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# On Credit-Spread Slopes and Predicting Bank Risk

We examine whether bank credit-spread curves, engendered by subordinated debt, 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, over and above other bank-specific and market-wide information.

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Policymakers are actively considering the use of subordinated debt 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 subordinated debt as a mechanism for enhancing market discipline of banks. The Gramm-Leach-Bliley Act of 1999 requires all large banking firms to have at least one subordinated debt issue outstanding at all times. In this paper, we examine whether credit-spread slopes engendered by subordinated debt of banks would help predict bank risk. We analyze the information content of the current term structure of credit spreads on future credit spreads of banks and future bank-specific risk.

Economists have extensively analyzed the information content of the term structure of riskless interest rates. Numerous studies, for example, have been undertaken to

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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. Fama and Bliss (1987), for example, 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 hump-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 today's term structure of credit spreads conveys any information about the future direction of forward credit spreads. This is our first objective in this paper: to examine whether the current period credit-spread slopes of banking firms contain information on future 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 (2005) 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 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 et al. (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 (2005) 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 the current period credit-spread slopes of banking firms convey information on future bank-specific risk variables.

Our study differs from the above-mentioned articles in three fundamental ways. First, with the exception of Krishnan, Ritchken, and Thomson (2005), none of the

1. For excellent reviews of this literature, see Rudebusch (1995) and Backus et al. (2001).

above studies computed the slopes of credit-spread curves since the term structure of credit spreads was never computed. Our data reveals that constructing the term structure of credit spreads is important. We find that in about 18% of cases, the short-term (3-year) credit spread and the long-term (7-year) credit spread move in opposite directions in the same time period. So, the shocks to the credit-spread curve need not be positively correlated across the maturity spectrum. 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, 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 evaluate the benefits, if any, of traded subordinated debt of banking firms.

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 recent studies that have shown that default risk accounts for a smaller component of credit spreads than had previously been thought, 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) criticize such evidence because of self-selection bias over the maturities of bonds with the same credit rating (safer issuers would tend to issue longer-term bonds). Helwege and Turner (1999) show that speculative-grade issuers have positively sloped credit spreads. Our paper is not subject to the Helwege and Turner (1999) criticism because we extract the entire term structure of credit spreads for each banking firm each quarter. 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. However, it must be noted that our sample is for banking firms only and that our sample period does not overlap with Helwege and Turner's.

Can information on today's term structure of credit spreads be helpful in predicting future credit-spread changes of a firm? In particular, are forward credit spreads unbiased predictors of future spot credit spreads? 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 et al. (2001), who investigate predictability of riskless forward rates. We find that the degree of predictability, offered by the slope of future credit spreads depends on the maturity of the credit spread. 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. Interestingly, the role of economy-wide and firm-specific information, in adding power to the forecasts of forward credit spreads, also varies by maturity. Future forward credit spreads with maturities less than a year are influenced by current stock market information. Future forward credit spreads with maturities in the one- to three-year range are influenced by current riskless term structure information, and longer-dated future forward spreads are influenced by firm-specific risk factors. Thus, shorter-maturity forward credit spreads are predicted by common market-wide factors while longer-maturity forward credit spreads are predicted by firm-specific factors.

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, we examine whether there is any relationship between today's forward credit-spread slope variables and *linear combinations* of *future* firm-specific accounting risk variables, net of the effects of current firm risk variables, economy-wide factors, as well as current period credit spreads, using canonical correlation analysis. We find evidence that credit-spread slopes do contain information, over and above other firm-specific and market-wide factors, on combinations of future bank risk variables. This relationship is especially strong for smaller banking firms, for highly levered banking firms, and for banking firms with high current Net-Chargeoff levels.

We conclude that the credit-spread slope for banking firms, in conjunction with credit ratings, is not only helpful for predicting future credit spreads, but also provides information on future bank-specific risk variables.

The remainder of the paper is organized as follows. Section 1 describes the data. Section 2 describes the model used to construct the credit-spread curves for each firm each quarter, and discusses the fit. Sections 3 and 4 examine the predictability of future credit spreads and future bank risk variables, respectively, using current period credit-spread slopes. Section 5 concludes.

## 1. DATA

### *1.1 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 Insurance 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 1994–99 by life insurance, property and casualty insurance, and health maintenance companies.[2]

For our sample of banking firms, we have 18,776 trades across 185 different firms.[3] 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 a 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.

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 seven 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 1 quarter before our data begins and 1 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.

We are, finally, left with a database that contains the transaction prices, trading dates, and the specific terms of subordinated debt, ordered by firm-quarters. The details on maturity and coupon of the debt 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 a year, and 25% of issues have maturities between

2. 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 et al. (2000, 2001) and is the one used by Campbell and Taksler (2002).

3. We use the term banking firms to refer to both banks and bank holding companies.

TABLE 1
DESCRIPTIVE STATISTICS OF BANKING FIRM SUBORDINATED DEBT TRADES

| | Initial sample | | Sample after first screen | | Sample after second screen | | Sample after third screen | |
|---|---|---|---|---|---|---|---|---|
| Quarter | # 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 |

NOTES: Our initial sample contains all banking firm debt transactions found in the National Association of Security Commissioners (NAIC) database for the period 1994–99. The first screen eliminates all debt other than fixed-rate U.S. 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 seven 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, 1 quarter before our data begins and 1 quarter after it ends.

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 by 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 subordinated debt 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).

### *1.2 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, 1-, 2-, 3-, 5-, 7-, 10, 20-, and 30-year constant-maturity-treasury rate data from January 1993 to December 2000 obtained from the website 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 3- and 6-month rates, and for the 1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-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.

### *1.3 Firm-Specific Risk Variables*

We use the following five 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 chargeoffs, computed as (Chargeoffs 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 four 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 define $F_t$ as the five-vector of firm variables at date $t$. Since the effects of these variables on credit spreads may be non-linear, we include quadratic terms and interaction effects. Let $NF_t$ be the five-vector containing the square of each of these firm-specific variables, and, following Flannery and Sorescu (1996), let $IF_t$ be a four-vector of the interaction effects obtained by multiplying leverage with each of the other firm variables.

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.

### *1.4 Market Variables*

We use three 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. We define $M_t$ as the three-vector of market variables known at date $t$.

### *1.5 Term Structure Variables*

We use two-term structure variables in our analyses. These are (a) 5-year Treasury yield and (b) the slope of the yield curve defined as the 10-year Treasury yield minus 3-year Treasury yield. The data comes from the website of the Federal Reserve Bank of St. Louis. We define $T_t$ as the two-vector of riskless term structure variables known at date $t$.

## 2. EXTRACTING CREDIT SPREADS

We 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 two-factor model to estimate the parameters of the riskless term structure 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 re-estimated 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.

### *2.1 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, $\tau$, to be a fraction, $\phi$, 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 $T$, and expectations are taken under the risk-neutralized process $Q$. 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 (2005). 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 (2005), 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 three-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, $P$, is given by

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

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

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

where $E_t^P[dw_r(t)dw_u(t)] = \rho_{ur}dt$, $E_t^P[dw_u(t)dw_s(t)] = \rho_{us}dt$, $E_t^P[dw_r(t)dw_s(t)] = \rho_{rs}dt$, $\bar{a} = a + \lambda_r\sigma_r$, and $\bar{\alpha}_1 = \alpha_1 + \lambda_s\sigma_s$.

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 $a$, $b$, $\sigma_r$, and $\sigma_u$ 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, $\sigma_s$, 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 $s(t)$.

### *2.2 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. For more details on how we estimate the credit-spread parameters, see Krishnan, Ritchken, and Thomson (2005). It should be noted that the default process for banking firms could be different from other firms; but, as mentioned before, the model is used only as a calibrating device to fit the actual price data.

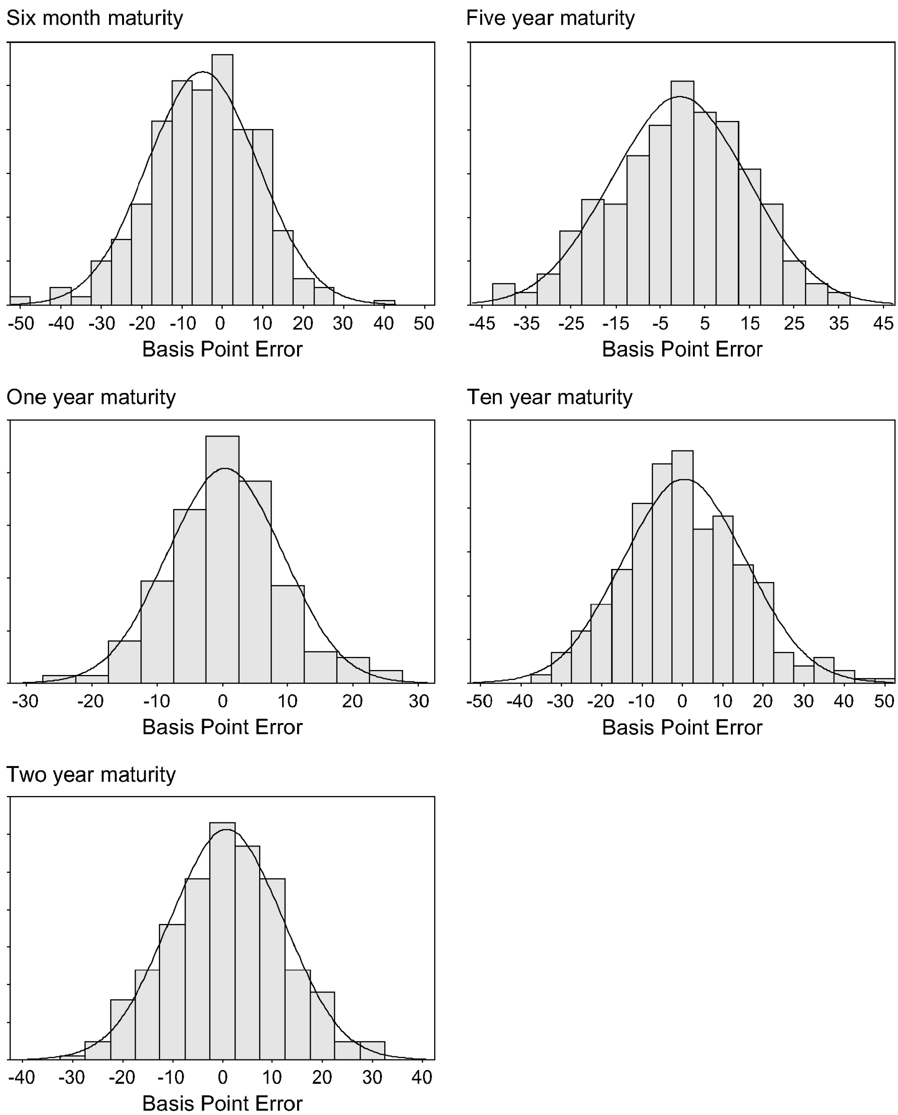



FIG. 1 Model Pricing Errors for Riskless Interest Rates
(Note: This figure shows histograms of the basis point errors, by maturity, when our two-factor double mean-reverting model is used to estimate the riskless yield curves. Each histogram consists of 364 points corresponding to consecutive weekly observations from January 1993 to December 2000. The parameter values are estimated using a Kalman filter. The errors reported are 1-week ahead prediction errors.)

### *2.3 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 1-week-ahead prediction errors, by maturity.

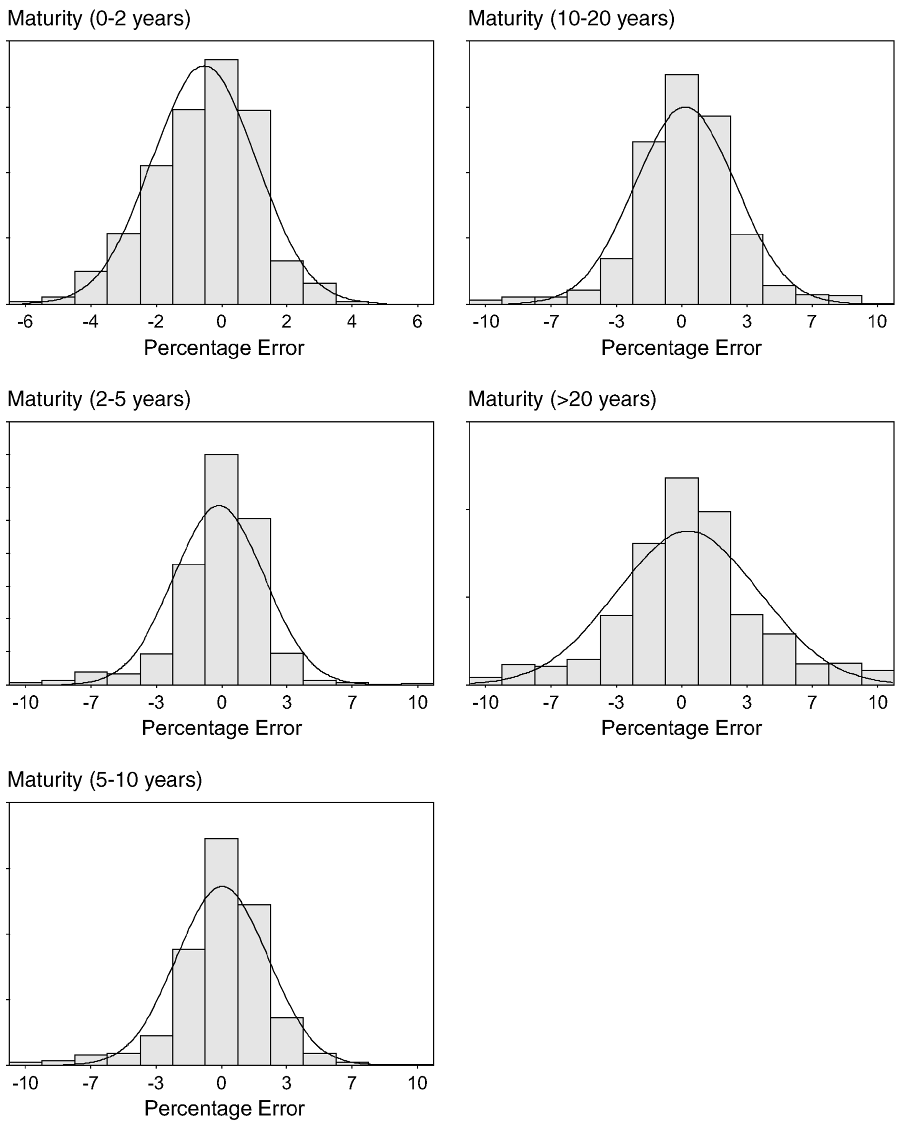
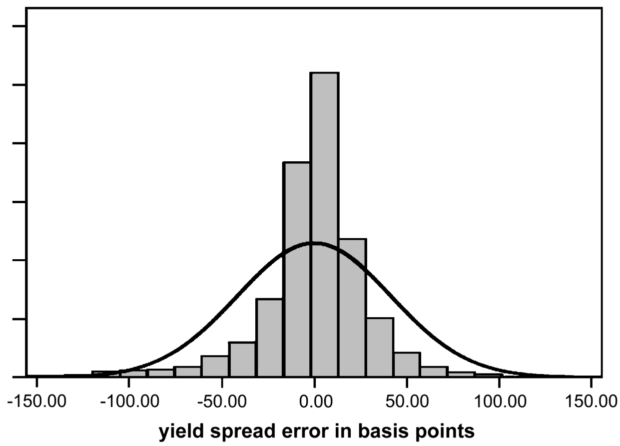



FIG. 2 Model Pricing Errors for Banking Firm Subordinated Debt
(Note: The percentage errors when our three-factor model is used to price subordinated debt issued by banking firms for different maturity buckets—defined as (0,2) years, (2,5) years, (5,10) years, (10,20) years, and $>$ 20 years.)

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 1-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




Percentiles

| 5 | 10 | 25 | 50 | 75 | 90 | 95 |
|---|---|---|---|---|---|---|
| -56.9 | -32.4 | -11.3 | 1.6 | 13.9 | 31.2 | 43.6 |

FIG. 3 Model Yield-Spread Errors for Banking Firm Subordinated Debt
(Note: The figure shows the frequency distribution plot of the yield to maturity spread differentials (in basis points) between the actual bond yields and the theoretical bond yields (from our model) for all the banking firms in our data set. Some percentiles of the distribution are also reported.)

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. In aggregate, the mean (median) pricing error was 0.22% (0.16%). In addition, we also show the distribution of errors expressed in terms of yield spreads in Figure 3. The mean yield-spread error is less than 1 basis point, the standard deviation is 41 basis points, and the inter-quartile range is about 25 basis points. These results indicate that the model is fitting actual data remarkably well with no obvious biases along the maturity spectrum.

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%. The remarkable fit confirms the fact that our model does act as an unbiased calibrating device, and the credit-spread curves do indeed effectively incorporate the information on bond prices.

Table 2 summarizes the average credit-spread levels and the average credit-spread slopes for various subsamples segregated by credit ratings, firm 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
Credit-spread Levels and Slopes

| | | Credit Ratings | | | Size | | Leverage | |
|---|---|---|---|---|---|---|---|---|
| | Maturity (Years) | Not Rated | Low | High | Small | Large | Low | High |
| Levels | 3 | 134.3<br>(10.77) | 176.2<br>(12.02) | 123.4<br>(2.22) | 135.7<br>(5.20) | 131.6<br>(3.16) | 130.5<br>(5.15) | 136.8<br>(3.21) |
| | 5 | 138.4<br>(11.18) | 156.9<br>(12.01) | 113.9<br>(1.91) | 125.9<br>(5.09) | 122.9<br>(2.89) | 122.6<br>(5.04) | 126.1<br>(2.96) |
| | 7 | 140.5<br>(11.63) | 146.7<br>(12.24) | 109.3<br>(1.92) | 120.8<br>(5.21) | 118.6<br>(2.89) | 118.6<br>(5.09) | 120.7<br>(3.07) |
| | 10 | 142.0<br>(12.15) | 138.1<br>(12.52) | 105.5<br>(2.04) | 116.6<br>(5.39) | 115.0<br>(2.98) | 115.4<br>(5.19) | 116.2<br>(3.29) |
| | Spread (Years) | | | | | | | |
| Slopes | 3–1 | 8.7<br>(5.12) | −45.3<br>(5.75) | −25.3<br>(2.40) | −24.8<br>(3.37) | −23.7<br>(2.71) | −21.8<br>(2.96) | −26.6<br>(3.14) |
| | 7–3 | 6.2<br>(4.09) | −29.4<br>(4.26) | −14.1<br>(1.51) | −15.0<br>(2.35) | −13.0<br>(1.71) | −11.9<br>(1.92) | −16.1<br>(2.18) |
| | 10–5 | 3.7<br>(2.90) | −18.8<br>(2.96) | −8.4<br>(1.03) | −9.3<br>(1.56) | −7.9<br>(1.22) | −7.2<br>(1.27) | −10.0<br>(1.52) |
| | 10–3 | 7.8<br>(5.46) | −38.0<br>(5.63) | −17.8<br>(1.97) | −19.2<br>(3.07) | −16.6<br>(2.28) | −15.1<br>(2.50) | −20.6<br>(2.88) |
| | | 63 | 81 | 338 | 241 | 241 | 241 | 241 |

Notes: The panels report the average credit-spread levels and credit-spread slopes for our final sample of 482 credit-spread curves by Credit Rating, Banking Firm 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.

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 40 basis points for most maturities, reaching a maximum of over 50 basis points for the 3-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 slope is typically twice as steep. The average 10–3 year slope for low rated firms, for example, is −38 basis points. In contrast, for the higher rated firms, the slope is −18 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%.

## 3. 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:

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

Backus et al. (2001) develop a powerful methodology for testing the expectations hypothesis for the riskless term structure by using the slope of the term structure of forward rates as an independent variable. Their regression model, adapted for forward credit spreads, is given by

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n (g_t^n - s_t) + \varepsilon_{t+1} \tag{6}$$

for all maturities, $n$. In our application, the maturities range from 1 quarter to 10 years in increments of a quarter. If the credit-spread slope can predict the $n$-quarter forward rates, then $\beta_n$ should be significantly different from 0. For the expectations hypothesis to hold, with no time varying risk premia, $\beta_n$ should be insignificantly different from 1. We estimate Equation (6) first in a pooled setting over all banking firms, and then separately for each firm in our sample.

The top panel of Figure 4 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 et al. and suggests that the nature of predictability of credit spreads might follow along lines similar to predictability of riskless forward rates.

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 is similar to the pooled regression results of the top panel. 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.

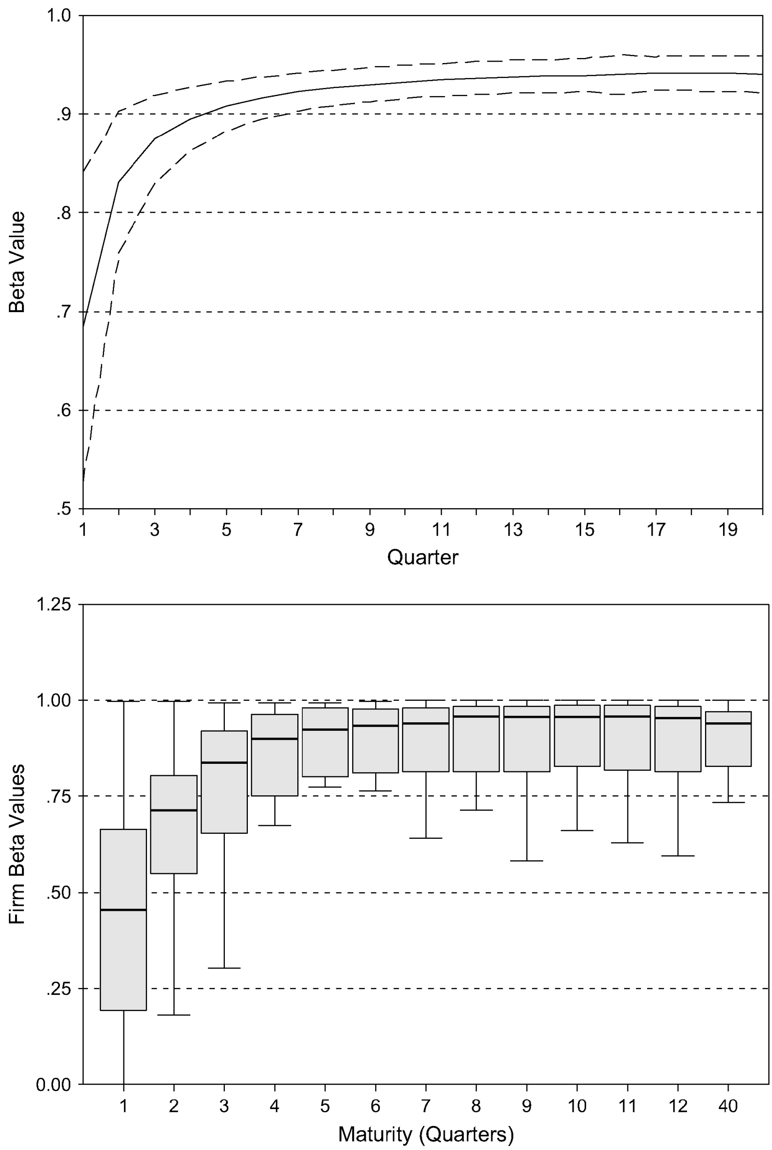



FIG. 4 Predictability of Future Changes in Forward Credit Spreads

(Note: The top figure plots the beta coefficients that predict the future (next quarter's) $n$-period forward credit spread 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 1 quarter to 20 quarters. The 95% confidence interval for the beta values is indicated by the dashed lines. The bottom figure shows a box and whiskers plot of the beta values when the regressions are performed separately for each firm and each maturity.)

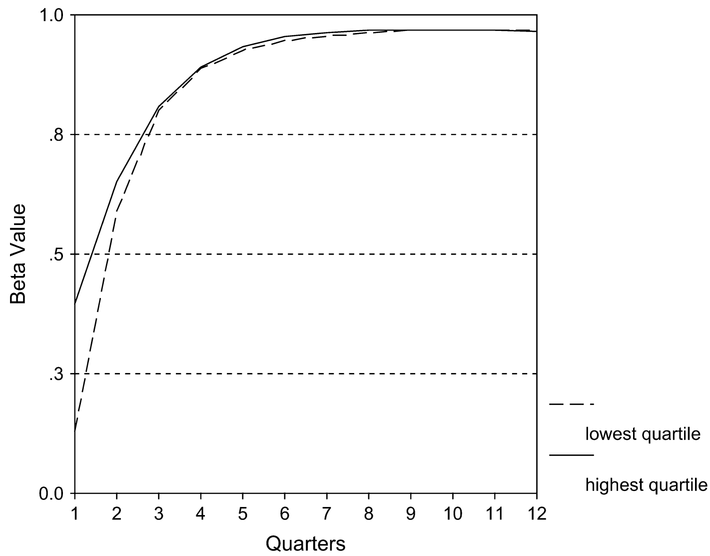



FIG. 5 Predictability of Future Changes in Forward Credit Spreads: High and Low Rated Banking Firms (Note: The figure plots the beta coefficients that predict the future (next quarter's) $n$-period forward credit spread from its current level and from the current credit-spread slope. We separated banking firms into high and low quality. The high-quality firms comprised of all banking firms in the top rating quartile; the low-quality firms were all those banking firms in the lowest rating 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 one of the two classes of firms, and $n$ ranges from 1 quarter to 12 quarters. The figure shows the beta coefficient for each of first 12 quarterly forward rates for both rating quartiles.)

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 5.

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:

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n^{(1)} R_t + \beta_n^{(2)} R_t^2 + \varepsilon_{t+1} . \tag{7}$$

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 three-vector of the slope, $g_t^n - s_t$, the slope interacted with ratings, $(g_t^n - s_t)R_t$ and the slope interacted with the square of ratings,

TABLE 3

FUTURE FORWARD CREDIT SPREADS: PREDICTIVE POWER OF CURRENT PERIOD CREDIT RATINGS AND CREDIT-SPREAD SLOPE

| Explanatory Variable | Maturity (in years) 0.25 | 0.50 | 0.75 | 1 | 2 | 3 | 5 | 10 |
|---|---|---|---|---|---|---|---|---|
| Ratings | 0.141 | −0.052 | −0.135 | −0.173 | **−0.191** | **−0.171** | −0.139 | −0.113 |
| | (0.35) | (0.26) | (0.27) | (0.17) | **(0.09)** | **(0.09)** | (0.09) | (0.11) |
| Ratings$^2$ | −0.181 | 0.008 | 0.097 | 0.140 | 0.171 | 0.158 | 0.133 | 0.122 |
| | (0.40) | (0.16) | (0.24) | (0.16) | (0.09) | (0.08) | (0.09) | (0.11) |
| Slope | 0.405 | 0.743 | 0.739 | 0.669 | 0.414 | 0.273 | 0.163 | 0.122 |
| | (1.35) | (1.49) | (0.74) | (0.56) | (0.28) | (0.23) | (0.33) | (0.27) |
| Slope X Ratings | −0.902 | −0.928 | −0.384 | 0.105 | **1.163** | **1.599** | **1.908** | **2.008** |
| | (3.01) | (2.32) | (1.92) | (2.11) | **(0.58)** | **(0.46)** | **(0.48)** | **(0.45)** |
| Slope X Ratings$^2$ | 0.845 | 0.841 | 0.464 | 0.119 | −0.628 | **−0.927** | **−1.137** | **−1.209** |
| | (1.88) | (1.68) | (1.03) | (0.66) | (0.33) | **(0.26)** | **(0.28)** | **(0.27)** |
| Sequential $R^2$ Values | | | | | | | | |
| Rating Variables | 0.002 | 0.008 | **0.021** | **0.032** | **0.052** | **0.056** | **0.058** | **0.059** |
| Slope Variables\| Rating Variables | **0.114** | **0.401** | **0.632** | **0.759** | **0.876** | **0.879** | **0.868** | **0.851** |

NOTES: The top panel of the table shows the regression coefficients, along with the associated standard errors in parenthesis, of the following regression specification:

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

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 this quarter, and $R_t$ is the current period firm rating. The slope in this equation is $(g_t^n - s_t)$. The results are reported for different $n$ (maturities) ranging from 3 months ahead to 10 years ahead. The bottom panel reports the predictive power of the ratings variables and the incremental predictive power of the slope variables given the ratings variables, measured in terms of the $R^2$ changes and the $F$-value changes. The regression analysis is performed over all the banking firms pooled together. The variables that are statistically significant at the 5% level are shown in bold font.

$(g_t^n - s_t)R_t^2$. Note that the slope variables are forward slopes for several maturities, $n$, ranging from 3 months to 10 years.

$$g_{t+1}^{n-1} - s_t = \alpha_n + \beta_n^{(1)}R_t + \beta_n^{(2)}R_t^2 + \delta_n^{(1)}(g_t^n - s_t) + \delta_n^{(2)}(g_t^n - s_t)R_t + \delta_n^{(3)}(g_t^n - s_t)R_t^2 + \varepsilon_{t+1}\,. \tag{8}$$

Table 3 shows the normalized beta coefficients of the individual regression equations, together with their $p$ values of the associated $t$-statistics.

For future forward credit spreads of maturities beyond a year, the two most important predictors are the slope-rating interaction terms. The individual predictive power of rating, rating squared, and the slope variable, by themselves, in the full model are, generally, insignificant. Collectively, however, as Table 3 shows, the three-vector of credit-spread slope variables are very informative of future credit spreads. The two-vector of ratings variables, by themselves, cannot predict forward credit spreads well. The slope variables add significantly to the explanatory power across all maturities, and especially for 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).

We now wish to establish whether credit-spread slope variables add significant predictive power of future forward credit spreads, over and above the predictive power of current credit-spread level, firm-specific variables and market-wide factors. Toward this goal, we now redefine $R_t$ as a two-vector consisting of the rating and squared rating terms at date $t$, and $\text{Slope}_t^{(n)}$ as a three-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. Note that we examine slopes of various maturities ranging from 3 months to 10 years in our analyses.[4]

In this analysis, we need to be cognizant of the fact that the bank accounting variables are not publicly known 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 Y-9 (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 five 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

$$\begin{aligned} g_{t+1}^{n-1} - s_t = \alpha_n &+ \beta_R R_t + \beta_S Slope_t^{(n)} + \beta_F F_t \\ &+ \beta_{IF} IF_t + \beta_{NF} NF_t + \beta_M M_t + \beta_T T_t + \varepsilon_{t+1} \, . \end{aligned} \tag{9}$$

where $F_t$ is the five-vector of linear firm risk variables, $NF_t$ the five-vector of non-linear (squared) firm risk variables, $IF_t$ the four-vector of interaction firm risk variables, $M_t$ is the three-vector of market variables known at date $t$, and $T_t$ is the two-vector of riskless term structure variables known at date $t$.

Table 4 reports the sequential contribution of each block of variables in predicting the next quarter's forward credit spreads. We start with the three-vector of slope variables, then sequentially add the credit rating variables, the firm accounting risk variables, the firm risk interaction variables, the firm risk non-linear variables, the market variables, and finally the riskless term structure variables. The table reports the *incremental* $R^2$ values, the sequential partial $F$ values, and the resulting $p$ values, for the different maturities of future forward credit spreads.

The block of current period credit-spread slope variables is a significant predictor of forward credit spreads for all maturities. The market variables block, consisting of GIP, S&P, and the VIX index, is a significant predictor of forward credit spreads of up to 1-year maturity, while the two-vector of term structure variables, consisting of the 5-year Treasury rate and the slope of the riskless yield curve, is significant for up to the 2-year maturity. Thus, economy-wide variables are significant predictors of

4. We use $R_t$ as a predictor because current ratings and future ratings are related through the transition matrix, and future ratings are likely correlated with future credit spreads. However, an alternate measure could be the annual ranking of corporate disclosure practices published by the Association for Investment and Management Research that measures the transparency of accounting information. This transparency measure has been used in Yu (2005) and other papers. Unfortunately, this data covers the period 1979–1996, and contains no data for banking firms for the overlapping years with our sample: 1994–1996.

TABLE 4

Future Forward Credit Spreads: Sequential Predictive Power of Current Period Variables

| Block of Variables | Maturity (years) | Sequential Contribution of Each Block: R Square Change | F Value | P Value | Maturity (years) | Sequential Contribution of Each Block: R Square Change | F Value | P Value |
|---|---|---|---|---|---|---|---|---|
| Slope variables | | **0.113** | **12.14** | **0.00** | | **0.926** | **1204.46** | **0.00** |
| Ratings variables | | 0.001 | 0.37 | 0.54 | | **0.001** | **3.64** | **0.06** |
| Firm variables (linear) | | 0.007 | 0.63 | 0.67 | | 0.000 | 0.42 | 0.83 |
| Firm interaction variables | **0.25** | 0.007 | 0.79 | 0.53 | **2** | 0.000 | 0.42 | 0.79 |
| Firm variables (non-linear) | | 0.013 | 1.09 | 0.36 | | 0.001 | 1.02 | 0.41 |
| Market variables | | **0.034** | **5.05** | **0.00** | | 0.001 | 1.29 | 0.28 |
| Term structure variables | | **0.011** | **2.40** | **0.09** | | **0.001** | **2.28** | **0.10** |
| Slope variables | | **0.405** | **65.21** | **0.00** | | **0.934** | **1356.82** | **0.00** |
| Ratings variables | | 0.000 | 0.00 | 0.98 | | **0.001** | **3.47** | **0.06** |
| Firm variables (linear) | | 0.002 | 0.28 | 0.92 | | 0.001 | 0.63 | 0.67 |
| Firm interaction variables | **0.5** | 0.007 | 1.04 | 0.38 | **3** | 0.000 | 0.55 | 0.70 |
| Firm variables (non-linear) | | 0.007 | 0.85 | 0.52 | | **0.002** | **2.20** | **0.05** |
| Market variables | | **0.024** | **5.23** | **0.00** | | 0.000 | 0.92 | 0.43 |
| Term structure variables | | 0.007 | 2.26 | 0.11 | | 0.000 | 1.19 | 0.30 |
| Slope variables | | **0.650** | **177.78** | **0.00** | | **0.925** | **1177.20** | **0.00** |
| Ratings variables | | 0.000 | 0.24 | 0.63 | | 0.000 | 2.15 | 0.14 |
| Firm variables (linear) | | 0.001 | 0.12 | 0.99 | | 0.001 | 0.83 | 0.53 |
| Firm interaction variables | **0.75** | 0.004 | 1.22 | 0.30 | **5** | 0.001 | 1.64 | 0.16 |
| Firm variables (non-linear) | | 0.003 | 0.64 | 0.67 | | **0.004** | **4.17** | **0.00** |
| Market variables | | **0.013** | **4.75** | **0.00** | | 0.001 | 1.10 | 0.35 |
| Term structure variables | | **0.005** | **2.52** | **0.08** | | 0.000 | 0.59 | 0.55 |
| Slope variables | | **0.789** | **358.71** | **0.00** | | **0.908** | **942.08** | **0.00** |
| Ratings variables | | 0.000 | 0.84 | 0.36 | | 0.000 | 1.24 | 0.27 |
| Firm variables (linear) | | 0.000 | 0.09 | 0.99 | | 0.001 | 0.94 | 0.45 |
| Firm interaction variables | | 0.003 | 1.24 | 0.29 | **10** | **0.003** | **2.68** | **0.03** |
| Firm variables (non-linear) | | 0.001 | 0.52 | 0.76 | | **0.007** | **6.02** | **0.00** |
| Market variables | | **0.007** | **3.99** | **0.01** | | 0.001 | 1.03 | 0.38 |
| Term structure variables | | **0.003** | **2.83** | **0.06** | | 0.000 | 0.50 | 0.61 |

Notes: This table shows the incremental predictive power (the $R^2$ change, $F$-statistic, and the $p$ values) of next quarter's forward credit spreads when blocks of current period variables (credit-spread slope variables, credit ratings variables, firm-specific risk variables, stock market variables, and riskless term structure variables) are sequentially added. The results are reported for different $n$ (maturities) ranging from 3 months to 10 years. The regression analysis is performed over all the banking firms pooled together. The blocks of variables with statistically significant predictive power (at the 5% level) over future forward credit spreads are shown in bold font.

forward 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, for maturities beyond 3 years, firm-specific information becomes more relevant and the blocks of firm variables and squared firm variables surface as useful predictors of forward credit spreads.

In summary, once the credit-spread slope variables are in the model, the marginal predictive power of the remaining blocks over forward credit spreads vary by maturity, with shorter maturities being more sensitive to common market factors, and longer maturities being more sensitive to firm-specific factors.

The partial $R^2$ values reported in Table 4 clearly depend on the order in which the blocks are inserted. In Table 5, we examine the marginal contribution of each block in the presence of all other blocks of variables.

Even when the credit-spread slope block of variables is the last to enter, it still adds significantly to the explanatory power over future forward credit spreads. This

TABLE 5

FUTURE FORWARD CREDIT SPREADS: PREDICTIVE POWER OF CURRENT PERIOD VARIABLES IN THE FULL MODEL

| | | Contribution of Each Block in the Full Model | | | | Contribution of Each Block in the Full Model | | |
|---|---|---|---|---|---|---|---|---|
| Block of Variables | Maturity (years) | *R* Square Change | Partial *F* Value | *P* Value | Maturity (years) | *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 | 0.149 | 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 | **0.25** | 0.025 | 0.792 | 0.679 | **3** | 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 | **0.5** | 0.012 | 0.609 | 0.847 | **4** | 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 | **0.75** | 0.007 | 0.589 | 0.863 | **5** | 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** | 0.004 | 0.569 | 0.879 | **10** | 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** | 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** | | | | |

NOTES: This table shows the predictive power (the $R^2$ change, $F$-statistic, and the $p$ values) of next quarter's forward credit spreads for each block of current period variables (credit-spread slope variables, credit ratings variables, firm-specific risk variables, stock market variables, and riskless term structure variables) in the presence of all other variables. The results are reported for different $n$ (maturities) ranging from 3 months ahead to 10 years ahead. The regression analysis is performed over all the banking firms pooled together. The blocks of variables with statistically significant predictive power (at the 5% level) over future forward credit spreads are shown in bold font.

holds true for all maturities. Further, even if the market-wide variables are the last block to enter, they still add significantly to predictability of short-term forward credit spreads. Similarly, firm-specific accounting variables have significant predictive capability over forward credit spreads, beyond all other variables, for maturities longer than 3 years.

These results, we believe, are unique since they provide evidence that, for banking firms, forward credit spreads of differing maturities have sensitivities to different sets of information. Extant studies that extract credit spreads for an individual firm without regard to maturity, and then relate changes in (scalar) credit spreads to changes in a host of independent variables may not be able to find these results because of the maturity dependent effect.

Our final analysis in this section identifies the specific variables that significantly predict future forward credit spreads. Since the most important explanatory block of variables is our credit-spread slope variables block, we force these variables into a regression model, and allow all other variables to be freely determined, using the stepwise regression procedure. Interestingly, across the maturity spectrum of forward credit spreads, the same few variables surface as consistently significant predictors. The individual regression coefficients, by maturity, are shown in Table 6.[5] We find that the returns and volatility of the stock market (VIX and S&P) are significant predictors of future forward credit spreads of up to a year. Beyond 1 year, the only market-wide variable that is significant is the 5-year Treasury yield. Beyond 3 years, no single market factor has significant influence over future credit spreads, but two bank-specific risk variables—Net-Chargeoffs and squared Net-Chargeoffs—strongly influence future forward credit spreads.

To summarize our findings, common market-wide factors are significant predictors of the shorter-maturity forward credit spreads, while firm-specific variables are significant predictors of longer-maturity forward credit spreads. One reason for the shift in the relative importance of the predictors could be the shift in the balance between the default component of credit spreads and the non-default component at different maturities. Our results suggest that it may be more reliable to try and predict the default component of longer-maturity forward credit spreads for banking firms.

## 4. CREDIT-SPREAD SLOPE AS A PREDICTOR OF BANK RISK

As discussed earlier, even if the slope helps in predicting future forward credit spreads, it may not be the case that the slope is informative for predicting any one, or indeed, any combination of future firm risk variables. In this section we investigate this issue.

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 information on market-wide and firm risk variables as well as the credit-spread level. 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

5. Typically, we end up with the same set of final variables regardless of the starting model in the stepwise regression procedure.

TABLE 6

FUTURE FORWARD CREDIT SPREADS: PREDICTIVE POWER OF INDIVIDUAL CURRENT PERIOD VARIABLES

| | | Slope Variables | | | Market Variables | | | Firm Variables | |
|---|---|---|---|---|---|---|---|---|---|
| Maturity (years) | | Slope | Slope X Rating | Slope X Ratings$^2$ | VIX | S&P | 5-year Treasury | NETC$^2$ | NETC |
| 0.25 | beta | 0.769 | −2.134 | 1.709 | 0.127 | −0.102 | | | |
| | $t$-value | 0.771 | −0.979 | 1.390 | 2.531 | −2.061 | | | |
| | $p$-value | 0.441 | 0.328 | 0.165 | 0.012 | 0.040 | | | |
| 0.50 | beta | 0.734 | −1.262 | 1.180 | 0.108 | −0.081 | | | |
| | $t$-value | 0.929 | −0.733 | 1.215 | 2.638 | −2.003 | | | |
| | $p$-value | 0.353 | 0.464 | 0.225 | 0.009 | 0.046 | | | |
| 1.00 | beta | 0.416 | 0.457 | 0.020 | 0.072 | | | | |
| | $t$-value | 0.951 | 0.477 | 0.037 | 3.057 | | | | |
| | $p$-value | 0.342 | 0.633 | 0.971 | 0.002 | | | | |
| 1.25 | beta | 0.304 | 1.015 | −0.396 | | | −0.054 | | |
| | $t$-value | 0.890 | 1.357 | −0.931 | | | −2.854 | | |
| | $p$-value | 0.374 | 0.176 | 0.352 | | | 0.005 | | |
| 1.50 | beta | 0.234 | 1.320 | −0.616 | | | −0.045 | | |
| | $t$-value | 0.828 | 2.124 | −1.735 | | | −2.728 | | |
| | $p$-value | 0.408 | 0.034 | 0.083 | | | 0.007 | | |
| 2.00 | beta | 0.146 | 1.692 | −0.891 | | | −0.032 | | |
| | $t$-value | 0.649 | 3.407 | −3.109 | | | −2.323 | | |
| | $p$-value | 0.517 | 0.001 | 0.002 | | | 0.021 | | |
| 2.25 | beta | 0.116 | 1.812 | −0.981 | | | −0.028 | | |
| | $t$-value | 0.551 | 3.877 | −3.618 | | | −2.109 | | |
| | $p$-value | 0.582 | 0.000 | 0.000 | | | 0.036 | | |
| 2.50 | beta | 0.052 | 1.988 | −1.095 | | | | | |
| | $t$-value | 0.258 | 4.434 | −4.190 | | | | | |
| | $p$-value | 0.797 | 0.000 | 0.000 | | | | | |
| 3.00 | beta | 0.028 | 2.098 | −1.184 | | | | | |
| | $t$-value | 0.150 | 4.899 | −4.701 | | | | | |
| | $p$-value | 0.881 | 0.000 | 0.000 | | | | | |
| 4.00 | beta | −1.071 | 4.312 | −2.339 | | | | −0.184 | 0.102 |
| | $t$-value | −3.058 | 6.035 | −6.117 | | | | −3.584 | 2.808 |
| | $p$-value | 0.002 | 0.000 | 0.000 | | | | 0.000 | 0.005 |
| 5.00 | beta | −1.260 | 4.702 | −2.553 | | | | −0.231 | 0.129 |
| | $t$-value | −3.752 | 6.842 | −6.897 | | | | −4.381 | 3.439 |
| | $p$-value | 0.000 | 0.000 | 0.000 | | | | 0.000 | 0.001 |
| 10.00 | beta | −1.527 | 5.218 | −2.831 | | | | −0.327 | 0.185 |
| | $t$-value | −4.828 | 8.000 | −7.921 | | | | −5.753 | 4.528 |
| | $p$-value | 0.000 | 0.000 | 0.000 | | | | 0.000 | 0.000 |

NOTES: This table reports the regression coefficients, $t$-statistics, and $p$ values when the future (next quarter) forward credit spread is regressed on current period credit-spread slope variables, credit ratings variables, firm-specific risk variables (linear, non-linear, and interactive), stock market variables, and riskless term structure variables. The slope variables are forced in, and stepwise regression is used for all other variables. The regression analysis is performed over all the banking firms pooled together. The significant market variables are the VIX index, the S&P return, and the 5-year Treasury rate. The significant firm variables are Net-Chargeoffs (NETC) and Net-Chargeoffs square (NETC$^2$).

correlations, then slope variables may be useful for predicting the direction of the risk for the overall set of firm variables.

Let

$$Y_{t+1} = (F_{t+1}, NF_{t+1}, IF_{t+1})$$

$$C_t = (F_t, NF_t, IF_t, M_t, T_t, R_t, S_t)$$

$$X_t = (Slope_t^{(0.25)}, Slope_t^{(0.5)}, Slope_t^{(0.75)}, Slope_t^{(1)},$$

$$Slope_t^{(2)}, Slope_t^{(3)}, Slope_t^{(5)}, Slope_t^{(10)})\ .$$

Here $Y_{t+1}$ is a 14-vector of next quarter bank-specific risk variables (linear, nonlinear, and interaction variables), $C_t$ is a 22-vector consisting of current period firm, market, term structure, and ratings variables as well as the current credit-spread level. $X_t$ is a 24-vector of the three-vector of current period credit-spread slope variables for each of our eight 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 linear combinations of current period credit-spread slope variables, $X$, on 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 $C$ has 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.

The top panel of Table 7 reports the canonical correlations, canonical redundancy measures, as well as the chi square 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, $X$, are assessed above and beyond the effects of $C$ on $Y$.

Looking at the top left panel, the chi square test statistics reveal that the first five linear combinations of current period explanatory variables are all significantly correlated with linear combinations of future bank risk variables. The top right panel chi square test statistics show that, net of the effects of $C$, the best linear combination of current period slope variables with linear combinations of future bank risk variables has a canonical correlation of 0.787, while the next best orthogonal set has a correlation of 0.587. This means that the best linear combination of slope variables accounts for $0.787^2 = 62\%$ of the variability of the best linear combination of the future bank risk variables. Thus, current period slope variables add significant power to the prediction of future bank risk variables, above and beyond the information contained in current period bank risk variables, credit ratings, market variables, term structure variables, and current credit-spread level.

In the bottom left panel of Table 7, we report the canonical loadings associated with the firm risk variables, $Y$. The important canonical loadings for the first dependent canonical covariate are on Return on Assets, *ROA*, Non-Performing-Assets, *NPA*, Net-Chargeoffs, *NETC*, the quadratic effects, $NPA^2$, $NETC^2$, and on the interaction effect of leverage with Net-Chargeoffs, $LEV \times NETC$. The coefficients of these terms are all signed correctly, in the sense that variables that increase bank risk have positive coefficients and variables that decrease bank risk have negative coefficients. In this regard, the first dependent canonical covariate can be viewed as a measure of risk that is 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 dependent covariate. For example, the first

TABLE 7

FUTURE BANK RISK VARIABLES: PREDICTIVE POWER OF CURRENT PERIOD CREDIT-SPREAD SLOPE VARIABLES

| Full Model | | | | Slope Variables (given other variables partialled out) | | | |
|---|---|---|---|---|---|---|---|
| Canonical Factor | Canonical Correlation | Canonical Redundancy | Chi Square | Canonical Factor | Canonical Correlation | Canonical Redundancy | Chi Square |
| 1 | 0.989 | 0.213 | 5967* | 1 | 0.787 | 0.042 | 748* |
| 2 | 0.969 | 0.268 | 4626* | 2 | 0.587 | 0.003 | 422* |
| 3 | 0.928 | 0.061 | 3645* | 3 | 0.5 | 0.011 | 278 |
| 4 | 0.901 | 0.047 | 2953* | | | | |
| 5 | 0.882 | 0.072 | 2365* | | | | |

Canonical Loadings for the First Pair of Covariates for the Partialled Model

| | Dependent Future firm risk variables | Canonical Loading | | Independent Slope variables (maturity) | Canonical Loading |
|---|---|---|---|---|---|
| Linear | ROA | **−0.249** | Slope | 0.25 | 0.283 |
| | LOAN | −0.064 | | 0.5 | 0.281 |
| | NPA | **0.220** | | 0.75 | 0.270 |
| | NETC | **0.368** | | 1 | 0.254 |
| | LEV | −0.034 | | 2 | 0.179 |
| Non-linear | $ROA^2$ | −0.184 | | 3 | 0.119 |
| | $LOAN^2$ | −0.092 | | 5 | 0.052 |
| | $NPA^2$ | **0.341** | | 10 | 0.005 |
| | $NETC^2$ | **0.652** | Slope X Rating | 0.25 | 0.171 |
| | $LEV^2$ | −0.020 | | 0.5 | 0.173 |
| Interaction | LEV X ROA | **−0.230** | | 0.75 | 0.168 |
| | LEV X LOAN | −0.086 | | 1 | 0.160 |
| | LEV X NPA | 0.092 | | 2 | 0.122 |
| | LEV X NET | **0.238** | | 3 | 0.090 |
| | | | | 5 | 0.054 |
| | | | | 10 | 0.030 |
| | | | Slope X $Rating^2$ | 0.25 | 0.106 |
| | | | | 0.5 | 0.108 |
| | | | | 0.75 | 0.105 |
| | | | | 1 | 0.100 |
| | | | | 2 | 0.078 |
| | | | | 3 | 0.061 |
| | | | | 5 | 0.041 |
| | | | | 10 | 0.029 |

NOTES: The table shows the canonical correlations between the set of future (next quarter) firm risk variables and the set of current predictor variables. The future firm risk variables consist of five linear firm variables, five non-linear terms, and four interaction effects. The independent set consists of the same 14 firm risk variables in the current period, together with the market and riskless term structure variables, the current period short credit spread, and the three slope variables for each of the eight maturities. The top left panel reports the canonical correlations, redundancy measures, and chi squared statistics for the significant correlation pairs. The top right panel reports the same statistics when the effects of all independent variables except slope variables on the dependent variables have been partialled out. The regression analysis is performed over all the banking firms pooled together. The symbol * denotes significance at the 5% level. The bottom panel reports the canonical loadings for the most significant canonical pair of the partialled model. The bottom left panel shows the loadings of the dependent variables (the future firm risk variables), while the bottom right panel shows the loadings of the independent variables (the current period slope variables). The significant loadings (at the 5% level) of future firm risk variables are shown in bold font.

covariate explains about 6%, of the variability of *ROA*, 5% of *NPA*, 14% of *NETC*, 12% of $NPA^2$, 43% of $NETC^2$, and almost 6% of $LEV \times NETC$. All the loadings of the first independent canonical variate comprising the slope variables are positive.

In conclusion, there is a combination of future bank-specific accounting risk variables that can be well predicted by a combination of current period credit-spread slope variables, even after all other information known to the market, that is information on C, is removed.

Do the current period slope variables have power, net of other information already available to the market, to forecast *individual* bank accounting risk variables? This information is provided by the canonical redundancy measures shown in Table 7. The canonical redundancy measure for the first dependent canonical function is equivalent to first computing the average $R^2$ values between the dependent canonical function and each future bank risk variable. This provides an average statistic of how strongly each firm variable shares variability with its dependent covariate. The second stage is to multiply this number by the square of the canonical correlation. The resulting number provides a measure of how much the best linear combination of the predictor variables can, on average, predict each individual future bank risk variable. In our case, this "average" is about 4%. That is, once the information contained in $C$ is partialled out, the slope variables in the first independent canonical function, can explain on average about 4% of the variation of each of our 14 future firm risk variables.

### *4.1 Robustness Checks*

Canonical correlations analysis is 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 robustness tests to corroborate our finding that current period credit-spread slopes are indeed capable of signaling additional information about future firm risk, over and above information contained in credit-spread levels, current firm risk variable levels (including non-linear and interaction effects), market variables, and riskless term structure variables.

Our first analysis repeats the previous analysis, but rather than use slope information over all eight 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 three, the dimension of $X_n$, where $X_n = (Slope_t^{(n)})$. The top left panel of Table 8 shows the results for each of the future forward credit spreads over eight different maturities. The top right panel shows the impact of canonical correlations when the effects of $C$ are partialled out. In both cases, the first canonical correlation is consistently significant for all maturities. In all these cases, the canonical variate for the firm risk variables does indeed have the interpretation of being a bank risk variable, and the most significant firm risk loadings are on the same sets of variables as reported in Table 7.

Our final robustness check is to examine the canonical covariates for various banking firm subsamples. The bottom panel of Table 8 reports the canonical correlations, redundancy measures as well as the chi square test statistics for the full sample of banking firms and for various subsamples: small and large banking firms (based on total assets), high and low leveraged banking firms, and banking firms with high and low Net-Chargeoffs. High and low categories are defined in terms of being above

TABLE 8

Canonical Correlation Analysis: Robustness Checks of Slope Variables as Predictors of Future Bank Risk

| | Maturity (years) | Full Model Canonical Correlation | Full Model Canonical Redundancy | Full Model Chi Squared Value | Partialled Model Canonical Correlation | Partialled Model Canonical Redundancy | Partialled Model Chi Squared Value |
|---|---|---|---|---|---|---|---|
| By maturity | 0.25 | 0.988 | 0.222 | 5199.3* | 0.666 | 0.022 | 223.143* |
| | 0.50 | 0.988 | 0.222 | 5148.8* | 0.625 | 0.017 | 191.496* |
| | 0.75 | 0.988 | 0.222 | 5107.2* | 0.582 | 0.012 | 162.898* |
| | 1 | 0.988 | 0.222 | 5076.9* | 0.544 | 0.009 | 140.516* |
| | 2 | 0.988 | 0.221 | 5027.9* | 0.456 | 0.003 | 99.620* |
| | 3 | 0.988 | 0.221 | 5019.3* | 0.429 | 0.002 | 89.813* |
| | 5 | 0.988 | 0.221 | 5018.8* | 0.417 | 0.003 | 86.115* |
| | 10 | 0.988 | 0.221 | 5021.6* | 0.417 | 0.004 | 85.772* |
| All maturities | All Banking Firms | 0.989 | 0.213 | 5967.9* | 0.787 | 0.042 | 760.068* |
| | Small | 0.983 | 0.318 | 2856.1* | 0.819 | 0.046 | 463.54* |
| | Big | 0.992 | 0.312 | 2793.8* | 0.649 | 0.042 | 302.71 |
| | High Leverage | 0.986 | 0.371 | 3272.9* | 0.779 | 0.047 | 505.37* |
| | Low Leverage | 0.993 | 0.311 | 2572.6* | 0.627 | 0.014 | 249.79 |
| | High Net-Chargeoffs | 0.989 | 0.351 | 3452.8* | 0.785 | 0.047 | 430.85* |
| | Low Net-Chargeoffs | 0.993 | 0.301 | 2222.6* | 0.607 | 0.013 | 226.74 |

Notes: The table shows the canonical correlations, canonical redundancies, and the chi squared values associated with the most significant correlation pair. The dependent variables are future (next quarter) firm risk variables: the linear, non-linear, and interaction variables. The left panel reports the statistics for the full model, while the right-hand side reports the statistics for the slope variables after the effects of the current period credit-spread level, firm risk variables, market effects, and riskless term structure effects have been partialled out. The top panel reports the results for future forward credit spreads of different maturities when the independent variables are the three slope variables for the given maturity. The regression analysis is performed over all the banking firms pooled together. The bottom panel reports the results when the three slope variables of eight different maturities are all used together, and the analysis is conducted for the full sample of banking firms as well as for different subsample of banking firms. The symbol * denotes significance at the 5% level.

and below the sample median respectively.[6] We segregate banking firms based on their current level of Net-Chargeoffs because this particular bank-specific accounting risk variable turned out to be a significant predictor of future forward credit spreads of longer maturities (see Table 6). The bottom left panel of Table 8 shows the results when the effects of $C$ are not partialled out. The bottom right panel shows the first canonical correlations when the effects of $C$ are partialled out.

The left panel, not surprisingly, shows that the first canonical correlation is always significant for the full sample, as well as for the various subsamples. The right panel shows that the best linear combination of the current period credit-spread slope variables correlates highly with future bank risk variables, after the effects of credit-spread level, rating, firm, and economy-wide variables have been partialled out, for the full sample and for select subsamples: small banking firms, highly levered banking firms, and banking firms with high current Net-Chargeoffs. Thus, high current levels of Net-Chargeoffs, a cash flow variable, signals information to the market about bank risk. The canonical correlation between the first linear combination of future firm risk variables and the slope variables is about 0.80 for the full sample as well as for these four subsamples. The chi square statistics indicate that the first canonical variates have significant correlation for the full sample and for these

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

subsamples: about 60% of the variability of the linear combination of future bank risk variables is explained by the best linear combination of current period slope variables. In contrast, the canonical redundancy measures indicate that, on average, only between 4% and 5% of the variability of any individual future bank accounting variable is explained by the first independent canonical covariate. While slope information, at the margin, may not provide a strong signal for individual risk variables, it does provide a strong signal for combinations of firm accounting variables that collectively measure bank risk.

Overall, for smaller banking firms, for more leveraged banking firms, and for banking firms with high current levels of Net-Chargeoffs, the slope and slope-rating interaction variables collectively are capable of predicting bank-specific risk in the aggregate, above and beyond other information that the market possesses.

## 5. CONCLUSION

In this paper, we examine two issues. First, we investigate whether the shape of the term structure of credit spreads of banking firms conveys any information about the future direction of credit spreads. Second, we assess whether current period credit-spread slopes convey additional predictive information on future bank-specific risk variables above and beyond information that the market possesses. Our study confines itself to investigating banking firms because the information content of bank subordinated debt has policy-specific implications.

We find strong evidence that current credit-spread slopes can predict future forward credit spreads. Predictability is always present across all maturities. However, the expectations hypothesis for forward credit spreads is rejected in favor of time varying risk premia. Further, we find that forward credit spreads of different maturities have sensitivities to different sets of information. At the short end, market variables significantly influence future forward credit spreads. At the longer end, current period bank-specific risk variables significantly influence future forward credit spreads.

We also find evidence that there is a significant linear association between current period slope variables and future bank risk variables, even after all our firm-specific, ratings, credit-spread level effects, and economy-wide information is accounted for. Further, this association is strongest for small banks, for highly leveraged banks, and for banks that have high Net-Chargeoffs. These results indicate that current period credit slope contains information not only for predicting future credit-spread levels, but also for assessing future levels of bank-specific risk.

Our results lead us to conclude that credit-spread curves engendered by a mandatory subordinated debt requirement for banks will provide useful additional information not only about future credit-spread levels but also about future bank risk variables, above and beyond the accounting risk information, economy-wide information, and credit ratings information known to the market. However, such a conclusion must be tempered with the realization that, currently, in the absence of any mandatory requirement, our sample consists only of banks that have voluntarily selected to issue subordinated debt. Further, the benefits of predictability arising from making subordinated debt issue mandatory for banks will be paid for, at least in part, by the opportunity cost of sub-optimal debt issuances.

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