	0.456	0.768
firm variables (non linear)		0.001	0.233	0.920		0.005	5.568	**0.000**
all firm variables	**1 year**	0.004	0.569	0.879	**10 years**	0.010	3.473	**0.000**
market variables		0.004	2.663	**0.048**		0.001	1.455	0.227
term structure variables		0.003	2.893	**0.057**		0.000	0.517	0.596
slope variables		0.690	424.641	**0.000**		0.769	1150.723	**0.000**
ratings variables		0.001	2.716	0.100				
firm variables (linear)		0.001	0.544	0.743				
firm interaction variables		0.001	1.100	0.356				
firm variables (non linear)		0.001	0.716	0.581				
all firm variables	**2 years**	0.001	0.525	0.909				
market variables		0.000	0.831	0.477				
term structure variables		0.001	2.332	**0.099**				
slope variables		0.801	1390.374	**0.000**				

Table 7
Regression Models for Predicting Forward Credit Spreads.

This table reports the regression coefficients and the corresponding p-values (in parenthesis) when the n-period forward credit spreads for the next quarter is regressed on the slope of the forward credit-spread curve, interaction term of slope with ratings, the market and riskless term structure variables, and the firm variables (linear, quadratic and interaction). The slope variables are forced in and stepwise regression methodology is used for all other variables. Only the variables that were significant in the regressions are shown. The significant market variables are the VIX index, the S&P return and the 5 year Treasury rate. The firm variables that are significant are the Net Charge Offs and the square of the Net Charge Offs.

	Slope Variables			Market Variables			Firm Variables	
Maturity	**Slope**	**Slope *Rating**	**Slope*Rating^2**	**VIX**	**S&P**	**5 year Treasury**	**(Net)^2**	**Net**
0.25	0.769 (0.44)	-2.134 (0.33)	1.709 (0.17)	0.127 (0.01)	-0.102 (0.04)			
0.5	0.734 (0.35)	-1.262 (0.46)	1.180 (0.23)	0.108 (0.01)	-0.081 (0.05)			
0.75	0.936 (0.00)	-1.186 (0.00)	1.074 (0.00)	0.106 (0.00)				
1	0.416 (0.34)	0.457 (0.63)	0.020 (0.97)	0.072 (0.00)				
1.25	0.304 (0.37)	1.015 (0.18)	-0.396 (0.35)			-0.054 (0.00)		
1.5	0.234 (0.41)	1.320 (0.03)	-0.616 (0.08)			-0.045 (0.01)		
1.75	0.183 (0.46)	1.535 (0.01)	-0.774 (0.01)			-0.037 (0.01)		
2	0.146 (0.52)	1.692 (0.00)	-0.891 (0.00)			-0.032 (0.02)		
2.25	0.116 (0.58)	1.812 (0.00)	-0.981 (0.00)			-0.028 (0.04)		
2.5	0.052 (0.80)	1.988 (0.00)	-1.095 (0.00)					
2.75	0.038 (0.84)	2.050 (0.00)	-1.145 (0.00)					
3	0.028 (0.88)	2.098 (0.00)	-1.184 (0.00)					
3.25	0.021 (0.91)	2.136 (0.00)	-1.216 (0.00)					
3.5	-0.926 (0.01)	4.007 (0.00)	-2.171 (0.00)				-0.154 (0.00)	0.085 (0.02)
3.75	-1.002 (0.01)	4.168 (0.00)	-2.260 (0.00)				-0.170 (0.00)	0.094 (0.01)
4	-1.071 (0.00)	4.312 (0.00)	-2.339 (0.00)				-0.184 (0.00)	0.102 (0.01)
5	-1.260 (0.00)	4.702 (0.00)	-2.553 (0.00)				-0.231 (0.00)	0.129 (0.00)
10	-1.527 (0.00)	5.218 (0.00)	-2.831 (0.00)				-0.327 (0.00)	0.185 (0.00)

Table 8
Canonical Correlation Analysis. And canonical Loadings

The top table shows the canonical correlations between the set of future firm risk variables and the set of current variables. The future firm risk variables consist of 5-linear firm variables, 5 quadratic terms and 4 interaction effects. The independent set consists of the same 14 variables in the current period, together with the market and riskless term structure variables In addition, the short credit spread is provided, as well as the 3-slope variables for each of the 8 maturities. The left hand panel reports the canonical correlations, redundancy measures and chi squared statistics for the significant correlation pairs. The right hand side reports the same statistics for the case where the effects of all independent variables except slope variables on the dependent variables have been accounted for. The bottom panel reports the canonical loadings for the two significant canonical pairs of the partialled model. The left hand side shows the loadings of the independent variables, while the right hand side shows the loadings of the dependent variables.

Full Model				Slope Variables with Other Variables Partialled Out			
Canonical Factors	**Canonical Correlation**	**Canonical Redundancy**	**Chi Squared Value**	**Canonical Factors**	**Canonical Correlation**	**Canonical Redundancy**	**Chi Squared Value**
1	0.989	0.213	5967.9*				
2	0.969	0.268	4626.8*	1	0.787	0.042	748.05*
3	0.928	0.061	3645.7*	2	0.587	0.003	421.56*
4	0.901	0.047	2952.9*	3	0.500	0.011	278.75
5	0.882	0.072	2364.5*				

Canonical Loadings for the Two Significant Covariates

	Independent Variable (maturity)	**Canonical Loadings First Covariate**	**Canonical Loadings Second Covariate**
	0.25	0.283	0.118
	0.5	0.281	-0.139
Slopes	0.75	0.270	-0.157
	1	0.254	-0.172
	2	0.179	-0.202
	3	0.119	-0.206
	5	0.052	-0.199
	10	0.005	-0.185
	0.25	0.171	-0.047
	0.5	0.173	-0.052
Rating X slope	0.75	0.168	-0.055
	1	0.160	-0.056
	2	0.122	-0.050
	3	0.090	-0.038
	5	0.054	-0.018
	10	0.030	0.006
	0.25	0.106	0.001
	0.5	0.108	0.004
	0.75	0.105	0.008
Rating^2 X Slope	1	0.100	0.013
	2	0.078	0.032
	3	0.061	0.049
	5	0.041	0.073
	10	0.029	0.100

	Dependent Variable	**Canonical Loadings First Covariate**	**Canonical Loadings Second Covariate**
	ROA	**-0.249**	0.008
	LOAN	-0.064	0.001
Linear	NPA	**0.220**	**-0.123**
	NETC	**0.368**	0.089
	LEV	-0.034	-0.011
	ROA^2	-0.184	**-0.107**
	LOAN^2	-0.092	0.001
Quadratic	NPA^2	**0.341**	**-0.194**
	NET^2	**0.652**	**0.205**
	LEV^2	-0.020	0.001
	LEV.ROA	-0.230	-0.024
Interaction	LEV.LOAN	-0.086	-0.021
	LEV.NPA	0.092	**-0.144**
	LEV.NET	**0.238**	0.032

Table 9
Canonical Correlation Analysis:
Slope Variables of Different Maturities as Predictors of Future Bank Risk

The table shows the canonical correlations, canonical redundancies and the chi squared values associated with the Bartlett test statistic for different maturities. The independent variables are the 3-slope variables for the given maturity. The dependent variables are next quarters firm risk variables. These include the linear, non-linear and interaction effects. The left panel reports the statistics for the full model, while the right hand side reports the results, once the effects of the credit spread levels, current firm risk variables, market effects and riskless term structure effects have been accounted for. The symbol * denotes significance at the 5% level.

	Full Model				Slope variables given everything else			
Maturity	Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value	Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value
	1	0.988	0.222	5199.3*				
	2	0.959	0.263	3854.6*	1	0.666	0.022	223.143*
3 months	3	0.904	0.057	2947.4*	2	0.197	0.001	18.030
	4	0.888	0.059	2333.7*	3	0.108	0.000	4.142
	5	0.825	0.080	1773.3*				
	1	0.988	0.222	5148.8*				
	2	0.959	0.262	3804.4*	1	0.625	0.017	191.496*
6 months	3	0.904	0.057	2898.4*	2	0.198	0.001	18.012
	4	0.888	0.059	2286.1*	3	0.107	0.000	4.013
	5	0.824	0.074	1725.3*				
	1	0.988	0.222	5107.2*				
	2	0.958	0.260	3762.9*	1	0.582	0.012	162.898*
9 months	3	0.904	0.056	2858.1*	2	0.197	0.001	17.855
	4	0.888	0.059	2246.1*	3	0.106	0.000	3.990
	5	0.823	0.072	1685.2*				
	1	0.988	0.222	5076.9*				
	2	0.958	0.259	3732.7*	1	0.544	0.009	140.516*
1 year	3	0.904	0.056	2828.6*	2	0.195	0.001	17.731
	4	0.888	0.059	2216.6*	3	0.108	0.000	4.109
	5	0.823	0.070	1655.6*				
	1	0.988	0.221	5027.9*				
	2	0.958	0.258	3684.1*	1	0.456	0.003	99.620*
2 years	3	0.904	0.057	2779.3*	2	0.188	0.001	18.112
	4	0.888	0.059	2166.6*	3	0.126	0.000	5.577
	5	0.823	0.068	1605.8*				
	1	0.988	0.221	5019.3*				
	2	0.959	0.257	3675.7*	1	0.429	0.002	89.813*
3 years	3	0.904	0.057	2768.9*	2	0.183	0.001	18.749
	4	0.888	0.059	2155.7*	3	0.138	0.001	6.772
	5	0.823	0.067	1595.1*				
	1	0.988	0.221	5018.8*				
	2	0.959	0.257	3675.3*	1	0.417	0.003	86.115*
5 years	3	0.904	0.058	2765.3*	2	0.183	0.002	19.128
	4	0.888	0.059	2151.8*	3	0.143	0.001	7.262
	5	0.823	0.067	1591.3*				
	1	0.988	0.221	5021.6*				
	2	0.960	0.257	3678.3*	1	0.417	0.004	85.772*
10 years	3	0.904	0.058	2764.8*	2	0.184	0.002	19.054
	4	0.888	0.059	2151.4*	3	0.141	0.001	6.984
	5	0.823	0.066	1590.8*				

Table 10
Robustness Checks of Canonical Correlation Analysis:

The table reports the canonical correlations between the set of future firm risk variables and the set of current variables. The future firm risk variables consist of 5-linear firm variables, 5 quadratic terms and 4 interaction effects. The independent set consists of the same 14 variables in the current period, together with the market and riskless term structure variables In addition, the short credit spread is provided, as well as the 3-slope variables for each of the 8 maturities. The left hand panel reports the canonical correlations, redundancy measures and chi squared statistics for the significant correlation pairs. The left hand side reports the same statistics for the case where the effects of all independent variables except slope variables on the dependent variables have been accounted for. The analysis is conducted for the full sample, as well as for different sub samples of banking firms: banks and BHCs, big and small banking firms, and high leverage and low leverage banking firms. High and Low categories based on size (total assets), and leverage are defined in terms of being above and below the sample median respectively. The symbol * denotes significance at the 5% level.

	Full Model			All slope variables given everything else			
Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value	Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value
All Banking firms							
1	0.989	0.213	5967.9*				
2	0.969	0.268	4626.8*	1	0.787	0.042	760.068*
3	0.928	0.061	3645.7*	2	0.587	0.003	432.55*
4	0.901	0.047	2952.9*	3	0.510	0.011	289.52
5	0.882	0.072	2364.5*				
Banks							
1	0.986	0.321	2346.0*				
2	0.979	0.109	1985.3*	1	0.843	0.036	358.18
3	0.973	0.150	1666.30*	2	0.724	0.019	247.24
4	0.956	0.069	1371.6*	3	0.670	0.014	180.66
5	0.951	0.049	1126.5*				
BHCs							
1	0.993	0.329	3670.4*				
2	0.950	0.130	2746.2*	1	0.467	0.004	214.12
3	0.936	0.054	2246.9*	2	0.427	0.016	163.93
4	0.914	0.029	1799.2*	3	0.377	0.014	122.72
5	0.893	0.026	1410.4*				
Small Banking firms							
1	0.983	0.318	2856.1*				
2	0.969	0.123	2367.5*	1	0.819	0.046	463.54*
3	0.941	0.073	1966.0*	2	0.706	0.005	313.75
4	0.935	0.124	1655.3*	3	0.607	0.011	220.71
5	0.925	0.035	1359.7*				
Large Banking firms							
1	0.992	0.312	2793.8*				
2	0.945	0.111	2058.9*	1	0.649	0.042	302.71
3	0.928	0.088	1655.4*	2	0.579	0.005	208.70
4	0.881	0.022	1300.0*	3	0.462	0.007	138.37
5	0.868	0.033	1031.2*				
Higher Leverage Banking firms							
1	0.986	0.371	3272.9*				
2	0.970	0.101	2715.8*	1	0.779	0.047	505.37*
3	0.952	0.131	2276.4*	2	0.693	0.006	369.29
4	0.937	0.038	1905.6*	3	0.616	0.004	273.98
5	0.930	0.061	1577.2*				
Lower Leverage Banking firms							
1	0.993	0.311	2572.6*				
2	0.954	0.066	1896.7*	1	0.627	0.014	249.79
3	0.885	0.029	1515.7*	2	0.540	0.010	175.75
4	0.879	0.152	1272.1*	3	0.453	0.005	124.65
5	0.827	0.032	1036.0*				

Figure 1
Riskless Interest Rates: Pricing Errors

This figure shows histograms of the basis point errors, by maturity, when our two factor double mean reverting model is used to estimate the riskless yield curves. Each histogram consists of 364 points corresponding to consecutive weekly observations from January 1993 to December 2000. The parameter values are estimated using a Kalman filter. The errors reported are one week ahead prediction errors.

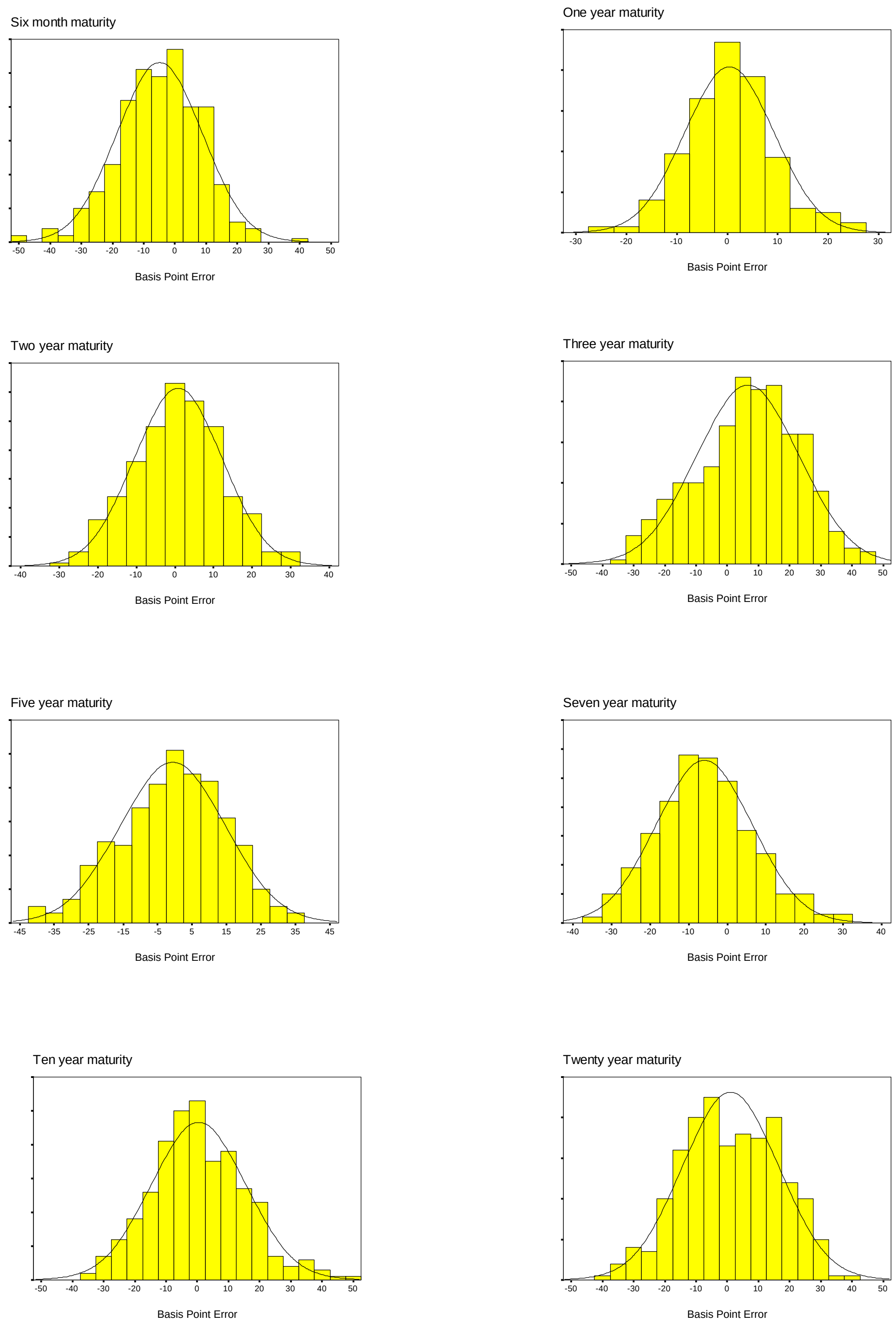


Figure 2

Pricing Errors for Banking Firm Subordinated Debt

The left panel shows the percentage errors when our 3 factor model is used to price subordinated debt issued by banking firms for different maturity buckets – defined as (0,2] years, (2, 5] years, (5, 10] years, (10, 20] years and > 20 years. The right panel shows the percentage errors when our model is used to price subordinated debt issued by non-banking firms for the same maturity buckets.

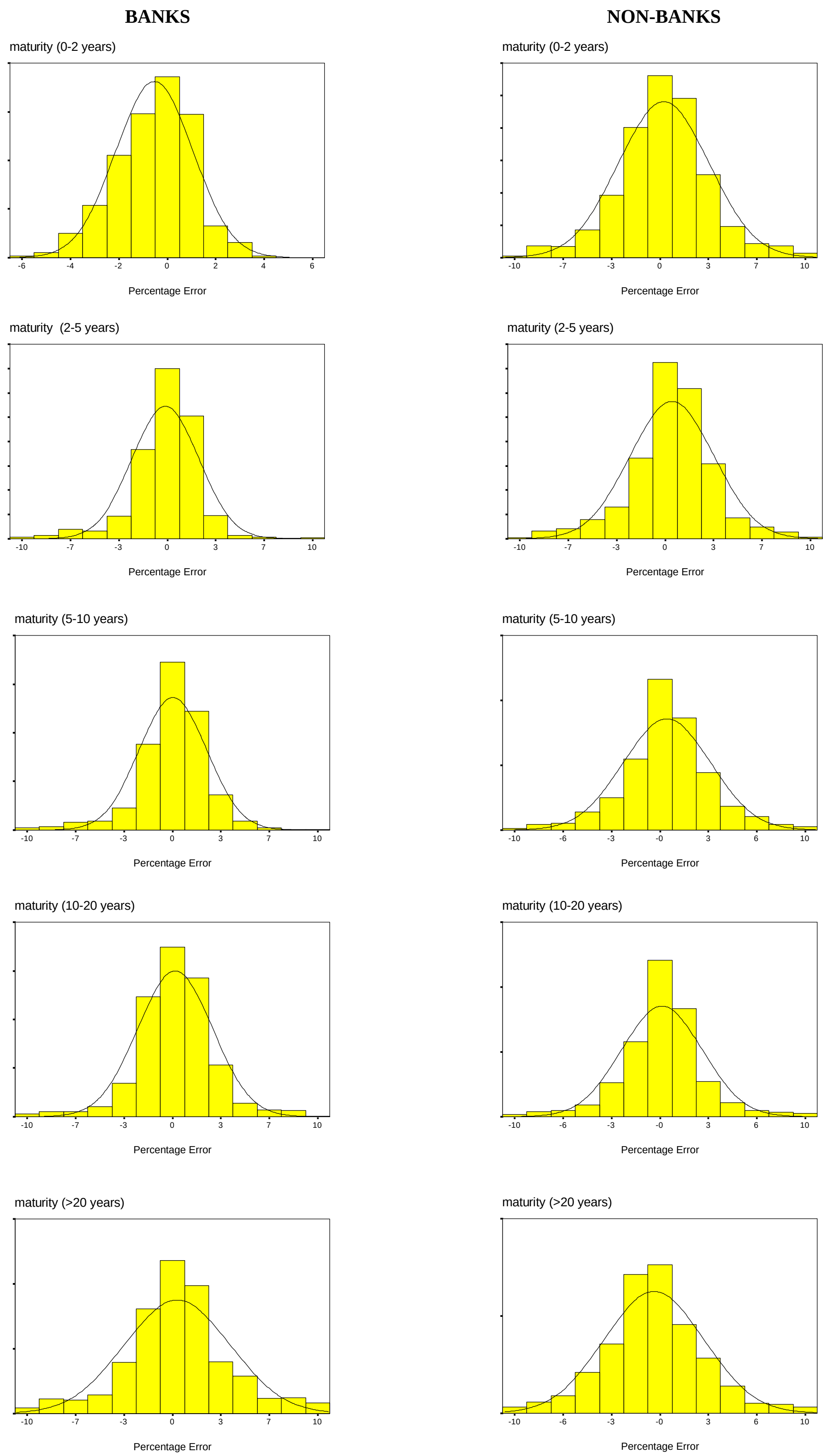
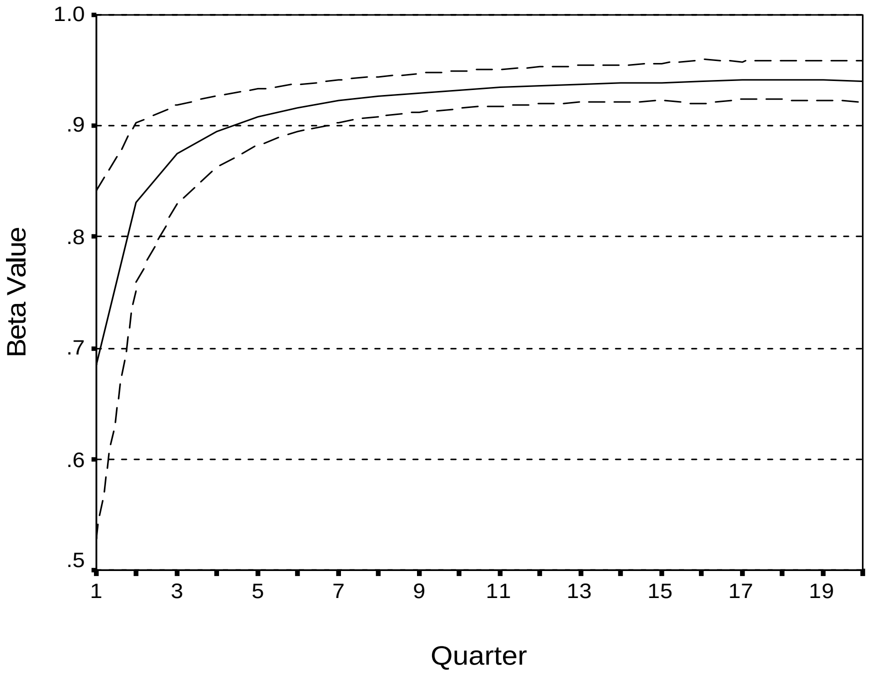


Figure 3
Predictability of Future Changes in Forward rates

The figure plots the beta coefficients that predict the next quarter's n-period forward rate from its current level and from the current credit-spread slope, using the following regression specification:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n (g_t^n - s_t) + \varepsilon_{t+1}$$

where n ranges from 1quarter to 20 quarters. The 95% confidence interval for the beta values is indicated by the dashed lines. The second figure shows a box and whiskers plot of the beta values when the regressions are performed separately for each firm and each maturity.



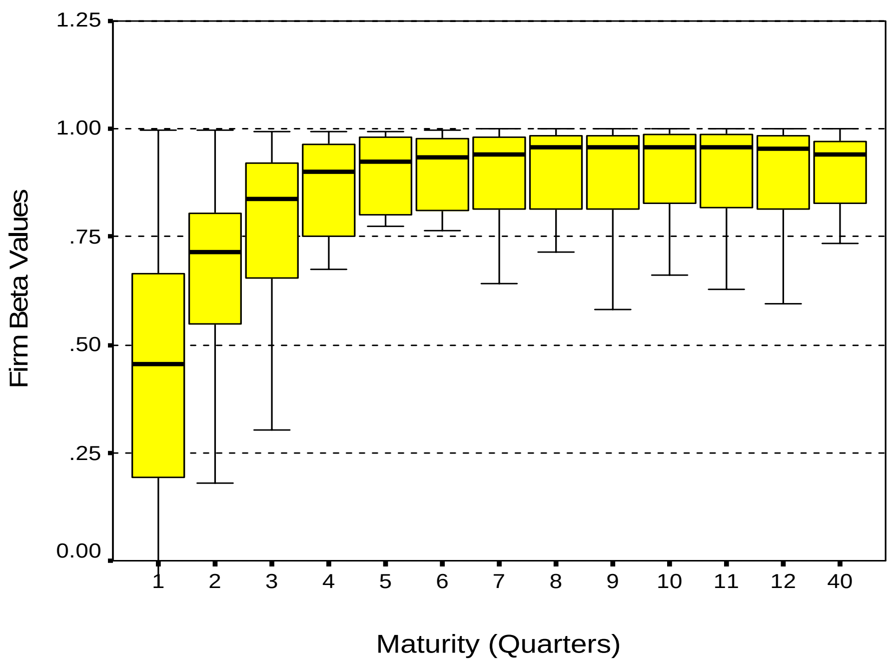


Figure 4

Predictability of Future Changes in Forward rates: Higher and Lower Rated Banking Firms

The figure plots the beta coefficients that predict the next quarter's n-period forward rate from its current level and from the current credit-spread slope. We separated firms into high and low quality class. The high quality class comprised of all firms in the top rating quartile; the low quality firms were all those firms in the lowest quartile. The regression equation used is:

$$g_{t+1}^{n-1}(k) - s_t(k) = \alpha_n^k + \beta_n^k (g_t^n(k) - s_t(k)) + \varepsilon_{t+1}(k)$$

where k indicates which of the two classes of firms, and n ranges from 1quarter to 12 quarters. The figure shows the beta coefficient for each of first 12 quarterly forward rates for both rating quartiles.