On Credit Spread Slopes and Predicting Bank Risk

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Abstract

We examine whether credit-spread curves, engendered by a mandatory subordinated-debt requirement for banks, would help predict bank risk. We extract the credit-spread curves each quarter for each bank in our sample, and analyze the information content of credit-spread slopes. We find that credit-spread slopes are significant predictors of future credit spreads. However, credit-spread slopes do not provide significant additional information on future bank-risk variables, 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. In contrast, very few studies have investigated the information content of credit-spread slopes. At any point in time the shapes of credit-spread curves for different firms can be different. Some firms may have upward-sloping credit-spread curves while other firms may have downward-sloping curves. Over time, credit-spread slopes can move in similar or different directions. Our objective, in this paper, is to understand why credit-spread curves differ across firms, how they move over time, and what information they convey about future firm risk. We first examine whether credit-spread slopes convey information on future credit spreads. Of course, the ability to predict future credit spreads does not necessarily imply that credit-spread curves have the ability to predict future firm-risk variables. Therefore, we also examine whether credit-spread slopes convey information on future firm-specific accounting-risk variables.

Our study focuses on banking firms because policymakers are actively considering the use of subordinated debt (SND) as a regulatory tool. They believe that the resulting credit-spread curves could be informative of bank risk. A consultative paper issued by the Basel Committee on Banking Supervision (1999) (Basel II) proposes new risk-based capital standards with a view to increased granularity in risk measurement and improved supervision. Mandatory SND requirement appears to be the cornerstone of Basel II's proposals. The U.S Shadow Regulatory Committee has also 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. If credit-spread slopes that would be spawned by a mandatory SND requirement contain information about future bank risk, then monitoring credit-spread slopes will be an effective way of monitoring bank risk.

Numerous studies have been undertaken to establish whether the rational expectations theory of the riskless term structure holds. The tests have examined 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 long rates had useful information for predicting short-rate movements.[1]

In contrast, very few studies have been conducted at the firm level to establish whether

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

credit-spread slopes carry useful information for predicting future firm risk. There are several possible reasons for this. Unlike the Treasury market, extracting the term structure of credit spreads for individual firms is delicate. In order to do it, the firm has to have several issues of publicly traded debt with maturities that span the term structure. Further, the debt must be frequently traded, and prices must be publicly available. Finally, because of the limited availability of traded bonds for each firm, exchanging maturities to alter yields is more difficult in the corporate bonds market than in the Treasury bond market.

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. The empirical evidence, however, has been somewhat mixed. Fons (1994) and Sarig and Warga (1989) have provided support for this theory, while Helwege and Turner (1999) find that speculative-grade issuers have positively sloped credit spreads.

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, recent studies have shown that default risk may account for a small component of credit spreads. Huang and Huang (2002) 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. Similarly, 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. They find that changes in firm-risk variables account for a small fraction of the variability in changes in credit spreads.[2] As a result, the term structure of credit spreads and changes in credit spreads may reflect events other than default and recovery assessments. It is therefore unclear what firm-specific information is contained in the shape of the credit-spread curve in general, and the credit-spread slope in particular.

Our paper is most closely related to Krishnan, Ritchken and Thomson (2003), who extract

[2]Other factors have also been found to affect credit spreads. Elton, Gruber, Agrawal and Mann (2001) estimate a state tax premium of the order of 40 basis points. Perraudin and Taylor (2003), and Houweling, Mentink and Vorst (2003) use different methods to estimate a liquidity premium of the order of 20 basis points. Yu (2002) investigates a transparency premium.

credit-spread curves for banking firms to determine whether firm risk changes get reflected in credit spread changes. Our study uses the same database of debt transaction prices and the same credit-spread-extraction process as theirs. However, rather than focus on the contemporaneous determinants of credit-spread changes, our goal here is to investigate whether the credit-spread slopes of banks contain information on future credit spreads and, more importantly, on future bank-risk variables.

We find that the credit-spread curves of banks can be upward or downward sloping, but the average credit-spread slope is negative. Credit spreads of lower-quality firms are typically higher, and their slopes more steeply downward sloping. Moreover, there is significant information contained in the 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 results on the predictability of riskless-rate changes obtained by Backus, Foresi, Mozumdar and Wu (2001). The degree of predictability of future credit spreads depends on the maturity of the spread. We find that longer-dated credit spreads are more predictable, and not significantly influenced by firm-specific and market-wide factors. However, shorter-dated credit spreads are influenced by firm-risk variables and market variables. In particular, firm ratings, Treasury yields, market returns and market volatility influence shorter-dated future credit spreads.

These findings lead us to suspect that perhaps credit-spread slopes carry information about future bank-risk variables. We ascertain whether credit-spread slopes have predictive power with respect to future bank-risk variables, over and above other known information about a bank such as its current period balance-sheet information and credit rating. We do not find significant evidence that credit-spread slopes can predict future bank-risk variables. We also examine whether this finding is specific to banks or is more general. We use a control sample of non-banking firms and get the same result: current period credit-spread slope cannot predict future firm-risk variables.

Hence, we conclude that credit-spread curves engendered by a mandatory SND requirement for banks are unlikely to provide significant additional information to investors and regulators on future bank-risk, over and above the information they would already possess in the absence of any 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]

We separate all data into two broad categories of banking firms and non-banking firms.[4] For banking firms, we have $18,776$ trades across 185 different firms. The distribution of trades and banking firms across the 24 consecutive quarters is shown in the first two columns of Table 1. For non-banking firms, we have $240,876$ trades involving $3,265$ different firms. The first two columns of Table 2 show the breakdown of trades for non-banks for the successive quarters.

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.

Tables 1 and 2 Here

Columns 3 and 4 of Tables 1 and 2 show the distribution of trades by quarter that remain

[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 generically to both banks and bank holding companies.

after applying this filter for banks and non-banks. For banking firms, we are left with $14,660$ trades over 144 different banking firms. For non-banks, we are left with $26,808$ transactions from 245 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. For banking firms, this leaves us with $9,167$ transactions over 81 different banking firms, while for non-banking firms, we are left with $16,480$ transactions from 210 different firms. Columns 5 and 6 of Tables 1 and 2 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). For banks, that leaves us with our final database of $6,590$ transactions from 50 firms. For non-banks, we have $9,703$ transactions from 133 firms. The distributions of the trades and firms over each quarter are shown in the final two columns of Tables 1 and 2.

We are, finally, left with a database that contains the transaction prices, trading dates, and the specific terms of SNDs, ordered by firm-quarters. Table 3 provides details on maturity and coupon of SNDs as well as firm ratings of our final sample of banking and non-banking firms.

Table 3 Here

Table 3 shows that the descriptive statistics of bonds issued by our sample of non-banking firms are roughly similar to those issued by our sample of banking firms. We use these final samples of banking and non-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 for banking firms was 5.01 (13.67). Almost 60% of all banking issues (and about 70% of all non-banking issues) in our final sample have time to maturity between 1 and 10 years. Based on these results, in some of our analyses, we focus on the 3 year credit spreads, and 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.

We use the following 5 risk variables for non-banking firms: (a) Return on Assets (ROA), computed as Net Income Before Taxes and Extraordinary Items divided by Total Assets; (b) Interest Cover, Operating Income Before Depreciation divided by Interest expense; (c) Profit Margin, computed as Operating Income Before Depreciation divided by Sales; (d) Market-to-Book Ratio, computed as (Number of shares outstanding times Closing share price) divided by Stockholder Equity; and (e) Leverage, computed as (Total Assets minus Stockholder Equity) divided by Stockholder Equity. As ROA, Interest Cover, Profit Margin, or Market-to-Book Ratio increases, firm risk decreases, while as leverage increases, firm risk increases. All the firm risk ratios are calculated from the quarterly data files of Compustat.

In addition, we use credit-rating information on issues made by each banking and non-banking firm. The credit ratings come from Duff and Phelp, Standard and Poor's, Moody's, and Fitch. 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.

Figure 1 plots the distribution of subordinated debt maturities issued by our final sample of banking firms for which we have issue ratings. Consistent with the premise behind the paper of Helwege and Turner (1999), we find that the longer maturity debt are issued by the higher rated banking firms.

Figure 1 Here

2.4 Market Variables

We use 5 market variables in our analyses. These are (a) the Growth in Industrial Production (GIP), (b) S&P 500 buy and hold return (S&P), (c) 5-year Treasury yield (T5), (d) the slope of the yield curve defined as the 10-year Treasury yield minus 3-year Treasury yield (TSlope) and (e) a stock market volatility index - the VIX Index. The data on GIP, T5 and TSlope 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.

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 requires only that the short credit-spread process for each firm be mean reverting, correlated with interest rates, and have constant volatility over each quarter. Since the parameters are reestimated each quarter, and at each traded date take the riskless term structure as given, the model's primary purpose is to provide a very close fit to the observed credit spreads.

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,

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

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

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, $s(t)$.

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

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

$$du(t) = -bu(t)dt + \sigma_u dw_u(t) \tag{4}$$

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

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.

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

3.3 Empirical Results

Figure 2 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 2 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.

The left panel of Figure 3 shows the distribution of errors in bond prices produced by our model, for banking firms. 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 reveals 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 3 Here

We compare the distribution of pricing errors for banks to the pricing errors for non-banks. The right panel of Figure 3 shows the histograms of pricing errors for our sample of non-banks. The results are fairly similar to those of banks. 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 for banking firms has indeed effectively incorporated the information on bond prices.

4 Credit-Spread Slopes

We examine the properties of the credit spreads that we have extracted for each bank each quarter. The first two panels of Table 4 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 4 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%.

We next investigate how the credit-spread slopes depend on the type of banking firms. We categorize all credit-spread curves into 4 groups, with the first group comprising the most negative sloped credit spread curves (slope less than -30 basis points). The second group consists of the remaining negative (and flatter) credit-spread slopes; the third group comprises slightly positive slopes of upto 2 basis points; and the fourth group consists of the remaining (steeper) positive credit spread curves. The proportions of all credit-spread curves in each group are indicated in the table and are roughly equal. The bottom panel of Table 4 shows the proportion of credit-spread curves in each of these groups. For the lower rated banking firms, almost 40% of the curves are in group 1 (steeply negative), while only 17% are in group 4. The profiles of slopes for the sub-samples that are based on firm type, size, and leverage are all close to the profile of the full sample. Clearly, credit-spread slopes of the lower-rated banking firms are different from those of the higher-rated banking firms.

4.1 Time-Series Properties of Credit-Spread Slopes

The top panel in Figure 4 shows the time series patterns of bank credit-spread slopes. Slopes can be positive or negative and the patterns in signs for each firm appear to be stable over time. The second panel in Figure 4 shows the *changes* in credit-spread slopes over time. In each quarter, we test the null hypothesis that the proportion of increases in slope equals the proportion of decreases. Over the 24 quarters, the null hypothesis was never rejected. On average, the slope changes are negative for 48% and positive for 52% of the banking firms each quarter. When we examine the high and low rated banking firms separately, slope change patterns are almost identical: on average, for the low rated banking firms, slope changes are negative for 49% of the banks and positive 51% of the banks each quarter, and for the high rated banking firms, slope changes are negative for 48% of the banks and positive 52% of the banks each quarter. Since there is no systematic pattern over time, it appears that common market factors are not a driving force for determining slopes.

Figure 4 Here

The scatter diagram in the third plot of Figure 4 shows the relationship between future (next-period) changes in credit-spread slopes as a function of current slopes. A pattern of mean reversion can be seen. When the slope of the credit-spread curve is very steep, positive or negative, then there is an increased likelihood that in the next quarter the slope will flatten.

4.2 Future changes in Credit-Spread Slopes

The left panel of Table 5 reports the distribution of future credit-spread changes conditional on current credit-spread slopes. As before, we set up 4 groups for future credit spread changes as well as future slope changes, again with group 1 representing the most negative change group and group 4 the most positive change group.

Table 5 Here

If there were no relationship between current credit-spread slopes and future credit spreads, then for each row, the proportion of observations in each cell would be 25%. However, we find that, for all firms, when the credit spread curve is very steeply negative, the likelihood of a large negative change in the 3-year credit spread is 44%. When the current slopes are flatter, future changes in the 3-year spreads are also small. Finally, when the credit-spread curve is steeply positive, the modal class for changes in the 3-year spread is the largest positive change group. These results suggest that the slope of the credit spread is informative on credit-spread changes, with a steeper slope indicating a larger likelihood of a big change in spreads.

When we redo the analysis for the higher rated and lower rated banking firms separately, we find predictability to be high for the higher quality firms. When the slope is steeply negative, 46% of credit-spread changes are large negative changes. When the slope is steeply positive, 37% of the changes are large positive changes. In contrast, for the lower quality banks, when the slope is steeply negative, 39% of changes are large positive changes, and when the slope is positive, only 16% of changes are large positive changes.

The right panels of Table 5 repeat the analysis for future slope changes. There is strong mean-reversion tendency in credit-spread slopes for the higher-rated banking firms, but not for the lower-rated banking firms.

These descriptive statistics suggest that credit-spread slopes may be informative about future credit spreads, and that the predictability of future spreads may be related to current credit ratings.

5 Credit-Spread Slope as a Predictor of 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 5 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. The smallest deviations from the expectations hypothesis come at maturities beyond 2 years. This plot is very similar to the plot of slopes of *riskless forward rate* regressions obtained by Backus, Foresi, Mozumdar and Wu.

Figure 5 Here

The bottom panel shows the 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. Since all future forward credit spreads depend on the slope of the current credit-spread curve, and since credit spreads are averages of forward rates, future 3-year credit spreads will also depend on credit-spread slopes.

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 6.

Figure 6 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:

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

In this equation, the credit rating, R, interacts with the credit spread slope variable. Table 6 compares regression specification (10) with the regression specification equation (11).

Table 6 Here

Table 6 shows that the interaction effect of ratings with slopes adds significantly to the predictability of forward credit spreads, especially for the shorter maturities. The adjusted R^2 values for the model with the interaction term range from 10% at the short end, and increase to around 90% at the longer end of 10 years. Thus, credit-spread slopes are very informative of future credit spreads at the longer end of the maturity spectrum. At the shorter end, current credit spread slopes are significantly less informative of future credit spreads, and, moreover, current firm risk characteristics (as encapsulated by credit ratings) also matter.

We now wish to establish whether credit-spread slopes have significant explanatory power over future credit spreads, over and above other information known to the market on firm-specific risk and market-wide factors.

When considering firm risk variables and relating them to the current period credit-spread slope, we need to be cognizant of when the firm information becomes known to the market. On the last day of a quarter, the firm specific variables are not yet publicly released. 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. Thus, at the end of quarter t, the firm-specific variables pertaining to firm i in quarter, t, denoted by the 5 vector F_t, are not yet publicly known. However, F_{t-1}, the vector of the 5 firm specific variables pertaining to the previous quarter are known precisely to the market at date t. We use the following regression specification to predict future forward credit spreads:

$$\begin{aligned} g_{t+1}^{n-1} - s_t &= \alpha_n + \beta_n(g_t^n - s_t) + \gamma_n(g_t^n - s_t)R + \beta_F F_t + \beta_M M_t + \epsilon_{t+1} \\ F_t &= \alpha_0 + A_1 F_{t-1} + A_2 M_t + e_t. \end{aligned}$$

Here A_1 and A_2 are appropriately sized matrices of coefficients and e_t is a vector of mean zero errors. The last 3 columns of Table 7 examine whether the contribution of the slope variables toward the predictability of forward credit spreads, in the presence of firm and market variables, is significant. As can be seen, for all maturities, the slope variables have predictive power over forward credit spreads.

Table 7 Here

Table 7 also reports the sequential contribution of each block of variables in predicting the next quarter's forward credit spreads. We start with the credit-spread slope, then sequentially add the slope-rating interaction variable, the 5-vector of firm variables, and finally, the 5-vector of market variables. Consider the results of predicting next quarter's forward rate for the 3 month period starting in 6 months. The slope accounts for 38.9% of the explainable sum of squares. The slope-rating interaction term explains an additional 1.4%, the entire block of firm variables explain an insignificant amount, while the entire block of market variables explain a further 3.1%. The p-values report the significance of the sequential contributions for each set of explanatory variables for each maturity.

The slope-rating interaction variable is significant in predicting future forward credit spreads up to 2 years, but not thereafter. In the presence of the slope and ratings-slope interaction variables, firm variables do not add to the explanatory power. This is true for all maturities. However, economy-wide effects add to the explanatory power in predicting future credit spreads, especially for short maturities.

To examine which market variables are important in predicting forward credit spreads over and above the slope variables, we force the slope and the slope-rating interaction variable into our regression model, and allow market variables to enter into the model in a stepwise regression procedure. The firm-specific variables are not included since as a block they did not add significantly to predictive capability. Table 8 reports the regression coefficients and the corresponding p-values for several maturities.

Table 8 Here

At the short end of the maturity spectrum, future forward credit spreads are determined, to some extent, by the returns and volatility of the market (VIX and $S\&P$). Beyond one year, these variables have no significant predictive power, and the only market factor that appears to be significant is the 5-year Treasury yield. Beyond 3-years, no single market factor has significant influence over future credit spreads. These results indicate that for the short maturity forward credit spreads, the time varying risk premia may be linked to stock market factors.

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 changes over and above other information that is available to the market, such as credit ratings, firm-specific risk information and market-wide information.

We examine the information content of current credit-spread slopes about future firm risk in two ways. First, we conduct a canonical correlation analysis between the next quarter's firm risk variables and our two slope variables after controlling for firm and market variables. The purpose of this exercise is to examine whether there is any linear relationship between current period slope variables and next period's firm risk variables. 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 is significant correlation, then slope variables may be useful for predicting the direction of firm risk variables.

In particular, let $X_1 = F'_{t+1}$ be a 5-vector of banking-firm-specific risk variables and let $X_2^n = (F'_t,\ M'_t,\ g_t^n \text{ - } s_t,\ (g_t^n \text{ - } s_t)R)'$ be a 13-vector of explanatory variables. Let $u = \alpha' X_1$ and $v_n = \gamma'_n X_2^n$ be two arbitrary linear functions of the dependent and independent variables. The left panel reports the canonical correlations and redundancy between u and v_n, as well as the Bartlett test statistics for a range of maturity values, n. The right panel reports the same statistics when the effects of F_t and M_t have been partialled out. The results are shown in Table 9.

Table 9 Here

Across the entire maturity spectrum, the canonical correlation between the best linear combinations of future firm risk variables and the predictor variables is very high at around 0.97. The Bartlett tests, shown by the chi squared statistics, and p-values indicate that all canonical variates have significant correlation. However, these tests, by themselves, do not imply that risk variables can be significantly predicted by current period slope, firm and market variables. To establish this, additional statistics need to be computed to assess the amount of the dependent variable variation that is shared or accounted for by the set of independent variables. The redundancy index reports the proportion of variance of the criterion variables explained by the canonical variable. Table 9 shows that the redundancy index for the first set is around 0.378. Roughly, this means that about 38% of the variance of the dependent variables is explained by the first canonical variate of the predictor set. The redundancy measure gives a more realistic picture of the amount of shared variance between the dependent and predictor variables than does the correlation measure. The second canonical redundancy measure is about 29%, and then there is a big drop off. The first two canonical covariates, thus, explain a significant fraction of the variability of the dependent variables.

The right panel shows the predictive power of only the two slope-related variables. Once all the other market and firm specific variables have been partialled out, the best linear combinations of the slope variables do not correlate highly with future bank-risk variables. Only the 3-month forward credit spreads has some predictive ability over future firm risks. The overall results indicate that the marginal information content of credit-spread slopes on future firm risk variables is not significant.

As a second confirmatory test, we regress each of the future (next quarter) firm-risk variables on current firm, market, and slope variables, and we examine whether, in the presence of F_t and M_t, the block of slope variables has any explanatory power, using the following regression specification:

$$\begin{aligned} F^s_{t+1} &= \beta_0 + \beta_1 F_t + \beta_2 M_t + \beta_3 (g^n_t - s_t) + \beta_4 (g^n_t - s_t) R_t + \epsilon_{t+1} \\ F_t &= \alpha_0 + A_1 F_{t-1} + A_2 M_t + e_t, \end{aligned} \tag{12}$$

where F^s_{t+1} represents the firm specific variable next quarter. The percentage contribution of the slope variables toward the explainable sum of squares is shown in Table 10 for each of our 5 explanatory firm risk variables.

Table 10 Here

The results show that the short maturity forward credit-spread slopes can predict the future loan to assets ratio, non-performing assets and net charge-offs. However, while statistically significant, the overall marginal contribution of the slope variables to the explanatory sums of squares is small: less than 3.5% in all cases. In general, the longer-maturity forward slopes cannot predict the next quarter's bank risk variables. Thus, we find that while the current period credit-spread slope variables can predict future credit spreads, their predictive power over future firm risk variables is limited, especially when we consider the longer maturity forward slopes.

To examine whether this result is specific to banking firms, which are highly regulated, or whether it is a more general result across other industries, we repeat the analysis for our sample of non-banking firms.

Table 11 Here

Table 11 shows that once the firm-risk and market variables have been factored out, the best linear combination of the slope variables does not correlate at all with future firm-risk variables, across all maturities. This indicates that the marginal information content of credit-spread slopes on future firm risk variables is insignificant for non-banking firms. Our results lead us to conclude that credit-spread slopes engendered by mandatory SND may not provide significant information on future bank risk changes, over and above the information the market already possesses.

7 Conclusion

In this paper, we examine three issues. First, we examine the features of credit-spread slopes for banking firms. Second, we evaluate whether credit-spread slopes can predict credit spreads. Third, we examine whether the credit-spread slope can predict firm risk variables, above and beyond information currently available to the market. To address these issues, we carefully extract a time series of credit-spread curves for a set of banking and non-banking firms, and then analyze the resulting slopes of these curves.

We find that, on average, credit-spread slopes are negative for banking firms. Credit-spread slopes of the lower credit-rated banking firms are more negative than those of the higher-rated banking firms. Credit spreads across maturities are also significantly higher for the lower rated banking firms. When we examine credit-spread slope changes from quarter to quarter, we find strong evidence of mean-reversion tendency in credit-spread slopes. If the credit-spread slope of a banking firm is steeply negative, it is more likely to be less steeply negative in the next quarter. However, this result is considerably weaker for the lower-rated banking firms. This leads us to suspect that the predictability of future firm risk, as measured by future credit spreads, may depend on current firm risk, as measured by a firm's credit rating.

We find strong evidence that the current credit-spread slopes can predict future forward credit spreads. Predictability is always present across all maturities. The greatest departures from the expectations hypothesis occur for the short maturity forward credit spreads. At the shorter end of the maturity spectrum, credit ratings and general stock market conditions affect future credit spreads in systematic ways.

The fact that slopes are important for predicting future credit spread levels does not imply that slopes can predict future bank risk variables. Indeed, we find that current period credit-spread slopes, in general, do not provide economically significant information about future firm risk ratios over and above the other information the market already possesses. This result is not unique to the banking sector, and also holds for our control sample of non-banking firms. Thus, we find little evidence that credit-spread curves resulting from any mandatory SND requirement contain additional information about future firm risk, over and above other information the market would already possess even in the absence of any subordinated debt.

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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
Descriptive statistics of non-bank subordinated debt trades

Our initial sample contains all non-bank 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 Compustat Quarterly database 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	2092	323	132	41	0	0	0	0
Q21994	1881	315	108	39	27	4	0	0
Q31994	1734	314	119	41	40	6	16	3
Q41994	1968	332	124	47	40	9	10	5
Q11995	4316	445	148	51	69	12	38	7
Q21995	4935	471	283	72	173	18	107	10
Q31995	4850	463	304	56	252	23	152	13
Q41995	6608	527	368	78	260	25	149	15
Q11996	7723	559	153	51	117	28	68	16
Q21996	5967	542	331	81	246	31	156	20
Q31996	5165	553	268	88	188	32	130	22
Q41996	7039	617	316	91	225	34	151	23
Q11997	6739	661	124	40	102	24	65	25
Q21997	6520	670	293	86	224	37	142	23
Q31997	7316	675	325	78	268	41	162	24
Q41997	8390	745	323	89	248	42	144	27
Q11998	16368	1344	1413	144	454	63	193	26
Q21998	15162	1383	1519	174	694	107	268	39
Q31998	14024	1286	1257	170	785	137	379	65
Q41998	16627	1437	1359	182	852	154	506	82
Q11999	25833	1772	4319	209	2707	168	1499	94
Q21999	25044	1856	4936	222	2705	185	1520	96
Q31999	21283	1713	3614	226	2459	202	1464	108
Q41999	23162	1896	4342	230	3345	220	2254	118
Total	240876	3265	26608	245	16480	210	9703	133

Table 3
Descriptive statistics of our final sample of subordinated debt issues made by banking and non-banking firms

Panels A and B show the frequency distribution of issues falling under different maturity, coupon, and rating categories for 50 banking firms (535 issues) and 133 non-banking firms (2335 issues) that make up our final sample of trades. 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, the average rating is reported.

Maturity (years)	Banks	Non-Banks
<1	12	13
1-5	33	45
5-10	26	26
10-25	25	11
>25	4	5

Coupon	Banks	Non-Banks
<3	3	0
3-6	7	19
6-7	45	37
7-8	27	25
>8	18	19

Credit	Banks	Non-Banks
AA and above	8	11
A	62	31
BBB	14	14
BB and below	3	3
Rating not found	13	41

Table 4
Banking Firms: Credit Spread Levels and Slopes

The first 2 panels report the average credit-spread levels and credit-spread slopes for our final sample of 482 credit spread curves for the period 1994 - 1999, for all banking firms, 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. In the third panel, all current period banking-firm credit-spread slopes are categorized into 4 groups such that Groups 1 and 2 are negative and Groups 3 and 4 are positive, with Group 1 being the most negative and Group 4 being the most positive. For each category of credit rating, type, size and leverage, the proportion of slopes in each group is reported. For example, for low rated banking firms, 39.5% of the slopes are most negatively sloped. In contrast, only 23.7% of high rated firms belonged to the same group.

			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)
10-3 Slope Group	**1**	23.9%	39.5%	23.7%	21.1%	29.4%	24.6%	23.1%	20.3%	27.4%
	2	28.6%	22.2%	27.5%	29.8%	26.3%	25.8%	31.4%	28.2%	29.0%
	3	23.9%	21.0%	27.5%	24.8%	21.9%	22.9%	24.8%	27.8%	19.9%
	4	23.6%	17.3%	21.3%	24.2%	22.5%	26.7%	20.7%	23.7%	23.7%
			81	338	322	160	241	241	241	241

Table 5
Future Changes in Credit-Spreads and Credit-Spread Slopes

The left panel shows how future changes in credit spreads depend on the current credit-spread slope for all banking firms. All the credit-spread slope changes from the current quarter to the next quarter are categorized into 4 groups such that Groups 1 and 2 are negative and Groups 3 and 4 are positive, with Group 1 being the most negative and Group 4 being the most positive. 23.4%, 23.8%, 25.7% and 27.1% of all credit-spread curves fall into the credit-spread slope change groups 1, 2, 3 and 4 respectively. As an example, consider banking firms that have the most negative credit-spread slopes: for such firms, 43.81% of the changes in the 3-year credit spreads from the current quarter to the next quarter fall in the most negative spread change group. The same analysis is repeated separately for high and low credit rated firms. The right panel shows how future changes in credit-spread slope depend on the current level of the slope for all banking firms. All the 3-year credit-spread changes from the current quarter to the next quarter are categorized into 4 groups such that Groups 1 and 2 are negative and Groups 3 and 4 are positive, with Group 1 being the most negative and Group 4 being the most positive. As an example, consider firms in the lowest group: 32.38% of these firms have very large negative changes in slopes, while 53.33% have very large positive changes in the slopes. The same analysis is repeated separately for high and low credit rated firms. The modal group(s) for future changes is (are) shown in bold text.

All Firms

Slope Group	Future Change in Spread Group				Future Change in Slope Group			
	1	2	3	4	1	2	3	4
1	**43.81**	15.24	17.14	23.81	32.38	5.71	8.57	**53.33**
2	16.39	**31.97**	26.23	25.41	24.59	21.31	**29.51**	**24.59**
3	18.63	24.51	**33.33**	23.53	12.75	**29.41**	**43.14**	14.71
4	22.33	31.07	19.42	**27.18**	**23.30**	**39.81**	21.36	15.53

Lower Credit Rated

Slope Group	1	2	3	4	1	2	3	4
1	38.71	9.68	12.90	**38.71**	**45.16**	3.23	3.23	48.39
2	23.53	23.53	29.41	23.53	35.29	11.76	47.06	5.88
3	6.25	31.25	25.00	37.50	12.50	50.00	37.50	0.00
4	41.67	25.00	16.67	16.67	8.33	50.00	33.33	8.33

Higher Credit Rated

Slope Group	1	2	3	4	1	2	3	4
1	**46.48**	16.90	18.31	18.31	28.17	7.04	9.86	**54.93**
2	15.66	22.89	**30.12**	**31.33**	25.30	16.87	**24.10**	**33.73**
3	21.69	22.89	**33.73**	21.69	13.25	**25.30**	**44.58**	16.87
4	22.39	22.39	17.91	**37.31**	**29.85**	**38.81**	17.91	13.43

Table 6
Future Changes in Forward Credit Spreads: Predictive Power of Slope and Ratings

The table shows the results of two different models for predicting n-period ahead forward credit spreads for the next quarter, based on the slope of the forward credit-spread curve and the interaction term of slope with firm ratings. The 2 regression specifications used are:

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

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 coefficients for the credit-spread slope, for the first regression equation, and the coefficients for the credit-spread slope and the interaction term are reported below, along with their p-values. The analysis is restricted to all firms-quarters with credit rating information.

		Slope Only		Full Model		
Maturity		**Beta Coefficient**	**p Value**	**Beta Coefficient**	**p Value**	**R Squared**
3 months	slope	0.307	0.000	-0.455	0.136	0.109
	interaction			0.773	0.012	
6 months	slope	0.624	0.000	-0.101	0.682	0.403
	interaction			0.735	0.003	
9 months	slope	0.800	0.000	0.221	0.240	0.649
	interaction			0.587	0.002	
1 year	slope	0.885	0.000	0.442	0.002	0.784
	interaction			0.449	0.002	
2 years	slope	0.961	0.000	0.783	0.000	0.924
	interaction			0.180	0.028	
3 years	slope	0.964	0.000	0.852	0.000	0.931
	interaction			0.114	0.129	
10 years	slope	0.949	0.000	0.843	0.000	0.902
	interaction			0.108	0.163	

Table 7
Determinants of Future Changes in Forward Credit Spreads

This table shows the explanatory power of the slope of the forward credit-spread curve, the interaction term of credit spread slope and firm rating, firm variables, and market variables in predicting future changes in the n-period ahead forward credit spreads. Since information on firm variables is released after the end of the quarter, they are instrumented using firm and market information that are known at the end of the quarter. The regression specification used is:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n (g_t^n - s_t) + \gamma_n (g_t^n - s_t) R + \beta_F F_t + \beta_M M_t + \varepsilon_{t+1}$$
$$F_t = \alpha_0 + A_1 F_{t-1} + A_2 M_t + e_t$$

where s_t is the current 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, R is the current period firm rating, F_t is the 5-vector of firm risk variables, M_t is the 5-vector of market variables, and F_{t-1} is the 5-vector of firm specific variables pertaining to the previous quarter and precisely known at time t. α_0 is a vector of size 5, A_1 and A_2 are appropriately sized matrices and e_t is a vector of residuals with mean 0.

The left panel of the table reports the sequential contribution to the explanatory power by each additional block of explanatory variables (the R squared change, F-statistic and the p-values). The right panel shows the contribution of the slope and the interaction of slope with rating variable to the explanatory power of the full model (with the firm and market variables included). The analysis is restricted to all firms-quarters with credit rating information.

Maturity (of 3-month Forward)	Block of Variables	Sequential Contribution of each Block			Contribution of Slope Variables in Full model		
		R Square Change	F Value	p Value	R Square Change	F Value	p Value
3 months	Slope	0.095	40.307	0.000			
	Slope/Ratings	0.015	6.418	0.012			
	Firm variables	0.010	0.841	0.521			
	Market Variables	0.048	4.330	0.001			
					0.116	26.225	0.000
6 months	Slope	0.389	245.930	0.000			
	Slope/Ratings	0.014	8.850	0.003			
	Firm variables	0.003	0.390	0.856			
	Market Variables	0.031	4.062	0.001			
					0.389	129.356	0.000
9 months	Slope	0.640	685.936	0.000			
	Slope/Ratings	0.009	9.827	0.002			
	Firm variables	0.001	0.163	0.976			
	Market Variables	0.016	3.695	0.003			
					0.619	347.500	0.000
1 year	Slope	0.783	1393.632	0.000			
	Slope/Ratings	0.005	9.749	0.002			
	Firm variables	0.000	0.096	0.993			
	Market Variables	0.009	3.355	0.006			
					0.752	697.432	0.000
2 years	Slope	0.923	4626.110	0.000			
	Slope/Ratings	0.001	4.846	0.028			
	Firm variables	0.000	0.496	0.779			
	Market Variables	0.002	2.525	0.029			
					0.888	2278.325	0.000
3 years	Slope	0.930	5105.883	0.000			
	Slope/Ratings	0.000	2.317	0.129			
	Firm variables	0.001	0.564	0.728			
	Market Variables	0.002	2.188	0.055			
					0.897	2495.237	0.000
10 years	Slope	0.901	3505.451	0.000			
	Slope/Ratings	0.001	1.955	0.163			
	Firm variables	0.000	0.156	0.978			
	Market Variables	0.002	1.791	0.114			
					0.864	1683.736	0.000

Table 8

Future Changes in Forward Credit Spreads: Importance of Market Variables

This table reports the regression coefficients and the corresponding p-values (in parenthesis) when the n-period ahead forward credit spreads for the next quarter is regressed on the slope of the forward credit-spread curve, interaction term of slope with ratings and the 5-vector of market variables, using the step-wise regression methodology on the following regression specification:

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

where s_t is the current 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, R is the current period firm rating, and M_t is the 5-vector of market variables.

	Slope Variables		Market Variables			
Maturity (years)	**Slope**	**Interaction**	**VIX**	**S&P**	**5 Year Treasury**	**Adjusted R Square**
0.25	-0.502 (0.095)	0.821 (0.006)	0.124 (0.012)	-0.100 (0.043)	-	0.136
0.50	-0.148 (0.541)	0.781 (0.001)	0.106 (0.009)	-0.080 (0.048)	-	0.423
0.75	0.181 (0.328)	0.629 (0.001)	0.098 (0.001)	-	-	0.658
1.00	0.413 (0.004)	0.480 (0.001)	0.074 (0.002)	-	-	0.794
1.25	0.614 (0.000)	0.317 (0.006)	-	-	-0.058 (0.002)	0.863
1.50	0.937 (0.000)	0.010 (0.816)	-	-	-0.050 (0.002)	0.897
1.75	0.762 (0.000)	0.198 (0.023)	-	-	-0.042 (0.005)	0.917
2.00	0.802 (0.000)	0.162 (0.046)	-	-	-0.037 (0.008)	0.925
2.25	0.828 (0.000)	0.138 (0.076)	-	-	-0.034 (0.013)	0.930
2.50	0.846 (0.000)	0.121 (0.112)	-	-	-0.031 (0.022)	0.931
2.75	-0.029 (0.033)	0.858 (0.000)	-	-	-0.029 (0.033)	0.931
3.00	-0.027 (0.046)	0.866 (0.000)	-	-	-0.027 (0.046)	0.931
4.00	0.867 (0.000)	0.097 (0.190)	-	-	-	0.927
10.00	0.846 (0.000)	0.106 (0.169)	-	-	-	0.901

Table 9

Determinants of Future Bank Risk Variables: Canonical Correlation Analysis

Let $X_1 = F_{t+1}$' be a 5-vector of banking-firm-specific risk variables and let $X_2^n = (F_t', M_t', (g_t^n - s_t), (g_t^n - s_t) R)'$ be a 13-vector of independent variables. Let $u = \alpha' X_1$ and $v_n = \gamma_n' X_2^n$ be two arbitrary linear functions of the dependent and independent variables. The left panel reports the canonical correlations between u and v_n, as well as the canonical redundancies and Bartlett test statistics for a range of maturity values, n. The right panel reports the same statistics when the effects of F_t and M_t have been partialled out, and X_2^n is now $((g_t^n - s_t), (g_t^n - s_t) R)'$. The symbol * denotes significance at the 5% level.

	Full Model				Slope & Interaction variable given everything else			
Maturity	Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value	Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value
	1	0.971	0.378	2408.7*				
	2	0.908	0.290	1348.5*	1	0.206	0.007	16.188
3 months	3	0.810	0.036	702.5*	2	0.032	0.000	0.366
	4	0.671	0.058	306.2*				
	5	0.451	0.013	84.2*				
	1	0.971	0.378	2400.5*				
	2	0.907	0.289	1340.1*	1	0.173	0.005	11.513
6 months	3	0.810	0.036	697.3*	2	0.032	0.000	0.378
	4	0.670	0.057	300.9*				
	5	0.440	0.013	79.7*				
	1	0.971	0.378	2394.8*				
	2	0.907	0.289	1334.3*	1	0.147	0.004	8.336
9 months	3	0.810	0.036	693.9*	2	0.032	0.000	0.369
	4	0.670	0.057	297.4*				
	5	0.432	0.012	76.5*				
	1	0.971	0.378	2390.8*				
	2	0.906	0.288	1330.2*	1	0.126	0.004	6.209
1 year	3	0.810	0.036	691.7*	2	0.030	0.000	0.340
	4	0.670	0.056	295.2*				
	5	0.426	0.012	74.3*				
	1	0.971	0.377	2383.4*				
	2	0.905	0.288	1323.3*	1	0.087	0.002	2.959
2 years	3	0.810	0.036	689.2*	2	0.022	0.000	0.171
	4	0.671	0.056	292.6*				
	5	0.416	0.012	70.6*				
	1	0.971	0.376	2381.4*				
	2	0.904	0.288	1321.6*	1	0.083	0.002	2.673
3 years	3	0.810	0.036	689.7*	2	0.018	0.000	0.118
	4	0.672	0.057	293.1*				
	5	0.415	0.012	70.0*				
	1	0.971	0.376	2380.8*				
	2	0.903	0.288	1321.8*	1	0.109	0.002	4.528
10 years	3	0.810	0.036	693.5*	2	0.020	0.000	0.141
	4	0.674	0.058	296.7*				
	5	0.420	0.012	71.9*				

Table 10
Credit Spread Slope as a Determinant of Future Bank Risk Variables

The table shows the marginal contribution of the slope and the interaction term of the slope with credit-ratings,to the total explainable sums of squares when the future (next quarter) banking firm risk ratios are individually regressed on the slope of the forward credit-spread curve, interaction term of slope with ratings, the 5-vector of bank risk variables, and the 5-vector of market variables, using the following regression equation:

$$F_{t+1}^{s} = \alpha_n + \beta_n(g_t^n - s_t) + \gamma_n(g_t^n - s_t)R + \beta_F F_t + \beta_M M_t + \varepsilon_{t+1}$$

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

where s_t is the current period spot credit spread, g_t^n is the n-period ahead forward credit spread in the current quarter, R is the current period firm rating, F_t is the 5-vector of firm risk variables, M_t is the 5-vector of market variables, and F_{t-1} is the 5-vector of firm specific variables pertaining to the previous quarter and precisely known at time t. The dependent variable is the specific firm risk variable at time t+1, F_{t+1}^{s}. The p-value for the significance of the slope and interaction terms is shown in parentheses. For example, in the first regression, where ROA is the firm specific dependent variable, and the 3 month slope variables are used, the slope and its interaction effects account for 0.34% of the explained sums of squares and the partial F test indicates that this is not significant. (The p-value is 0.43)
The numbers that are shown in bold text are significant at the 5% level. The analysis is restricted to all firms-quarters with credit rating information.

Marginal Percentage Contribution by Slope Variables to Explainable SSQ

Maturity	ROA	Loan to Total Assets	Non Performing Assets	Net Charge offs	Leverage
3 months	0.34%	**3.22%**	**1.04%**	**3.48%**	0.12%
	(0.43)	(0.01)	(0.00)	(0.00)	(0.21)
6 months	0.17%	0.00%	**0.78%**	**2.81%**	0.12%
	(0.67)	(0.27)	(0.01)	(0.00)	(0.22)
9 months	1.68%	0.00%	**0.65%**	**2.26%**	0.12%
	(0.70)	(0.51)	(0.03)	(0.00)	(0.23)
1 year	0.17%	0.00%	0.52%	**1.70%**	0.12%
	(0.60)	(0.70)	(0.06)	(0.00)	(0.25)
2 years	0.68%	0.00%	0.26%	**0.72%**	0.12%
	(0.19)	(0.83)	(0.26)	(0.04)	(0.35)
3 years	1.01%	0.00%	0.13%	0.29%	0.12%
	(0.07)	(0.97)	(0.47)	(0.24)	(0.46)
10 years	1.68%	0.00%	0.00%	0.00%	0.00%
	(0.70)	(0.88)	(0.84)	(0.97)	(0.77)
R Square values with just firm and market variables	0.69	0.81	0.81	0.75	0.92

Table 11
Determinants of Future Non-Bank Risk Variables: Canonical Correlation Analysis

Let $X_1 = F_{t+1}$' be a 5-vector of banking-firm-specific risk variables and let $X_2^n = (F_t', M_t', (g_t^n - s_t), (g_t^n - s_t) R)'$ be a 13-vector of independent variables. Let $u = \alpha' X_1$ and $v_n = \gamma_n' X_2^n$ be two arbitrary linear functions of the dependent and independent variables. The left panel reports the canonical correlations between u and v_n, as well as the canonical redundancies and Bartlett test statistics for a range of maturity values, n. The right panel reports the same statistics when the effects of F_t and M_t have been partialled out, and X_2^n is now $((g_t^n - s_t), (g_t^n - s_t) R)'$. The symbol * denotes significance at the 5% level.

	Full Model				Slope & Interaction variable given everything else			
Maturity	Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value	Canonical Factors	Canonical Correlation	Canonical Redundancy	Chi Squared Value
	1	0.909	0.242	2330.16*				
	2	0.838	0.102	1239.13*	1	0.064	0.000	2.851
3 months	3	0.620	0.079	482.09*	2	0.022	0.000	0.302
	4	0.475	0.034	178.97*				
	5	0.176	0.006	19.7*				
	1	0.909	0.242	2329.96*				
	2	0.838	0.102	1239.218*	1	0.065	0.000	2.863
6 months	3	0.620	0.079	482.17*	2	0.018	0.000	0.210
	4	0.475	0.034	179.03*				
	5	0.176	0.006	19.7*				
	1	0.909	0.242	2329.92*				
	2	0.838	0.102	1239.36*	1	0.067	0.001	2.938
9 months	3	0.620	0.079	482.32*	2	0.016	0.000	0.163
	4	0.475	0.034	179.11*				
	5	0.176	0.006	19.72*				
	1	0.909	0.242	2329.95*				
	2	0.838	0.102	1239.54*	1	0.068	0.001	3.040
1 year	3	0.620	0.079	482.5*	2	0.015	0.000	0.137
	4	0.475	0.034	179.2*				
	5	0.176	0.006	19.74*				
	1	0.909	0.242	2330.25*				
	2	0.838	0.102	1240.14*	1	0.073	0.005	3.424
2 years	3	0.621	0.079	483.1*	2	0.014	0.000	0.123
	4	0.475	0.034	179.5*				
	5	0.177	0.006	19.83*				
	1	0.909	0.242	2330.41*				
	2	0.838	0.102	1240.42*	1	0.075	0.005	3.616
3 years	3	0.621	0.079	483.38*	2	0.016	0.000	0.165
	4	0.475	0.034	179.65*				
	5	0.177	0.007	19.92*				
	1	0.909	0.242	2329.44*				
	2	0.838	0.102	1239.58*	1	0.065	0.001	3.069
10 years	3	0.620	0.079	482.55*	2	0.027	0.000	0.443
	4	0.475	0.034	179.4*				
	5	0.178	0.007	20.09*				

Figure 1
Banking Firm Subordinated Debt Maturities by Credit Rating

Banking firm credit ratings come from one or more of the following rating agencies: Duff and Phelp, Standard and Poor's, Moody's, and Fitch. We translate the letter ratings of all agencies for each issue 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 associated with an issue to arrive at a single numerical rating score for an issue. Using the Standard & Poor notation, BBB+, A- and A correspond to numerical scores of 9, 10 and 11 respectively. Our final sample comprises 535 outstanding issues made by 50 banking firms, of which we have credit ratings for 518 issues. This figure shows the distribution of the maturities (in years) of these 518 issues as a function of their average credit rating.

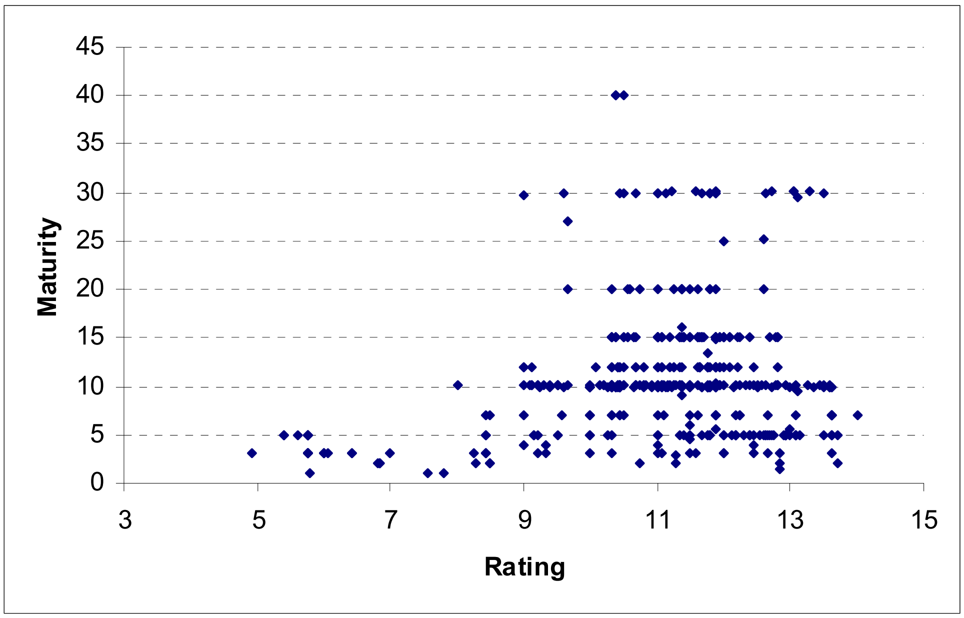
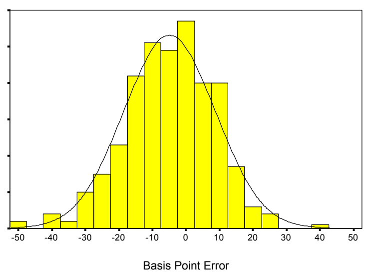


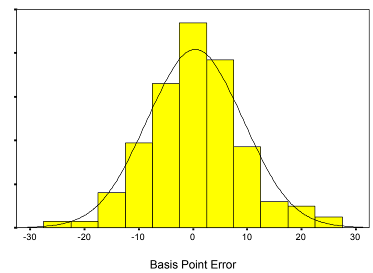
Figure 2
Riskless Interest Rates: Pricing Errors

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.

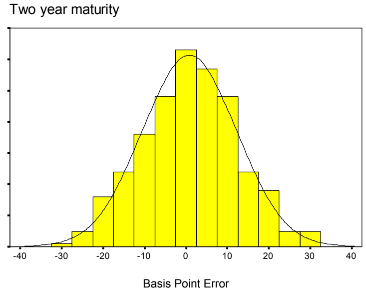
Six month maturity



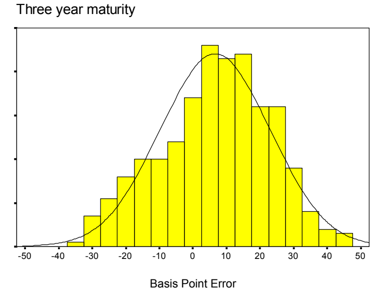
One year maturity



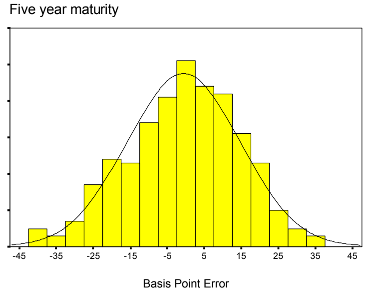
Two year maturity



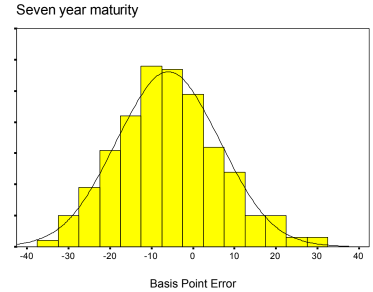
Three year maturity



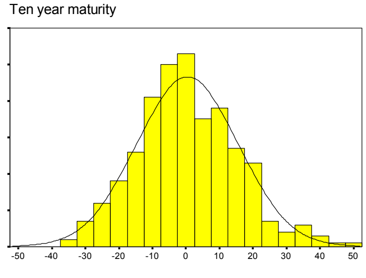
Five year maturity



Seven year maturity



Ten year maturity



Twenty year maturity

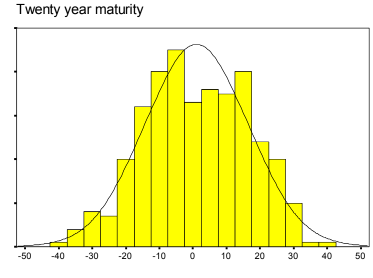


Figure 3
Pricing Errors for Subordinated Debt for Banks and Non-Banks

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.

BANKS **NON-BANKS**

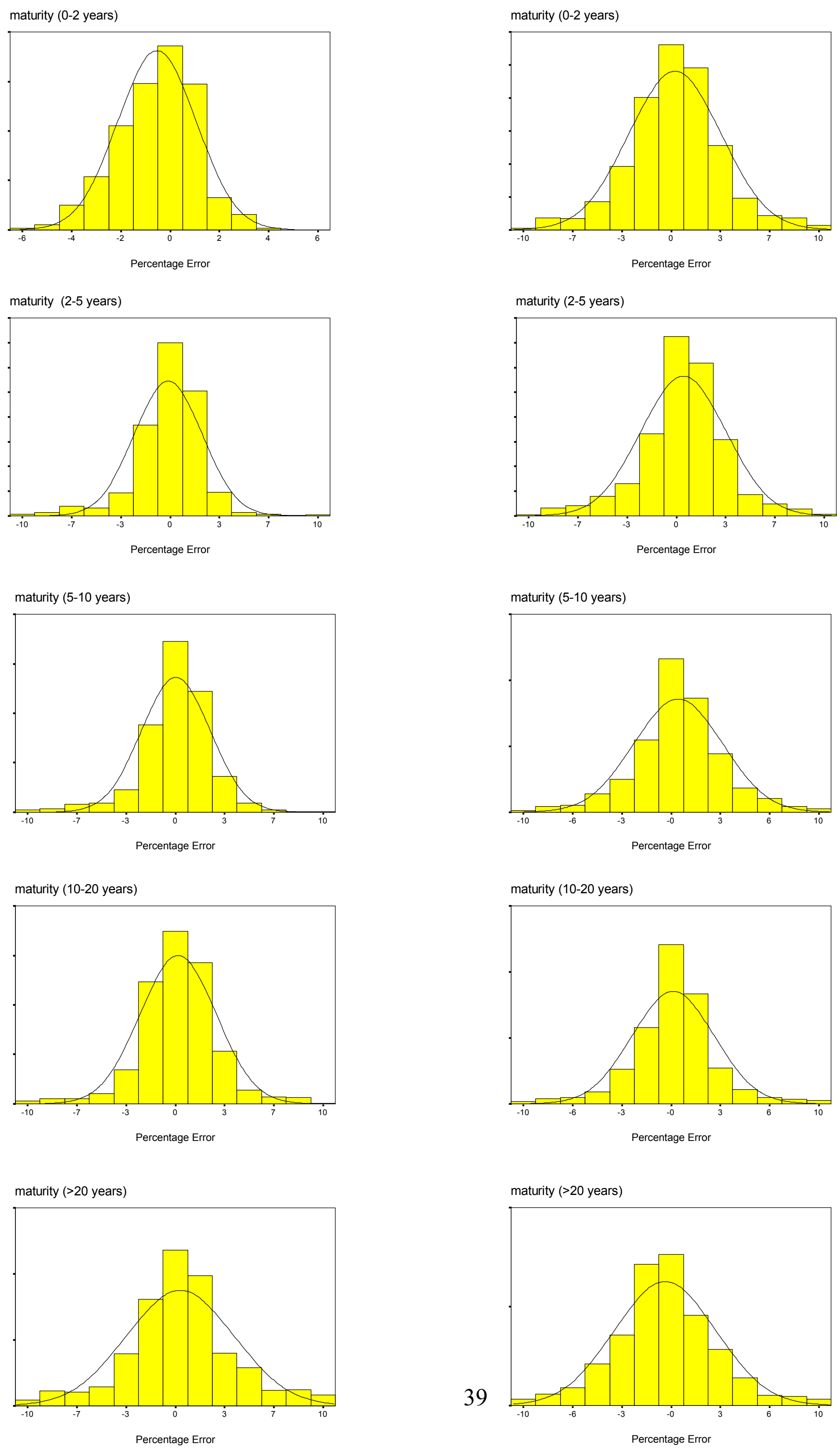
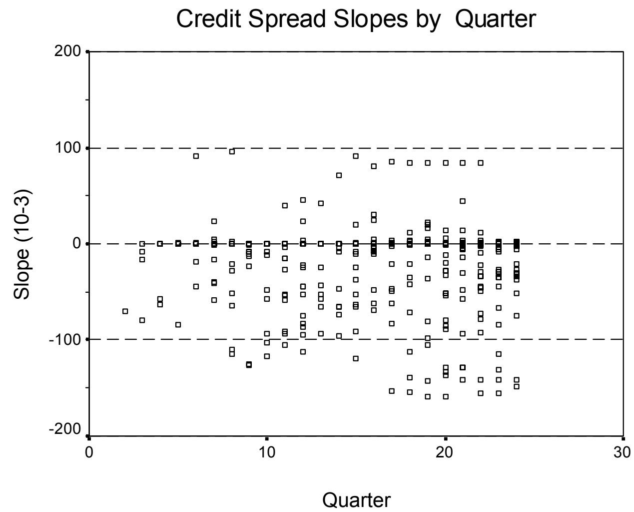
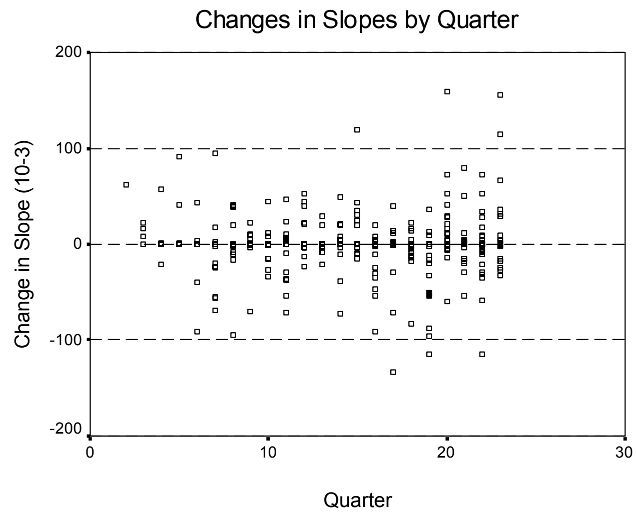


Figure 4
Credit Spread Slopes and Future Changes

The top figure shows a scatter diagram of the 10-year minus 3-year credit-spread slopes over each quarter for all banking firms. The second figure shows the changes in 10-year minus 3-year credit-spread slopes from one quarter to the next. The third figure shows the relationship between credit spread slope changes and credit spread slopes.





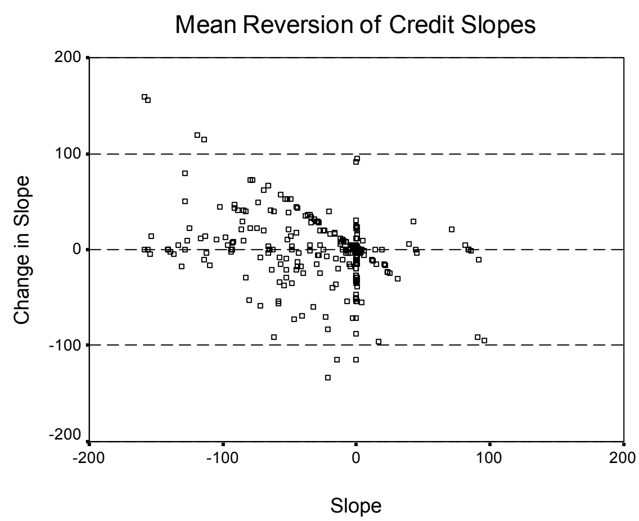
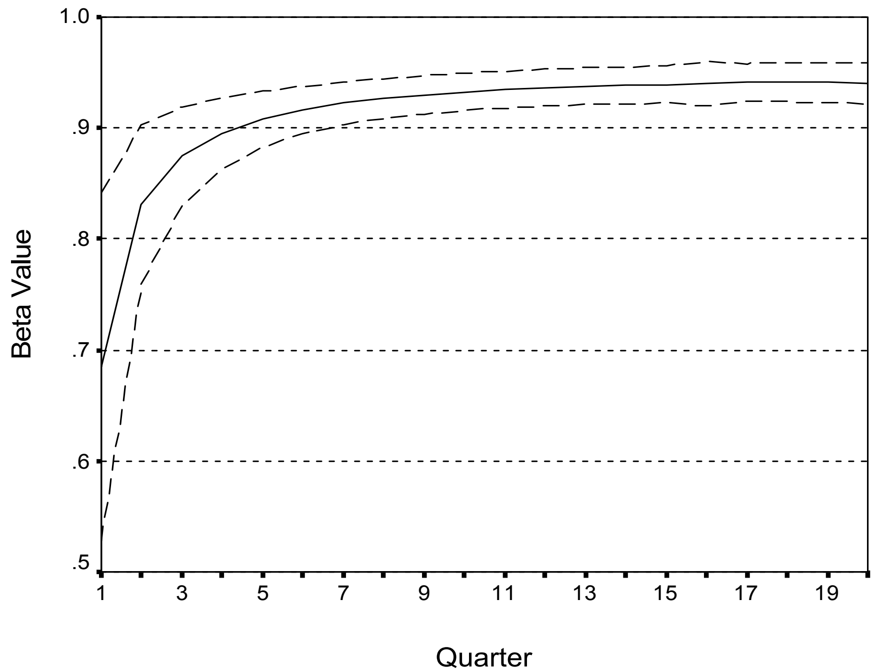


Figure 5
Predictability of Future Changes in Forward rates

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.



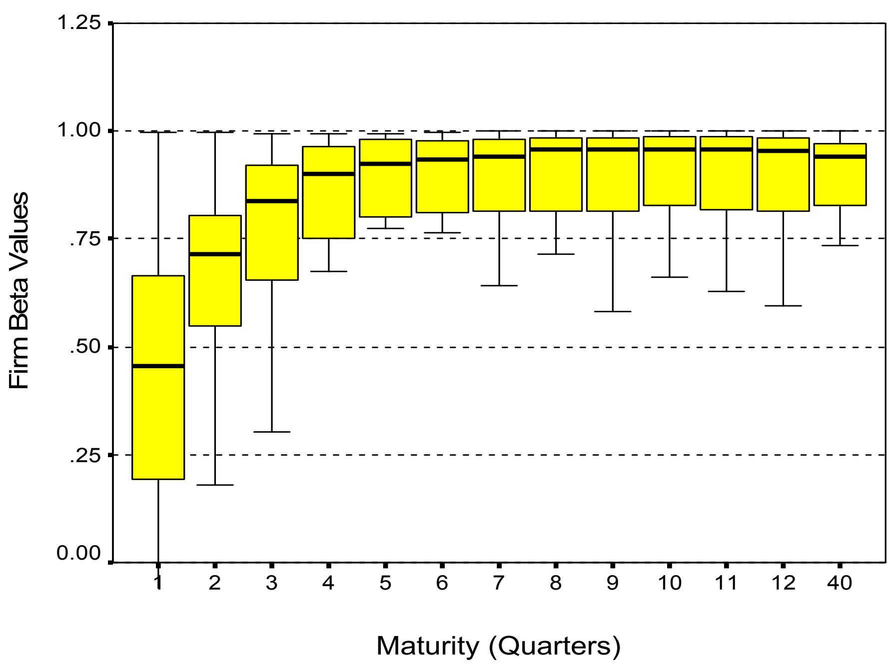


Figure 6
Predictability of Future Changes in Forward rates: Higher and Lower Rated Banking Firms

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.