Monitoring and Controlling Bank Risk: Does Risky Debt Serve any Purpose?

C.N.V. Krishnan * P.H. Ritchken † J.B. Thomson ‡

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*Weatherhead School of Management, Case Western Reserve University, Cleveland, Ohio. Email: cnk2@cwru.edu

†Weatherhead School of Management, Case Western Reserve University, Cleveland, Ohio. Email: phr@weatherhead.cwru.edu

‡Federal Reserve Bank of Cleveland, Cleveland, Ohio. Email: JB.Thomson@clev.frb.org

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Abstract

We examine whether mandating banks to issue subordinated debt would serve to enhance market monitoring and control risk taking. To evaluate whether subordinated debt enhances risk monitoring, we extract the credit-spread curve for each banking firm in our sample and examine whether changes in credit spreads reflect changes in bank risk variables, after controlling for changes in market and liquidity variables. We find that they do not. Our result is robust to firm type, examination rating, size, leverage and profitability, as well as to different model specifications. To evaluate whether subordinated debt controls risk taking, we examine whether issuing subordinated debt changes the risk-taking behavior of a bank. We find that it does not. We conclude that a mandatory subordinated debt requirement for banks is unlikely to provide the purported benefits of enhancing risk monitoring or controlling risk-taking.

(*Bank Risk Changes; Estimation of Credit-Spread Curves*)

Since the mid 1980s economists have debated the merits of regulations that would require banks to issue a minimum level of subordinated notes and debentures (SND). Proponents of this regulation suggest that SND will enhance market discipline and curb excessive risk taking in two ways: through *risk monitoring* and through *preventative influence*. The benefits of monitoring are realized if investors accurately understand changes in a firm's risk condition and incorporate their assessment promptly into the prices of risky debt issued by the firm. If they do, then changes in credit spreads will provide useful information to regulators and assist in supervision. This is referred to as indirect market discipline. The direct effect results from the increased costs of funding that result from investors being able to accurately reprice debt, should the bank adopt riskier strategies. Due to market risk monitoring, banks with SND may be less likely to adopt risky strategies in the first place. This is the preventative influence role of SND.

The purpose of this paper is to examine whether SND issued by banks and bank holding companies (BHCs) (together referred to as banking firms) enhance risk monitoring and/or have preventative influence. To evaluate risk monitoring, we examine whether changes in firm-specific risks get reflected in changes in credit spreads of SND issued by banking firms, after controlling for economy wide factors and liquidity factors. To evaluate preventative influence, we examine changes in risk characteristics of banks and BHCs after they first issued SND.

We focus on banking firms because 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 (Basel II) that seeks to improve the incentive effects of capital regulation through increased granularity in risk measurement, improved supervision, and increased market discipline. Mandatory subordinated debt requirement appears to be the cornerstone of Basel II's market discipline provisions. In addition, the U.S Shadow Regulatory Committee has come out strongly in favor of mandatory SND as a mechanism for realizing enhanced market discipline of banks. Finally, the Gramm-Leach-Bliley Act of 1999 mandated a joint Federal Reserve and U. S. Treasury study of bank subordinated debt requirements. This legislation also requires all large banking firms to have at least one issue of subordinated debt outstanding at all times.

A lengthy literature exists that addresses the question of whether market prices of liabilities respond to individual bank risk taking. To date the results of empirical studies have been mixed. Studies done prior to 1992 fail to find a significant relationship between firm risk and yields on subordinated debt.[1] More recent studies, however, do indicate that risk is being appropriately priced. For example, Flannery and Sorescu (1996) find that for banks over the 1983-1991

[1] Examples include Avery, Belton and Goldberg (1988), Gorton and Santomero (1990), who find no effects, Cramer and Rogowski (1985) and Goldberg, Jooyd-Davies (1985) who obtain mixed conclusions, and Baer and Brewer (1986), and Hannan and Hanweck (1988). For excellent reviews of this literature see Flannery (1998) and Bliss (2000).

period, yields on SND were affected by accounting measures of risk. Jagtiani, Kaufman and Lemieux (2000) confirm this result for the post-1991 period; a period that follows the passage of the Federal Deposit Insurance Corporation Improvement Act (FDICIA) that supposedly made the breadth of the safety net for banks more restrictive.[2] A related literature concerns itself with the extent to which financial market prices contain timely and accurate information on the financial condition of banks that is of use to bank supervisors. Empirical studies by Berger, Davies and Flannery (2000), DeYoung, Flannery, Lang and Sorescu (2001) and Evanoff and Wall (2001) indicate that neither the market nor the supervisors possess all information on firm-specific risk.

In almost all of the SND studies, the credit spread of SND is defined as the difference in basis points between the yield to maturity (YTM) of the issue and the YTM of an equivalent Treasury security. For example, Flannery and Sorescu (1996) calculate the default risk premium as the SND yield minus the YTM of a treasury bond with approximately the same maturity date. Yu (2002) uses credit spreads as the dependent variable that is defined as the difference between the yield to maturity on a corporate bond and the interpolated constant maturity Treasury yields.[3] Once obtained, these spread measures are often used as dependent variables, in a regression equation against risk variables.[4] No studies in this literature, that we are aware of, attempt to extract the *term structure* of credit-spreads for each bank. The importance of this is now well recognized. There is now much empirical evidence to suggest that credit spreads of different maturities for the same firm may move in different directions. In particular, the credit-spread curve can, over time, move upward, downward, or reflect humped shaped shocks. We contribute to the literature by carefully extracting entire credit-spread curve for each firm for each quarter, and then relating *changes* in credit spreads at different points on the credit-spread curve to *changes* in risk variables.

We first examine whether firm-specific risk variables influence credit spreads *levels*, and confirm that they do, even after controlling for market-wide and liquidity variables. However, relating levels of credit spreads to levels of firm risk variables is a necessary but not sufficient condition for credit spreads to serve as a information signal on changing bank risk. We need *changes* in bank risk to be reflected in credit spread *changes*. Hence, we examine whether changes in credit spreads reflect changes in firm-specific risks after controlling for market-wide and liquidity factors, and find that they do not. We subdivide our sample of banking firms

[2]Other recent studies include De Young et al (2001), Morgan and Stiroh (2001) and Sironi (2002).

[3]The economic interpretation of the resulting spread is ambiguous since coupon differentials between the risky and riskless bonds are not explicitly accounted for, and the durations of the two bonds could be quite different. Moreover, even if the durations were identical, comparing credit spreads for two issues from the same firm, could lead to very different results due to maturity effects.

[4]Alternatively, structural option pricing models can be used in which the relationship of large uninsured liabilities cannot be described by a linear function of risk variables.

by banks and BHCs, by examination rating, by size, by leverage, and by profitability, and reestimate our model. We find that our result is robust. Next we reestimate our model with three new regression specifications. We replace all variables that are time dependent with time fixed effects dummies to capture all time varying factors. We include lagged firm risk levels in our regression models to capture the possibility that the effect of firm risk changes may be a function of the starting risk level. We include stock returns and changes in examination (CAMELS and BOPEC) ratings as control factors in our regression models. We do not find a statistically significant relationship between changes in bank risk variables and changes in credit spreads.

Our result could be due to the fact that banking firms are highly regulated. Therefore, we use a sample of non-banking firms as a control group. We again find that changes in credit spreads do not reflect changes in firm-specific risk characteristics, after controlling for changes in market and liquidity variables. Thus, our result appears to be more general than for just banking firms.

Because we extracted the term structure of credit spreads for each firm, we analyze the determinants of credit-spread slope and changes in credit-spread slope. Consistent with our results on credit spread levels and changes in credit spread levels, we find that while credit-spread slope is determined by firm risk variables, we are unable to relate *changes* in credit-spread slope to changes in firm risk variables.

Since credit spread changes are not informative of firm-specific risk changes, our results cast doubt on the usefulness of credit spread changes as an information signal for bank supervisors, and in particular, as a triggering mechanism for special audits. However, this result does not imply that the issuance of SND serves no purpose. After all, given that credit spread levels and slope reflect firm-specific risk, the very issuance of SND may alter the incentives of managers and effect the risk taking behavior of a bank. Specifically, banks may take actions that result in lower risk just because risky debt exists on the balance sheet. This is the disciplinary effect, or *preventative influence* role of risky debt that helps regulators by reducing risk-taking in the first place. To address this possible role of SND, we examine how bank risk changes after a banking firm first issues SND. We use two measures of firm risk changes: raw risk changes and matched-adjusted risk changes over and above a portfolio of size, leverage and profitability matched non SND-issuing banking firms for each SND-issuing banking firm. We find no significant change in the firm-specific risk characteristics. Thus, we fail to find evidence consistent with preventative influence effect for SND.

We therefore conclude that making issuance of SND mandatory for banking firms is unlikely to provide the purported benefits of enhanced risk monitoring or preventative influence, as envisioned by the Basel committee. Nevertheless, our results do not mean that mandatory SND serves no purpose whatsoever. SND can still reduce the exposure of the deposit insurance fund and uninsured depositors to losses associated with bank failures.

The remainder of the paper is organized as follows. The first section describes the data extraction process and our final data. Section 2 sets out the model we use to construct the credit spread curves for each firm and discusses the fit. Section 3 describes our sets of firm specific risk variables, market variables and liquidity variables. Section 4 examines whether risky debt facilitates market monitoring of bank risk. Section 5 examines whether risky debt has preventative influence benefits for banking firms. Section 6 concludes.

1 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 large set 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, which is only available over quarterly intervals.

The data for our analysis comes from the Fixed Income Securities Database (FISD) on corporate bond characteristics matched to the National Association of Security Commissioners (NAIC) database on bond transactions for the period January 1994 through December 1999. The FISD database contains issue and issuer-specific information such as coupon rate and frequency, maturity, credit rating, callability, puttability, convertability, and sinking fund provisions, on all US 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 Organization companies as distributed by Warga (2000). This database is an alternative to the no longer available Warga (1998) database used by Collin-Dufresne, Goldstein and Martin (2001) and Elton, Gruber, Agrawal and Mann (2000, 2001) and is the one used by Campbell and Taksler (2002).

We first record the transaction prices and all the characteristics of each traded bond. We separate all data into two broad categories of banking and non-banking firms. For banks we have $18,776$ trades across 185 different banks. The number of trades and firms are shown in the first two columns of Panel A of Table I. For non-banks we have $240,876$ trades involving $3,266$ different firms.

Our first screen eliminates all bonds other than fixed-rate US dollar denominated bonds in the industrial, banking, and services sectors that have no derivative features. In particular we focus on 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 eliminate non investment-grade debt because insurance company regulation often limits or prohibits these firms' purchases of such issues. We use only quote prices. Further, we eliminate all data that have inconsistent or suspicious issue/dates/maturity/coupon etc., or otherwise does not look reasonable.

Table I Here

Columns 3 and 4 of Panel A of Table I show the number of trades and firms that remain after applying this filter for banks and non-banks. For banks we are left with 14,660 trades over 144 different banks. This culling of data represents just over 20% of the transactions. For non-banks we are left with 26,808 transactions from 246 firms. This represents a much more dramatic culling of data by a factor of 88%.

A major reason for this difference is that the number of non-banks issuing convertible, callable or puttable debt and debt with sinking fund provisions is much higher than the number of banks issuing such debt. Güntay, Prabhala and Unal (2002) document that over 80% of debt issues in the 1980s were callable, but less than 50% of new issues in the 1990s were callable. They explain that this could be due to the rapid growth in over-the-counter derivative products. They document that firms with more experience in derivative products were more likely to abandon issuing callable debt. Their result explains the higher proportion of straight debt issued by banks, who clearly have more experience with derivative products.

Our second screen eliminates all those firm-quarter combinations for which we had less than 6 trades for the quarter. The reason for this screen is to ensure that we could obtain reliable estimates for the credit spread curve for a firm at the end of each quarter. For banks, this left us with 9,167 transactions over 81 different banks, while for non-banks we were left with 16,480 transactions from 211 different firms. Columns 5 and 6 of Panel A of Table I show the resulting number of firms and transactions using this criterion. 62% of the bank as well as non-bank transactions survived this culling. By eliminating data from firms with infrequent transactions in any quarter we run the risk of biasing our results against finding liquidity premia. However, in order to estimate credit-spread curves at the end of each quarter we do need a minimum number of data points.

Our third and final screen removes the transactions from firms where we could not collect firm specific risk measures. The firm-specific risk data are collected from the Federal Reserve Bank Y-9 and call reports for banks and BHCs, and from Compustat quarterly for the non-banks. We needed data to compute all our firm risk measures for all the 24 quarters of our data set and one quarter before our data begins and one quarter after it ends. This enables us to compute the changes in firm risk ratios that will be used as independent variables in our regression on credit spread changes. The exact nature of these risk measures will be discussed later. For banks that left us with our final database of 6,590 transactions from 50 firms. For non-banks we have 9,703 transactions from 133 firms.

We are, finally, left with a database that contains the transaction prices, trading dates, and the specific terms of SNDs, ordered by firm and by quarter, and separated according to whether the firm is a banking or a non-banking firm. This is the first of the three databases we use in this paper. Panels B and C of Table 1 provide details on maturity and coupon of SNDs as well as firm ratings of our final sample of banking and non-banking firms.

For banking firms in our final sample, the highest proportions of SNDs issued have maturities between 1 and 5 years, and between 5 and 10 years (together around 60 percent of all SNDs), almost half the number of SNDs have coupons between 6 and 7 percent, and almost all the banking firms have an examiner rating of 1 or 2 (the top ratings). The descriptive statistics for the bonds issued by the non-banking firms are roughly similar to those issued by the banking firms. However, there is more dispersion in the firm ratings of the non-banking firms with only 11 percent of the firms in our final sample have a rating of AA and above.

Our second database comprises daily estimates of the zero riskless yield curve. Unlike corporate bonds, there is much information on treasury rates. To set this up, 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 par rates for every six-month interval, beyond six months and the short three-month rate. From this, we get the zero rates for every six-month period. The final saved output for each day is the annualized continuously compounded yields for the three and six month rates, and the one, two, three, five, seven ten, twenty and thirty year maturities.

Our third database consists of quarterly data on firm specific risk ratios, market variables, liquidity variables, as well as stock returns and firm ratings. The exact nature of this database is discussed in section 3.

2 Extracting Credit Spreads

Our goal is to use actual price information on all bonds of each firm that traded in a particular quarter, together with concurrent riskless term structures, to extract a term structure of credit spreads for each firm at the end of each quarter. In order to accomplish this we set up a model of credit spreads for a firm that has the following properties. First, given the limited data on trades of all debt issues of a firm in a particular quarter, the dynamics for credit spreads have to be relatively simple. In particular, we only require that the short credit spread process for each firm be mean reverting, correlated with interest rates, and have constant volatility over each quarter. In contrast, given the abundance of time series data on the yields of the term structure, the model for riskless bonds can be fairly rich, exploiting the many well known properties of the dynamics of the riskless yield curve. In this section we will establish our 3-factor model for pricing risky debt, describe the estimation process for the parameters of the riskless term structure and for the credit spreads, and present the results.

2.1 Pricing Risky Bonds

Valuation models of defaultable claims can be classified into two types, namely structural and reduced form models. The first is based on the structural notion that default occurs when the firms assets drops below its liabilities. In this approach, default is typically predictable and unless jumps in the underlying value of the firm are introduced, or errors in observing the underlying state variables, the resulting credit spreads on short term debt are generally observed to be much smaller than those observed in practice. The second approach dispenses with the idea of endogenous bankruptcy and treat defaults as a jump process with an exogenous intensity. Models such as Jarrow and Turnbull (1995), Duffie and Singleton (1999) and others, follow this approach, and are now routinely used to price defaultable claims.

We adopt a reduced form model where the default process is modeled directly as surprise stopping times. In particular 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,

$$\begin{aligned} G(t,T) &= E_t^Q\left[e^{-\int_t^T (r(v)+s(v))dv}\right] & (1) \\ P(t,T) &= E_t^Q\left[e^{-\int_t^T r(v)dv}\right], & (2) \end{aligned}$$

where $P(t,T)$ is the date t price of a riskless bond that pays \$1 at date T. Pricing risky coupon bonds follows by treating it as an appropriate portfolio of risky zero coupon bonds. Specifically, consider a risky firm that promises to pay \$$c_j$ at times t_j where $j = 1, \ldots, n$. Then, the value of the claim at time $t < t_1$ is $B(t)$ where:

$$B(t) = \sum_{j=1}^{n} c_j G(t, t_j). \tag{3}$$

We define the date t credit spread for the time interval $[t, t+m]$ to be $s_p(t; m)$, where:

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

with $s_p(t; 0) = s(t)$.

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, $s(t)$. Under the equivalent martingale measure, Q say, we assume the interest rate evolves according to a two factor double mean reverting model. Specifically,

$$dr(t) = [\theta(t) + u(t) - ar(t)]dt + \sigma_r dw_r(t) \quad (4)$$

$$du(t) = -bu(t)dt + \sigma_u dw_u, \quad (5)$$

where $E_t^Q[dw_r(t)dw_u(t)] = \rho_{ur}dt$. $\theta(t)$ may be 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, σ_u, are constants and $dw_r(t)$ and $dw_u(t)$ are standard Wiener processes, with correlation $\rho_{ur}dt$. This two-factor model has been considered by Hull and White (1993) who show that the date t price of a zero coupon riskless bond with face value \$1 that matures at date $t+m$, has the following form:

$$P(t, t+m) = e^{-A(t,m) - B(m)r(t) - C(m)u(t)},$$

where $B(m)$ and $C(m)$ are deterministic functions of m given by:

$$B(m) = \frac{1}{a}[1 - e^{-am}]$$

$$C(m) = \frac{1}{(a-b)}[\frac{1}{a}e^{-am} - \frac{1}{b}e^{-bm}] + \frac{1}{ab},$$

and $A(t, m)$ depends on whether $\theta(t)$ is chosen to be a constant, or whether it is chosen so as to match the observable discount factor. For the former case, $A(t, m) = A(m)$, where

$$A(m) = \theta \int_0^m B(v)dv - \int_0^m \ell(v)dv,$$

where $\ell(v) = \frac{1}{2}\sigma_r^2 B^2(v) + \frac{1}{2}\sigma_u^2 C^2(v) + \sigma_r \sigma_u \rho_{ru} B(v)C(v)$, and for the latter case, the expression is provided in the Appendix of Hull and White (1993). Notice that the continuously compounded yield to maturity is an affine function of the state variables. This model has been well studied. For example, Jegadeesh and Pennacchi (1996) evaluate how well this model performs for pricing Eurodollar Futures contracts. Further, a simple application of Ito's rule shows that the volatility structure of forward rates takes on a humped function of maturity. This property is consistent with empirical evidence on forward rates, and this type of model has been considered for pricing caps and swaptions.[5]

[5] Examples include Ritchken and Iyuan (2001), and Babbs and Nowman (1999).

In order to price risky bonds for a particular firm we require the joint dynamics of the instantaneous credit spread, $s(t)$, with the above interest rate state variables. Under the risk neutral measure, our full model for pricing risky bonds is driven by the three-factor model:

$$\begin{aligned} dr(t) &= [\theta(t) + u(t) - ar(t)]dt + \sigma_r dw_r(t) && (6) \\ du(t) &= -bu(t)dt + \sigma_u dw_u(t) && (7) \\ ds(t) &= [\alpha_0 - \alpha_1 s(t)]dt + \sigma_s dw_s(t), && (8) \end{aligned}$$

where $E_t^Q[dw_r(t)dw_u(t)] = \rho_{ur}dt$, $E_t^Q[dw_u(t)dw_s(t)] = \rho_{us}dt$, and $E_t^Q[dw_r(t)dw_s(t)] = \rho_{rs}dt$. Standard no arbitrage conditions for pricing a risky bond leads to a second order partial differential equation, with the following solution:

$$G(t,T) = P(t,T)e^{-D(t,T)s(t)-K(t,T)}, \tag{9}$$

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 the time $[t, t+m]$ is $s_p(t;m)$, where:

$$s_p(t;m) = \overline{D}(m)s(t) + \overline{K}(m), \tag{10}$$

and:

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

In the model the credit spread does not explicitly depend on the riskless term structure. However, the functions $\overline{D}(\cdot)$ and $\overline{K}(\cdot)$ depend on all the interest rate process parameters. Depending on these parameters the spread curve can be upward sloping, downward sloping or hump shaped. While this model is analytic and fairly flexible, it does suffer from the possibility that spreads can become negative. However with appropriately chosen parameter values the likelihood of this possibility should be small. Our objective is to estimate the spread curve $s_p(t, \cdot)$ for each firm at the beginning of each quarter, t.

2.2 Estimation Technique

Our state variables (r_t, u_t, s_t) are not directly observable. We do have a rich set of riskless terms structure data which allows us to measure, with error, functions of (r_t, u_t).

With regard to risky bond prices, trade information is rather infrequent. 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 cress sections of riskless bond prices, imposing both cross sectional model restrictions and conditional time series restrictions. We accomplish this using a Kalman filter approach.

While in principle, the Kalman filter approach could be used for the entire system of riskless and risky bonds, the amount of data available for estimating the risky bonds is small, and the resulting credit spread parameter estimates, for each quarter, would depend too heavily on the initial priors that need to be specified. To avoid this possible bias we adopted 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, where the underlying process is not observable.

2.2.1 Estimating Parameters From Riskless Bond 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. We shall assume that the market price of interest rate risk, $\lambda_r(t)$, is proportional to $r(t)$, and that 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 will assume the market price of credit spread risk, $\lambda_s(t)$ is proportional to $s(t)$. The full dynamics of the state variables under the data generating measure is then given by:

$$dr(t) = [\theta(t) + u(t) - \overline{a}r(t)]dt + \sigma_r dw_r(t) \tag{11}$$

$$du(t) = -bu(t)dt + \sigma_u dw_u(t) \tag{12}$$

$$ds(t) = [\alpha_0 - \overline{\alpha}_1 s(t)]dt + \sigma_s dw_s(t), \tag{13}$$

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 $\overline{\alpha}_1 = \alpha_1 + \lambda_s\sigma_s$.

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:

$$S_{t+h} = \gamma_0(h) + \gamma_1(h)S_t + \epsilon_t(h), \tag{14}$$

where:

$$\begin{aligned}
S_t &= \begin{pmatrix} r(t) \\ u(t) \end{pmatrix} \\
\gamma_0(h) &= \begin{pmatrix} \frac{\theta}{\overline{a}}(1 - e^{-\overline{a}h}) \\ 0 \end{pmatrix} \\
\gamma_1(h) &= \begin{pmatrix} e^{-\overline{a}h} & \frac{1}{(\overline{a}-b)}(e^{-bh} - e^{-\overline{a}h}) \\ 0 & e^{-bh} \end{pmatrix}
\end{aligned}$$

and $V_t(h) \sim N(0, Q(h))$, 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 (14) 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

$$Y_t = G + HS_t + \Upsilon_t, \tag{15}$$

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, $\Upsilon_t \sim N(0, \sigma_\Upsilon^2 I_n)$.

Equations (14) and (15) 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 updates 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.

2.2.2 Estimation of Credit Spread Parameters

Consider a particular firm and assume that over a particular 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 a 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. From equation (3) each risky coupon bond can be viewed as an appropriate portfolio of risky zero coupon bonds. Further, each zero risky bond is priced as a riskless zero coupon bond multiplied by a factor that depends on maturity, the state variable, $s(t)$, and on all the parameters, some of which we have estimated. The parameters that remain 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 due to the fact that 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 $\overline{t}_{ij} = Max[t_i, t_j]$ and $\underline{t}_{ij} = Min[t_i, t_j]$. Consistent least squares estimates are then generated by minimizing the following expected weighted sums of squares.

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

As discussed earlier, a Kalman filtering estimation approach could have been used for the entire system of interest rates and credit spreads, avoiding this two-phase approach. If we estimated the joint process of interest rates and credit spreads, then the resulting interest rate parameter estimates would differ in each quarter, depending on which firm we adopted. We wanted to use the same interest rate parameter estimates for all the firms. Second, the Kalman filter is a recursive, unbiased least squares estimator of a Gaussian random signal. Our smoothed credit spread parameters are also least squares estimates, but do not require priors for the state variable. The Kalman filter approach can be viewed as a Bayesian approach where the filter propagates the conditional probability density, conditional on knowledge of data coming from noisy measurements. When there are few measurements, then the final estimates can be sensitive to the initial priors. If we do not want to specify initial priors, then the smoothed estimates, like the least squares estimates derived above, are more appropriate. Finally, notice that when we estimate the interest rate parameters we use a time series of cross sectional bond prices, imposing both cross sectional and conditional time series restrictions, with *constant* θ, in the drift term of equations (6) and (11). However, when we estimate the credit spread, we use equation (9), where the riskless discount bond price is taken as data, rather then the estimated value. In this case, our credit spread at any date t is measured using all the riskless term structure at date t as data. Moreover, all firms at date t, measure their credit spreads relative to the same riskless term structure at date t, and use the same interest rate parameter values.[6]

2.3 Model Outputs

Figure 1 shows the one-week ahead prediction errors of the riskless yield-to maturities. In particular, we present a box whiskers plot of all the prediction errors for each maturity.

[6]Our model is similar to that of Bakshi, Madan and Zhang (2001), except our estimated credit spreads at all dates fully incorporate information on all riskless yields at each trade date.

Figure 1 Here

The model displays almost no bias in estimating yields, and the majority of predictions provided by the two-factor model fall within twenty basis points of the observed values. The average absolute one week prediction yield errors is 10.44 basis points.

Figure 2 shows the distribution of percentage errors in bond prices produced by the models for all banks. The percentage errors are bucketed by the underlying maturity of the bond, and the results presented in the form of box and whisker plots. The five maturity buckets correspond to: shorter than 2 years, $2-5$ years, $5-10$ years, $10-20$ years, and greater than 20 years.

Figure 2 Here

The box and whisker plots reveal that the interquartile ranges for percentage errors are symmetrically distributed about zero for all maturity contracts. The interquartile 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. The bottom panel of Figure 2 shows the box whisker plots for our sample of non-banks.

Figure 3 shows the distribution of average percentage errors in bond prices by bank in our data set.

Figure 3 Here

As can be seen, the average percentage pricing error per bank 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 banks has indeed effectively incorporated the information on bond prices.

The left panel of Figure 4 shows the time series of quarterly 3-year credit spreads of randomly selected banks and non-banking firms. Over this time period credit spreads, on average were rising slightly, but, as the figures show, there was substantial variation over time and among firms. In general, the range of credit spreads for the non-banking firms was greater than the range of credit spreads for banks. The right hand panel shows typical plots of the quarterly changes in 3-year credit spreads. The plots reveal that credit spread changes can be fairly volatile, with swings of over 50 basis points in a quarter, being possible.

Figure 4 Here

Panels B and C of Table I showed the distribution of maturities, coupons and ratings for our sample of banking and non-banking firms. Given the distribution of maturities, we have chosen, for the following analysis, to focus on representative maturities for credit spreads of 3 and 7 years. Interestingly, the 3 and 7 year credit spreads often move in opposite directions. For our bank data, for over 17% of the time, a decrease in one of the two spreads is accompanied by an increase in the other. This simple statistic reveals a limitation in previous studies, where credit spread curves were not explicitly extracted. In the analysis that follows our dependent variable will, therefore, be the 3 or 7 year credit spread level or its change. In addition, since the *slope* of the credit spread curve, and the *change* in the slope may be informative about the level and change in firm risk variables, we also include the slope, defined as the 7-year minus the 3-year credit spread, in our analyses.

3 Explanatory Variables

As described above, we have used a 3-factor model to construct credit-spread curves. One can view our use of this model as a calibrating device that constructs credit-spread curves such that they fit the observed transaction prices well. And, as evidenced by Figure 2, the 3-factor model fits our data remarkably well with no obvious biases along the maturity spectrum (see Figure 2). However, the credit spreads may be capturing default probability, anticipated recovery rates given default, liquidity or risk aversion effects. The magnitude of credit spreads could fluctuate according to changes in market and business cycle conditions, or due to bond liquidity factors and, of course, due to changes in firm specific variables. 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), and Bakshi, Madan and Zhang (2001). 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 was not possible to include many state variables. 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 while Bakshi, Madan and Zhang (2001), consider a variety of models with no more than 2 state variables.

Therefore, given the data constraint, we adopt an approach that is similar to Collin-Dufresne, Goldstein and Martin (2001). We first extract credit spreads that fit the observed transaction prices well, and then relate credit spreads changes 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 data per firm per quarter.

Our main concern now is to try and isolate the factors that drive changes in credit spread curve over successive quarters for banks. To address this, we identify three types of variables that can affect credit spreads. These are firm specific risk characteristics, market wide factors, and liquidity factors.

3.1 Firm Specific Risk Characteristics

The firm specific risk variables, their anticipated effect on credit spreads, and data sources are summarized below.

Firm Specific Risk Characteristics for Banks and Non-Banks

	Variable	**Description**	**As Variable Increases Spreads**	**Source of Data**
Banks				
	ROA	(Net Income Before Taxes and Extraordinary Items)/ Total Assets	decreases	Call Reports and Federal Reserve Board Y9 Reports
	Loan Assets	Loan Assets/Total Assets	increases	
	Non Performing Loans	(Loans past due 30-89 days + Loans due 90 days + Non accrual loans)/ Loans and leases net of unearned income	increases	
	Net charge-offs	(Charge-offs - recoveries)/loan assets	increases	
	Leverage	Total Assets/Total Equity Capital	increases	
Non-Banks				
	ROA	(Operating Income Before Depreciation)/ Total Assets	decreases	Compustat
	Interest Coverage	(Operating Income Before Depreciation)/ Interest Expense	decreases	
	Current Ratio	Current Assets/Current Liabilities	decreases	
	Leverage	(Total Assets- Stockholder Equity)/ Stockholder Equity	increases	
	Market to Book Ratio	(Total Shares $\times$ Closing Share Price)/ Stockholder Equity	decreases	

Let $F_i(t)$ represent a 5 vector of these 5 firm specific variables for firm i at the end of quarter t, and $\Delta F_i(t)$ a 5 vector that contains the change in these firm-specific variables for firm i over the t^{th} quarter.

3.2 Market Variables

The market variables, their anticipated effect on credit spreads, and data sources are summarized below.

Market Variables

Variable	**Source of Data**	**As Variable Increases Credit Spreads**
Growth Rate in Industrial Production	St Louis Fed. web-site	decreases
S&P buy and hold return	CRSP	decreases
5-year Treasury yields	St. Louis Fed. web-site	decreases
Slope of Yield Curve (10 Year - 2 Year)	St. Louis Fed. web-site	decreases
VIX Index	CBOE web-site	increases

Growth in Industrial Production is indicative of economic growth. Hence, ceteris paribus, higher growth should translate into lower credit spreads. Similarly, if the S&P 500 return is high, individual firms are likely to be prospering. According to structural models of the firm, such as Merton (1974), optimistic expectations benefit stock prices, reduce the likelihood of default, and lower credit spreads.

Longstaff and Schwartz (1995) and Duffee (1998), among others, find that treasury yields are negatively correlated with changes in credit spreads. Longstaff and Schwartz (1995) show that increase in the slope of treasury curve is negatively correlated with changes in credit spreads. Collin-Dufresne, Goldstein and Martin (2001) use the slope as a proxy for expectations on future short rates and an indication of overall economic health.

As firm volatility increases, the probability of default increases, and the credit spread increases. Since many of the firms we investigate do not have publically traded options, we cannot observe their implied volatilities. We use, as a market measure of the relative uncertainty in the economy, the VIX index. This is a weighted average of eight implied volatilities of near the money options on the $S\&P$ 100 index.

Let $M(t)$ represent a 5 vector of these 5 market variables at the end of quarter t, and $\Delta M(t)$ a 5 vector that contains the change in these variables over the t^{th} quarter. The second entry of $\Delta M(t)$ represents the actual return on the $S\&P$ 500 over the quarter.

3.3 Liquidity Variables

We use 4 liquidity variables, summarized below.

Liquidity Variables

Variable	**Description**	**Source of Data**	**As Variable Increases Spreads**
Relative Trade Frequency	(Number of trades in quarter for this firm)/ Average number of trades over all firms for this quarter	NAIC	decreases
TED Spread	1 month ED rate - 1 month Treasury rate	St. Louis Fed.	increases
New Issue	A dummy variable recording if the firm issued new debt in the quarter	FISD	-
Relative Trade Size	(Average dollar trade size for firm in quarter)/ Average trade size over all firms in the quarter	NAIC	increases

An increase in relative trade frequency for a firm in a quarter indicates that this firm's bonds have become more liquid compared to the average bond liquidity in the market, and credit spreads might decline.

Campbell and Taksler (2002) use the TED spread as a variable that measures liquidity. As the TED spread narrows, the liquidity premiums should shrink. A wider spread, indicating a flight to liquidity, should lead to an increase in the required compensation for holding corporate bonds.

The New Issue dummy variable controls for the fact that new issues may be priced differently, thereby affecting changes in credit spreads in that quarter for that firm.

The Size of Trade variable controls for the fact that a few large trades could impact spreads differently to a number of smaller trades.

Let $L_i(t)$ represent a 4 vector of these 4 firm specific variables for firm i at the end of quarter t, and $\Delta L_i(t)$ a 4 vector that contains the change in these firm specific variables for firm i over the t^{th} quarter. Notice that the third entry of $\Delta L_i(t)$ can be 0 if issues occurred in successive quarters; it is 1 if there is a new issue in this quarter but not in the previous quarter, and it is -1 if there was an issue in the last quarter but not in this quarter.

4 Market Monitoring

4.1 The Determinants of Credit Spread Levels

First, we want to establish the relative importance of firm-specific risk variables, market variables and liquidity variables in explaining the *levels* of credit spreads.

Let $S_i^k(t)$ represent a particular k-year credit spread. Pooling all firms together, we initially assume:

$$S_i^k(t) = \beta_0 + \beta_F^{k'} F_i(t) + \beta_L^{k'} L_i(t) + \beta_M^{k'} M(t) + \epsilon_i^k(t), \tag{16}$$

where the beta values measure the sensitivity to the independent variables but are not firm dependent, and the blocks of independent variables are defined earlier.

We regress the 3 and 7-year credit spreads on these 3 blocks of explanatory variables across all banking firms and all quarters, and then, as robustness checks, we repeat the regressions on subsets of the data broken down by: banks-BHCs, ratings, size (measured in terms of total assets), leverage, and profitablility (measured by ROA).

The reason for looking at banks and BHCs separately is that bank issued debt has a higher priority claim on the bank's assets in liquidation than BHC issued debt. An unresolved issue in the SND literature is whether it matters if the risky debt is issued at the bank level or the bank holding company level. In addition, banks are not subject to U.S. bankruptcy laws, and, in most cases, FDIC is named the receiver bank. BHCs, on the other hand, are subject to U.S. bankruptcy laws. Segregation on size takes into account the "Too Big to Fail" (TBTF) effect. Explicit TBTF policies in the 1980s undermined the incentives of uninsured depositors to monitor the firm (see O'Hara and Shaw(1990)). This effect is supposed to have come down after the passage of the Federal Deposit Insurance Corporation Improvement Act in 1991. However, the market still perceives the largest banking firms to be TBTF, particularly when there are complex derivative books with master netting agreements to contend with. For instance, the TBTF policy was materially reinforced in the handling of the Long Term Capital Management's demise in the late 1990s. Examiners can also influence the risk taking behavior of banks. Higher rated banks may not feel the same pressure from regulators to control risk taking. Hence, the effect of firm specific risk changes on changes in credit spreads may depend on the bank's examiner rating. Segregation by leverage follows from the accepted rationale that the risk of SND is higher for more levered firms, although banking firms, in general, are more levered than the non-banking firms. Finally, we segregate by profitability because the risk of SND may be viewed as higher for less profitable firms.

To determine the marginal contribution of each block on the *levels* of credit spreads, we conduct a series of partial F tests on the 3 blocks of independent variables. Table II shows the partial F statistics and the associated p values for each block of explanatory variables, first for the case when the dependent variable is the 3-year credit spread and then for the 7-year credit spread.

Table II Here

Both panels of Table II show that firm-specific risk and market variables are important in explaining credit spread levels, in the aggregate across all banking firms, and when the full sample is divided in terms of firm type, examiner rating, size, leverage and profitability.

However, while the above result replicates previous results using levels of credit spreads, our main purpose is to examine the relative importance of each set of independent variables in explaining *changes* in credit spreads. If credit spreads are to act as a monitoring device, then changes in firm risk variables should immediately be reflected into a changing credit spread curve.

4.2 The Determinants of Credit Spread Changes

We regress changes in credit spreads on changes in firm-specific risk, changes in market variables and changes in liquidity factors over all firm-quarters using the following regression model:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^{k'} S_i^k(t-1) + \beta_F^{k'} \Delta F_i(t) + \beta_L^{k'} \Delta L_i(t) + \beta_M^{k'} \Delta M(t) + \epsilon_i^k(t), \tag{17}$$

where $\Delta S_i^k(t)$ represent the change in a particular k-year credit spread over the t^{th} quarter for firm i. In this specification, since credit spreads are mean-reverting, we also permit their changes to depend on current levels.

As before, we conduct a series of partial F tests on the 3 blocks of independent variables to assess the marginal contribution provided by each block. Table III shows the partial F statistics, the associated p-values for each block of explanatory variables, and the adjusted R^2 values, for the full sample and for the various subgroups.

Table III Here

The results for changes in 3-year credit spreads are different from those for level effects in Table II. Changes in credit spreads do not reflect changes in firm specific risks, after controlling for changes in market-wide variables and liquidity variables.

Notice that all our market-wide variables and one liquidity variable, the TED spread, depend on calendar time alone. We, therefore, run our regression model again using quarterly dummy variables as the independent variables instead of our set of 5 market variables and the 1 liquidity variable that is quarter-specific. This regression equation model is given by:

$$\Delta S_i^k(t) = \beta_S^{k'} S_i^k(t-1) + \beta_F^{k'} \Delta F_i(t) + \beta_L^{k'} \Delta L_i(t) + \beta_M^{k} T + \epsilon_i^k(t), \tag{18}$$

where T is a vector of size 24 (one for each quarter that our data spans), that replaces the market block, and the liquidity block is now a vector of size 3 instead of 4. This specification allows us to capture all the time fixed effects, including changes in the market conditions from quarter to quarter. For instance, our data sample spans the Long Term Capital Management crisis, and the Russian crisis, neither of which are represented by a specific market variable. Time fixed effects dummy variables help capture all such calendar time differences, thereby allowing us to detect any statistically significant relationship between changes in firm-specific variables and changes in credit spreads more cleanly.

As shown in Panel B of Table III, when we reestimate the model controlling for fixed effects, our results do not change.

Similar results are obtained when using the 7-year credit spread, as shown in Table IV. We do not find any statistically significant relationship between changes in firm-specific variables and changes in credit spreads both for the full sample and for the sub samples.

Table IV Here

We are, however, able to find a strong statistically significant relationship between changes in the market variables and changes in credit spreads. Changes in market conditions appear to influence changes in credit spreads of banking firms significantly. To determine changes in which specific market variables affect changes in credit spreads, we need to look at the significance of the individual beta coefficients. Table V shows the standardized beta coefficients and the associated t statistics for all the individual variables comprising the block of market variables when equation model (17) is estimated over all the data and over the various subgroups.

Table V Here

Changes in the 5-year treasury yields is the single most important determinant of changes in 3-year credit spreads, while growth in industrial production and changes in the 5-year treasury yield are the two most important determinants in the changes in the 7-year credit spreads. The signs of the coefficients are as expected.

4.3 The Slope of the Credit Spread Curve

While we have found a statistically significant relationship between credit spread *levels* and firm-specific risk, we failed to find one between *changes* in credit spreads and *changes* in firm-specific risk. This being the case, monitoring *changes* in credit spreads of SND issued by banking firms may not yield information on how firm-specific risk has changed. However, the slope of the credit spread curve, and the change in the slope, could reflect changes in firm specific risk variables. Therefore, we examine whether there exist statistically significant relationships between credit spread slope and firm-specific risk and between *changes* in credit-spread slopes and *changes* in firm-specific risk.

We specify the level regression as:

$$SL_i(t) = \beta_0 + \beta_1 S_i^3(t) + \beta_F^{'} F_i(t) + \beta_L^{'} L_i(t) + \beta_M^{'} M(t) + \epsilon_i(t), \tag{19}$$

where $SL_i(t)$ is the slope as defined by 7 year credit spread minus 3 year credit spread, $S_i^7(t) - S_i^3(t)$. In equation (19), we allow for the slope to depend on the level of the 3 year credit spread.

We specify the change regression as:

$$\Delta SL_i(t) = \beta_0 + \beta_1 SL_i(t-1) + \beta_F^{'} \Delta F_i(t) + \beta_L^{'} \Delta L_i(t) + \beta_M^{'} \Delta M(t) + \epsilon_i(t), \tag{20}$$

where $\Delta SL_i(t)$ is the change in the credit-spread slope.

Panel A of Table VI summarizes the results for the level regressions. The results demonstrate that firm-specific risk factors do determine the slope of the credit spread curve. Interestingly, market and liquidity variables are not statistically significant. This result raises the possibility that changes in the slope may respond to changes in firm specific risk variables.

Table VI Here

Panel B of Table VI, however, does not confirm this result. Controlling for changes in market and liquidity variables, the reported partial F statistics reveal that changes in firm specific risk variables are not linearly related to changes in credit-spread slopes. These results hold for our entire group, as well as for all 10 subgroups.

In summary, then, we are unable to find any statistically significant relationship between changes in firm-specific variables and changes in credit spreads or changes in credit-spread slope.

4.4 More Robustness Checks

It may be that credit spread changes depend heavily on the *levels* of current firm specific levels as well as the changes in the levels. For example, it is possible that a leverage change from 60 percent to 70 percent has a different firm risk change implication than a change from 10 percent to 20 percent, although each change is 10 percent. To account for such differences, we could include the lagged firm risk level in our regression equation, as well as interaction effects between levels and changes. In Table VII we report the results of the following regression:

$$\begin{aligned} \Delta S_i^k(t) &= \beta_0 + \beta_S^k{}' S_i^k(t-1) + \beta_{FL}^{k\prime} F_i(t-1) + \beta_I^k{}' F_i(t-1)\Delta F_i(t) \\ &\quad + \beta_F^k{}' \Delta F_i(t) + \beta_L^k{}' \Delta L_i(t) + \beta_M^k{}' \Delta M(t) + \epsilon_i^k(t). \end{aligned} \tag{21}$$

The results are shown in Table VII. We cannot find a statistically significant relationship between changes in firm-specific variables and changes in credit spreads or changes in credit-spread slope.

Table VII Here

As a second robustness check, we recompute changes to firm specific variables in a slightly different way. We redefine changes in firm risk ratios to mean changes in the numerator that occurred during a quarter divided by the average level in the denominator. For instance, change in ROA is now measured as the change in the net income before taxes and extraordinary items from the beginning of the quarter to the end of the quarter in question divided by the average of the beginning of the quarter total assets and the end of the quarter total assets. We regress changes in the 3 year and 7 year credit spreads on changes in the redefined firm risk variables, liquidity variables and market variables, and find that the explanatory power of changes in firm risk variables is insignificant.[7]

4.5 Impact of Stock Prices and Ratings Information

It must be noted that regulators have other indicators of bank risk changes, in addition to credit spreads changes. These are stock returns and changes in the examination rating of a banking firm (the CAMELS and BOPEC ratings). For SND to have a market monitoring benefit, changes in credit spreads or credit spread slopes must reflect changes in firm risk *over and above* that reflected in stock prices and examination ratings. So far we have not required that market monitoring benefits of SND satisfy this additional requirement, and hence we may have biased our models in favor of finding relationships between changes in credit spreads and changes in firm specific risk variables.

The reason for not including stock returns from the start of our analyses is that stock returns from the CRSP database are available only for a subset of our sample of banking firms. In particular, stock returns are available for almost all BHCs but are available only for a small fraction of banks in our sample. The reason for not including examination rating changes from the start of our analyses is that full scope bank and BHC examinations are conducted once a

[7]The F statistics (p values) of the block of changes in firm risk variables are 1.169 (0.323) and 0.688 (0.633) when the dependent variables are changes in the 3 year and the 7 year credit spread changes respectively. The results for the various sub samples are not reported in this paper but are available from the authors.

year, and the rating assigned to that bank or BHC at the end of the review is, more often than not, the same as the previous rating. Nevertheless, to check for the robustness of our results, we include these two control variables and reestimate our regression models.

The control variables and the source of data are shown below:

Control Variables

Variable	**Source of Data**
Buy and Hold Stock Returns	CRSP
BOPEC ratings for BHCs	Federal Reserve System
CAMEL ratings for banks	Federal Reserve System
Average issue rating for each non-banking firm	FISD
(Averaged over the ratings of:	
Duff and Phelp, Standard and Poor's, Moody's, and Fitch.)	

Let $\Delta C_i(t)$ be a 2 vector of stock return of firm i in quarter t, and the change in its examination rating in period t. The rating change variable is either 0 if there is no change, 1 if the change is an upgrade, and -1 if the change is a downgrade.

When $\Delta C_i(t)$ is included as an additional explanatory variable, the results, as expected, do not change. Changes in firm risk variables are not reflected in changes in credit spreads or changes in credit spread slopes for banking firms. These results are shown in Table VIII.

Table VIII Here

The results show that stock returns have significant explanatory power over changes in the 3-year credit spreads (standardized beta coefficient = -0.104 and the t-statistic = -2.177, and so as stock returns increase, credit spreads decrease), but not over changes in the 7-year credit spreads. Stock returns can also explain changes in credit-spread slopes.

4.6 Common Factors Among Residuals

The explanatory power of our regression models is reasonable. For example, the adjusted R^2 for the model in which changes in the 3 year credit spreads are regressed on changes in firm-specific, liquidity and market variables is 49.2 percent. To understand the nature of the remaining variation in changes of credit spreads, we conducted a principal components analysis on the residuals of this regression model. We assigned each residual for a firm in a quarter to one of eight bins, determined by two leverage groups, two profitability (ROA) groups and two size groups. For each bin we computed an average residual for each quarter, and then extracted the principal components from the resulting covariance matrix. The first principal component accounted for 35% of the variation, the second for an additional 23%, and the third, a further 17%. This indicates that there may be some additional common factors that are driving changes in credit spreads that we have not accounted for. However, these factors influence the credit-spread changes for all banking firms systematically. Therefore, a large fraction of the unexplained variability is systematic, which makes it unlikely that we may have missed accounting for certain firm-specific risk variables that would have had explanatory power over changes in credit spreads.

4.7 Are the Results Specific to Banking Firms?

Our results could be due to the fact that we have examined highly regulated banking firms. In this case, it is unclear whether our results hold in general, or only hold for banking firms. In other words, we have found that credit spreads changes are influenced by other factors like market-wide effects and liquidity factors to such an extent that we are unable to find any statistically significant relationship between changes in credit spreads and changes in firm risk variables. We wish to examine whether this is true for all firms in general. To investigate this, we regress changes in credit spreads on changes in firm specific risks, changes in liquidity and changes in market variables, for non-banking firms. Table IX shows the partial F statistics and the associated p values for each block of explanatory variables when the dependent variables are the changes in the 3 and 7 year credit spreads across all firm-quarters, as well as when we subdivide the full sample in terms of firm type (manufacturing or service), credit rating, size, leverage and profitability.

Table IX Here

We find the same result for our sample of non-banking firms as well: changes in credit spreads do not reflect changes in firm specific risk changes, after controlling for changes in market-wide variables and liquidity variables. In summary, changes in credit spreads do not reflect changes in firm specific risks, not only for banking firms but also for non-banking firms.

5 Preventative Influence

One reason why changes in credit spreads do not reflect changes in firm-specific risk characteristics could be that firm-specific risk comes down after a bank or BHC issues risky debt. If investors are able to accurately price risky debt, then a banking firm will incur increased costs of funding if it were to adopt riskier strategies. Due to this market risk monitoring effect, banks with SND may be less likely to adopt risky strategies in the first place. This is the preventative influence role of SND. If this were true, then it would be incorrect to state that SND does not achieve its objective when we find that changes in SND credit spreads do not reflect changes in firm-specific risks.

We investigate whether SND has a preventative influence by examining whether firm-specific risks change significantly after a banking firm issues its first SND. Panels A and B of Table X respectively show the average change in the raw and the matched-adjusted firm-specific risk characteristics from before a firm first issued any subordinated debt to after it does, and the corresponding t statistics. For this exercise we are limited to 14 banks and 14 BHCs that first issued SND in or after 1988 because all data from the Y-9 and call reports are available only after 1988. For each bank (BHC) that issues subordinated debt for the first time, a matched portfolio of 10 non-issuing banks (BHCs) is constructed as follows. For each bank (BHC), we find the closest 250 non-issuing banks (BHCs) based on Total Assets (size). From out of these 250 banks (BHCs), we find the closest 50 firms based on leverage. At this stage, we have a set of 50 non-issuing banks or BHCs for each issuing bank or BHC that are matched to the issuer in terms of Total Assets and leverage. Next, from out of these 50 banks (BHCs), we find the closest 10 firms based on ROA. This set of 10 non-issuers (that are closest to the issuer in terms of Total Assets, Leverage, and ROA in addition to being the same type of firm (bank or BHC) and having the same examiner rating in the issuing quarter) form our matched portfolio for that issuer. We find such a set of matched non-issuing firms for each issuer in our sample.

Table X Here

Table X shows that firm specific risk characteristics did not change significantly from the quarter before the issue to the quarter after the issue, from the half year before the issue to the half year after the issue, and from the year before the issue to the year after the issue, both on raw basis or on matched-adjusted basis. Thus, SND issues by banking firms do not seem to have any preventative influence.

6 Conclusion

The purpose of this paper is to examine whether risky debt issued by banks and bank holding companies enhance risk monitoring and help control risk taking. In theory, if investors accurately understand changes in a firm's risk condition and incorporate their assessment promptly into the prices of risky debt issued by a firm, then changes in credit spreads should provide useful information on how firms-specific risks have changed. In this way, risky debt enhances risk monitoring. However, banks having risky debt may be less likely to adopt risky strategies in the first place, because if they take excessive risks, debt prices may reflect the risk taken by the firm and make borrowing costlier for the firm. This is the preventative influence benefit of risky debt that serves to control risk taking.

We fail to find evidence that risky debt facilitates risk monitoring. Specifically, there does not appear to be a statistically significant relationship between changes in firm risk variables and changes in credit spreads. Therefore, inferring firm specific risk changes from changes in credit spreads is not viable. We check the robustness of our results by splitting our sample by firm type, rating, size, leverage, and profitability. The result remains unchanged. We replace non firm-specific explanatory variables in our model with time indicator variables to capture all calendar time effects. The result does not change. We take into account the possibility that relative changes may matter by including lagged firm risk variables in our models. In general, the result does not change. We include stock returns and changes in examination ratings in our model, and our result still does not change. We find changes in credit-spread curve slope are not good signals of changes in firm specific risks as well.

We examine whether the above result obtains because risky debt has the effect of changing the risk taking behavior of firms. We find that neither the raw risk characteristics nor the risk-matched-firm adjusted characteristics change significantly fafter a banking firm first issues SND. Thus, SND does not significantly change risk-taking behavior of banking firms.

Our results strongly question the efficacy of mandating subordinated debt for banking firms as we find little evidence of risk change signaling benefit or preventative influence benefit. We cannot, however, conclude that mandating risky debt for banking firms serves no purpose. First, it must be noted that our sample period of 1994 to 1999 spans a relatively quiet period in banking with few bank failures and strong capital growth, although the Long Term Capital Management crisis and the Russian crisis did occur during this period. Second, we are forced to analyze those banking firms that have voluntarily chosen to issue subordinated debt. Hence, there can be a self-selection bias inherent in our results. And, finally, although we find that subordinated debt does not facilitate monitoring of firm risk taking, and does not significantly change the risk-taking behavior of the banking firms, subordinated debt still has the benefit of providing an additional cushion between the depositors/FDIC and banking losses.

To the best of our knowledge, our paper is the first in the banking literature that attempts to carefully extract the entire credit spread curve for each banking firm at each point in time, and to analyze changes in specific maturity credit spreads as well as changes in credit spread slopes. In this paper, our focus was to determine whether changes in credit spreads or changes in credit spread slopes provide information on changes in firm risk, after controlling for changes in market and liquidity variables. We could also investigate what the significant determinants of credit spread changes and credit slope changes are, both for the different sub samples within banking firms and across different industries. Understanding the determinants of credit-spread changes and credit-spread slope changes for firms across industries remains a topic for future research.

References

Avery, Robert, Terrence Belton, and Michael Goldberg (1988), "Market Discipline in Regulating Bank Risk: New Evidence from the Capital Markets," *Journal of Money, Credit, and Banking*, 20, 597-610.

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

Baer, Herbert and Elijah Brewer (1986) "Uninsured Deposits as a Source of Market Discipline: Some New Evidence" *Federal Reserve Bank of Chicago: Economic Perspectives*, September/October 23-31.

Basel Committee on Banking Supervision (1999), "New Capital Adequacy Framework" Basel, Switzerland

Babbs, Simon and Ben Nowman (1999), "Kalman Filtering of Generalized Vasicek Term Structure Models", *Journal of Financial and Quantitative Analysis*, 34, 115-130.

Berger, Allen, Sally Davies, and Mark Flannery (2000) "Comparing Market and Supervisory Assessments of Bank Performance: Who Knows What When?", *Journal of Money, Credit, and Banking* (Forthcoming).

Bliss, Robert (2000), "Market Discipline and Subordinated Debt: A Review of Some Salient Issues", Working Paper, Federal Reserve Bank of Chicago.

Bliss, Robert and Mark Flannery (2000), "Market Discipline in the Governance of U.S. Bank Holding Companies: Monitoring vs. Influencing", Working Paper, Federal Reserve Bank of Chicago.

Board of Governors of the Federal Reserve System (1999), "Using Subordinated Debt as an Instrument of Market Discipline", Staff Study, 172, Washington, DC, December.

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

Collin-Dufresne, Pierre, and Robert Goldstein (2001), "Do Credit Spreads Reflect Stationary Leverage Ratios? Journal of Finance 56, 1926-1957.

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

DeYoung, Robert, Mark Flannery, William Lang, and Sorin Sorescu (2001), "The Information Content of Nank Exam Ratings and Subordinated Debt Prices", *Journal of Money, Credit and Banking*, 33, 900-925

Duffee, Gregory (1998), "The Relation Between Treasury Yields and Corporate Bond Yield Spreads", *Journal of Finance* 53, 2225-2241.

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

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

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

Eom, Y., J. Helwege and J. Huang (2000), "Structural Models of Corporate Bond pricing: An Empirical Analysis", Working Paper, Pennsylvania State University.

Evanoff, Douglas and Larry Wall (2000), "Subordinated Debt as Bank Capital: A Proposal for Regulatory Reform", Federal Reserve Bank of Chicago, *Economic Perspectives*, 40-53.

Flannery, Mark (1998), "Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence", *Journal of Money, Credit, and Banking*, 273-305.

Flannery, Mark and Sorin Sorescu (1996), "Evidence of Bank Market Discipline in Subordinated Debenture Yields: 1983-1991", *Journal of Finance*, 1347-1377.

Goldberg, Michael and Peter Lloyd-Davies (1985), "Standby Letters of Credit: Are Banks Overextending Themselves?" Ĵournal of Bank Research, 16, 29-39.

Gorton, Gary and Anthony Santomero (1990), "Market Discipline and Bank Subordinated Debt", *Journal of Money, Credit, and Banking* 22, 119-128.

Guntay, Levent, N.R. Prabhala and Haluk Unal (2002), "Callable Bonds and Hedging", Working Paper, University of Maryland.

Hannan, Timothy, and Gerald Hanweck (1988), " Bank Insolvency Risk and yhe Market for Large Certificates of Deposit", *Journal of Money, Credit and Banking* 20, 203-212.

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

Hull, John and Alan White (1994), "Numerical Procedures for Implementing Term Structure Models II:Two Factor Models", *The Journal of Derivatives*, 2, 37-49.

Jagtiani, Julapa, George Kaufman and Catherine Lemieux (2000), "Do Markets Discipline Banks and Bank Holding Companies? Evidence from Debt Pricing", Working Paper, Federal Reserve Bank of Chicago.

Jarrow, Robert, and Stuart Turnbull (1995), "Pricing Derivatives on Financial Securities Subject to Credit Risk", *Journal of Finance*, 50, 53-86.

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

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

Kwan, Simon (1996), “Firm-Specific Information and the Correlation Between Individual Stocks and Bonds”, *Journal of Financial Economics*, 40, 63-80.

Leland, Hayne E (1994), “Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads”, *Journal of Finance*, 49, 1213-1253.

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

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

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

Ritchken, Peter and Iyuan Chuang (1999), “Interest Rate Option pricing with Volatility Humps”, *Review of Derivatives Research*, 237-262.

O’Hara, Maureen, and Shaw, Wayne (1990), “Deposit Insurance and Wealth Effects: The Value of Being ”Too Big to Fail.””, *Journal of Finance 45 (5)*, 1587-1600.

Sarig, Oded, and Arthur Warga (1989), “Some Empirical Estimates of the Risk Structure of Interest Rates”, *Journal of Finance*, 44, 1351-1360.

Sironi, Andrea (2002), “ Strengthening banks’ market discipline and leveling the plying field:Are the two compatible?”. *Journal of Banking and Finance*, 26, 1065-1091.

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

Warga, Arthur (2000), “National Asociation of Insurance Commissioners Database”, University of Houston, Houston, Texas.

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

Table I.
Descriptive statistics of subordinated debt trade sample

Panel A shows the number of trades and firms in our banking and non-banking firm samples, step-by-step, through our screening process. The first column records all data found in the NAIC database for 1994 through 1999. The first screen eliminates all debt instruments other than fixed-rate US dollar denominated debt 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 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 6 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 firm-specific risk measures are not found in the Y-9 and call reports for banking firms and Compustat Quarterly files for the non-banking firms, for all the 24 quarters of our trade data, one quarter before our trade data begins, and one quarter after our trade data ends.

Panels B and C 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.

PANEL A: The screening process

	Initial sample		Sample after first screen		Sample after second screen		Sample after third screen	
	# Trades	# Firms	# Trades	# Firms	# Trades	# Firms	# Trades	# Firms
Banking Firms	18776	185	14660	144	9167	81	6590	50
Non-banking Firms	240876	3265	26608	245	16480	210	9703	133

PANEL B: Banking firms: Final Sample

Maturity in years	Proportion of Issues	Coupon Rate	Proportion of Issues	Examiner Rating	Proportion of Issues
≤ 1	12%	≤ 3%	3%	1	50%
1 to 5	33%	3% to 6%	7%	2	45%
5 to 10	26%	6% to 7%	45%	3	5%
10 to 25	25%	7% to 8%	27%		
> 25	4%	> 8%	18%		

PANEL C: Non-Banking firms: Final Sample

Maturity in years	Proportion of Issues	Coupon Rate	Proportion of Issues	Credit Rating	Proportion of Issues
≤ 2	28%	4% to 6%	19%	AAA and AA	11%
2 to 5	30%	6% to 7%	37%	A	31%
5 to 10	26%	7% to 8%	25%	BBB	14%
10 to 25	11%	8% to 10%	13%	BB and below	3%
> 25	5%	> 10%	6%	Not Rated	41%

Table II.
The determinants of credit spread levels for banking firms

The table shows the partial F statistics and the p values of the blocks of explanatory variables given everything else, when k-year credit spread, S^k, is regressed on the vectors of firm-specific risk characteristics, F, liquidity variables, L, and market variables, M, using the following regression equation:

$$S_i^k(t) = \beta_0 + \beta_F^k F_i(t) + \beta_L^k L_i(t) + \beta_M^k M(t) + e_i^k(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3 or 7. High Rating category comprises banking firms with examination rating of 1, and low rating category the remaining banking firms. High and low categories based on total assets, leverage and Return on Assets (ROA) are defined in terms of being above the sample median or below the sample median respectively.

3 year credit spreads

Explanatory power of the variable block given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
F	22.292 (0.000)*	14.643 (0.000)*	6.680 (0.000)*	22.407 (0.000)*	20.561 (0.000)*	22.322 (0.000)*	10.552 (0.000)*	16.215 (0.000)*	14.792 (0.000)*	21.524 (0.000)*	7.572 (0.000)*
L	2.359 (0.053)	0.682 (0.605)	1.628 (0.167)	0.126 (0.973)	1.914 (0.109)	5.159 (0.001)*	0.704 (0.590)	3.570 (0.008)*	1.199 (0.312)	0.208 (0.934)	0.790 (0.533)
M	19.982 (0.000)*	5.034 (0.007)*	15.426 (0.000)*	10.787 (0.000)*	6.531 (0.000)*	17.026 (0.000)*	9.406 (0.000)*	19.942 (0.000)*	6.659 (0.006)*	11.257 (0.000)*	11.240 (0.000)*
Adjusted R^2	0.293	0.373	0.245	0.403	0.380	0.473	0.280	0.438	0.275	0.393	0.279

7 year credit spreads

Explanatory power of the variable block given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
F	16.106 (0.000)*	13.448 (0.000)*	5.048 (0.003)*	38.312 (0.000)*	12.046 (0.000)*	44.003 (0.000)*	7.272 (0.000)*	21.260 (0.000)*	8.682 (0.000)*	15.560 (0.000)*	4.495 (0.001)*
L	1.149 (0.333)	0.401 (0.808)	0.742 (0.564)	1.225 (0.301)	1.361 (0.248)	5.591 (0.000)*	0.341 (0.850)	1.887 (0.114)	0.605 (0.659)	0.256 (0.906)	1.122 (0.352)
M	18.452 (0.000)*	5.586 (0.000)*	12.484 (0.000)*	12.691 (0.000)*	5.815 (0.000)*	40.157 (0.000)*	5.407 (0.000)*	22.981 (0.000)*	5.717 (0.000)*	9.999 (0.000)*	10.438 (0.000)*
Adjusted R^2	0.244	0.363	0.192	0.512	0.288	0.642	0.181	0.475	0.215	0.328	0.233

* denotes significantly different from zero at the 5% significance level.

Table III.
The determinants of 3-year credit spread changes for banking firms

PANEL A shows the partial F statistics and p values of the blocks of explanatory variables given everything else, when changes in the k-year credit spread, ΔS^k, are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, using the following regression equation:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k\ S_i^k(t-1) + \beta_F^k\ \Delta F_i(t) + \beta_L^k\ \Delta L_i(t) + \beta_M^k\ \Delta M(t) + e_i^k(t)$$

PANEL B shows the partial F statistic and p value of the block of changes in firm-specific risk variables given everything else, when changes in the k-year credit spread, ΔS^k, are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and time effect dummy variables, T, using the following regression equation:

$$\Delta S_i^k(t) = \beta_S^k\ S_i^k(t-1) + \beta_F^k\ \Delta F_i(t) + \beta_L^k\ \Delta L_i(t) + \beta_M^k\ T + e_i^k(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3. High Rating category comprises banking firms with examination rating of 1, and low rating category the remaining banking firms. High and low categories based on total assets, leverage and Return on Assets (ROA) are defined in terms of being above the sample median or below the sample median respectively.

PANEL A

Explanatory power of the variable block given everything else	**All**	**Type of firm**		**Rating**		**Size: Total Assets**		**Leverage**		**Profitability: ROA**	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔF	0.981 (0.429)	1.621 (0.158)	0.628 (0.679)	0.329 (0.895)	0.912 (0.474)	0.678 (0.641)	1.143 (0.339)	0.535 (0.750)	0.788 (0.559)	0.691 (0.631)	0.828 (0.531)
ΔL	1.278 (0.278)	0.463 (0.763)	1.462 (0.214)	0.481 (0.750)	1.619 (0.170)	1.022 (0.397)	1.246 (0.292)	0.423 (0.792)	1.349 (0.253)	2.418 (0.076)	1.067 (0.374)
ΔM	6.969 (0.000)*	1.568 (0.173)	6.637 (0.000)*	2.673 (0.023)*	4.588 (0.001)*	4.515 (0.001)*	3.413 (0.005)*	2.815 (0.017)*	3.253 (0.007)*	6.910 (0.000)*	1.640 (0.150)
Adjusted R^2	0.476	0.432	0.525	0.475	0.471	0.641	0.393	0.538	0.435	0.517	0.418

PANEL B

Explanatory power of the variable block given everything else	**All**	**Type of firm**		**Rating**		**Size: Total Assets**		**Leverage**		**Profitability: ROA**	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔF	0.782 (0.563)	1.452 (0.210)	0.752 (0.585)	0.331 (0.894)	0.781 (0.564)	0.790 (0.558)	0.881 (0.495)	0.862 (0.508)	1.000 (0.418)	0.472 (0.797)	1.048 (0.390)
Adjusted R^2	0.442	0.430	0.495	0.449	0.423	0.631	0.359	0.517	0.413	0.464	0.408

* denotes significantly different from zero at the 5% significance level.

Table IV.
The determinants of 7-year credit spread changes for banking firms

PANEL A shows the partial F statistics and p values of the blocks of explanatory variables given everything else, when changes in the k-year credit spread, ΔS^k, are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, using the following regression equation:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + e_i^k(t)$$

PANEL B shows the partial F statistic and the p value of the block of changes in firm-specific risk variables given everything else, when changes in the k-year credit spread, ΔS^k, are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and time effect dummy variables, T, using the following regression equation:

$$\Delta S_i^k(t) = \beta_S^k S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \mathrm{T} + e_i^k(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 7. High Rating category comprises banking firms with examination rating of 1, and low rating category the remaining banking firms. High and low categories based on total assets, leverage and Return on Assets (ROA) are defined in terms of being above the sample median or below the sample median respectively.

Explanatory power of the variable block given everything else	**All**	**Type of firm**		**Rating**		**Size: Total Assets**		**Leverage**		**Profitability: ROA**	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
PANEL A											
ΔF	0.443 (0.818)	0.283 (0.922)	1.373 (0.234)	0.318 (0.902)	0.657 (0.656)	0.670 (0.646)	0.289 (0.919)	1.647 (0.149)	0.076 (0.996)	0.127 (0.986)	2.159 (0.060)
ΔL	1.554 (0.185)	0.589 (0.671)	0.855 (0.491)	0.677 (0.609)	0.846 (0.498)	0.847 (0.497)	1.063 (0.375)	0.603 (0.661)	1.254 (0.289)	2.436 (0.048)*	1.030 (0.392)
ΔM	6.245 (0.000)*	0.870 (0.503)	7.400 (0.000)*	1.470 (0.201)	4.876 (0.000)*	6.960 (0.000)*	1.572 (0.169)	4.362 (0.001)*	2.635 (0.024)*	4.438 (0.001)*	4.477 (0.001)*
Adjusted R^2	0.440	0.424	0.449	0.398	0.465	0.579	0.375	0.394	0.446	0.502	0.334

PANEL B

Explanatory power of the variable block given everything else	**All**	**Type of firm**		**Rating**		**Size: Total Assets**		**Leverage**		**Profitability: ROA**	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔF	0.668 (0.648)	0.494 (0.780)	1.469 (0.200)	0.486 (0.786)	1.277 (0.275)	0.929 (0.463)	0.388 (0.857)	2.855 (0.016)*	0.633 (0.675)	0.354 (0.879)	2.373 (0.040)*
Adjusted R^2	0.412	0.416	0.373	0.395	0.437	0.549	0.370	0.354	0.450	0.505	0.361

* denotes significantly different from zero at the 5% significance level.

Table V.
Market variables that explain changes in credit spreads for banking firms

The table shows the standardized beta coefficients and the t statistics of the elements of the market block of explanatory variables given everything else, when credit spread changes are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, using the following regression equation:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k \; S_i^k(t-1) + \beta_F^k \, \Delta F_i(t) + \beta_L^k \, \Delta L_i(t) + \beta_M^k \, \Delta M(t) + e_i^k(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3 or 7. High Rating category comprises banking firms with examination rating of 1, and low rating category the remaining banking firms. High and low categories based on total assets, leverage and Return on Assets (ROA) are defined in terms of being above the sample median or below the sample median respectively.

Changes in 3 year Credit Spreads

Market variable	**All**	**Type of firm**		**Rating**		**Size: Total Assets**		**Leverage**		**Profitability: ROA**	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔGIP	-0.059	-0.060	-0.062	-0.050	-0.067	-0.129	0.018	-0.064	-0.074	-0.045	-0.069
	(-1.563)	(-0.859)	(-1.386)	(-0.879)	(-1.290)	(-2.790)*	(0.317)	(-1.271)	(-1.298)	(-0.814)	(-1.245)
ΔS&P	-0.029	-0.072	-0.016	-0.072	0.003	-0.061	0.057	-0.024	-0.028	-0.005	-0.114
	(-0.550)	(-0.750)	(-0.262)	(0.929)	(0.044)	(-0.995)	(0.680)	(-0.341)	(-0.368)	(-0.071)	(-1.512)
Δ 5 Year Treasury Yields	-0.210	-0.083	-0.262	-0.175	-0.231	-0.116	-0.227	-0.172	-0.208	-0.316	-0.067
	(-4.277)*	(-0.964)	(-4.467)*	(-2.445)	(-3.304)*	(-1.923)	(-3.105)*	(-2.673)*	(-2.763)*	(-4.531)*	(-0.927)
Δ Slope of Yield Curve	-0.050	-0.124	-0.010	-0.019	-0.083	-0.005	-0.117	-0.006	-0.060	-0.089	0.011
	(-1.350)	(-1.804)	(-0.233)	(-0.358)	(-1.587)	(-0.107)	(-2.056)	(-0.119)	(-1.105)	(-1.753)	(0.198)
ΔVIX Index	0.053	0.072	0.034	0.049	0.029	-0.071	0.177	0.032	0.045	0.113	-0.032
	(0.842)	(0.643)	(0.446)	(0.520)	(0.327)	(-0.918)	(1.748)	(0.367)	(0.487)	(1.240)	(-0.355)

Changes in 7 year Credit Spreads

Market variable	**All**	**Type of firm**		**Rating**		**Size: Total Assets**		**Leverage**		**Profitability: ROA**	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔGIP	-0.109	-0.018	-0.160	-0.056	-0.154	-0.183	0.015	-0.155	-0.082	-0.044	-0.217
	(-2.787)*	(-0.262)	(-3.314)*	(-0.926)	(-2.918)*	(-3.651)*	(0.252)	(-2.689)*	(-1.449)	(-0.784)	(-3.684)*
ΔS&P	-0.008	-0.099	0.054	-0.055	0.037	-0.031	-0.011	0.016	-0.014	-0.033	0.006
	(-0.142)	(-1.022)	(0.797)	(-0.667)	(0.499)	(-0.493)	(-0.131)	(0.200)	(-0.179)	(-0.436)	(0.074)
Δ 5 Year Treasury Yields	-0.155	-0.054	-0.205	-0.140	-0.146	-0.158	-0.086	-0.177	-0.153	-0.249	-0.068
	(-3.049)*	(-0.620)	(-3.237)*	(-1.820)	(-2.078)*	(-2.425)*	(-1.164)	(-2.392)*	(-2.050)*	(-3.501)*	(-0.882)
Δ Slope of Yield Curve	-0.069	-0.080	-0.057	-0.030	-0.098	-0.006	-0.102	-0.079	-0.073	-0.060	-0.114
	(-1.821)	(-1.164)	(-1.215)	(-0.529)	(-1.878)	(-0.128)	(-1.784)	(-1.371)	(-1.352)	(-1.180)	(-1.910)
ΔVIX Index	-0.009	-0.107	0.063	-0.011	-0.004	-0.056	-0.060	0.066	-0.045	-0.048	0.097
	(-0.130)	(-0.960)	(0.774)	(-0.111)	(-0.045)	(-0.713)	(-0.589)	(0.658)	(-0.497)	(-0.517)	(1.011)

* denotes significantly different from zero at the 5% significance level.

Table VI.
The determinants of credit spread slope and changes in credit spread slope for banking firms

PANEL A shows the partial F statistics and the p values for all blocks of explanatory variables given everything else, when the 7 year minus 3 year credit spread slope, SL, is regressed on the vectors of firm-specific risk characteristics, F, liquidity variables, L, and market variables, M, using the following regression equation:

$$SL_i(t) = \beta_0 + \beta_1 \; S_i^3(t) + \beta_F F_i(t) + \beta_L L_i(t) + \beta_M M(t) + e_i(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t).

PANEL B shows the partial F statistic and the p value of the block of changes in firm-specific variables given everything else, when changes in the 7 year minus 3 year credit spread slope, ΔSL, is regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, using the following regression equation:

$$\Delta SL_i(t) = \beta_0 + \beta_1 \; SL_i(t-1) + \beta_F \Delta F_i(t) + \beta_L \Delta L_i(t) + \beta_M \Delta M(t) + e_i(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t). High Rating category comprises banking firms with examination rating of 1, and low rating category the remaining banking firms. High and low categories based on total assets, leverage and Return on Assets (ROA) are defined in terms of being above the sample median or below the sample median respectively.

PANEL A: 7 year minus 3 year credit spread slope

Explanatory power of the variable block given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
F	2.523 (0.018)*	2.455 (0.036)*	3.484 (0.002)*	12.628 (0.000)*	3.780 (0.003)*	16.020 (0.000)*	3.658 (0.003)*	8.124 (0.002)*	5.425 (0.000)*	4.714 (0.000)*	1.672 (0.142)
L	1.815 (0.125)	0.154 (0.961)	1.772 (0.134)	1.873 (0.116)	2.713 (0.031)*	2.893 (0.023)*	1.235 (0.297)	0.757 (0.554)	1.113 (0.351)	1.798 (0.130)	2.096 (0.082)
M	1.455 (0.203)	0.929 (0.464)	0.775 (0.568)	2.710 (0.021)*	0.773 (0.570)	17.346 (0.000)*	0.868 (0.504)	5.352 (0.000)*	0.999 (0.419)	1.253 (0.285)	1.584 (0.165)
Adjusted R^2	0.187	0.085	0.151	0.417	0.055	0.458	0.108	0.297	0.128	0.215	0.079

PANEL B: Changes in the 7 year minus 3 year credit spread slope

Explanatory power of the variable block given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔF	0.909 (0.475)	1.783 (0.120)	0.807 (0.545)	0.437 (0.322)	0.884 (0.492)	0.188 (0.967)	1.892 (0.097)	0.091 (0.994)	1.603 (0.160)	1.310 (0.261)	0.435 (0.824)
Adjusted R^2	0.580	0.645	0.542	0.559	0.599	0.668	0.528	0.577	0.580	0.621	0.538

* denotes significantly different from zero at the 5% significance level.

Table VII.
The importance of changes in firm variables in explaining changes in credit spreads for banking firms: Lagged firm variable effects

This table shows the partial F statistics and p values of the 2 blocks of changes in firm-specific risk variables given everything else, when changes in the k-year credit spread, ΔS^k, are regressed, on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, lagged firm risk characteristics, F_i (t-1), and the interaction between F_i (t-1) and ΔF, using the following regression equation:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k S_i^k(t-1) + \beta_{FL}^k F_i(t\text{-}1) + \beta_I^k F_i(t\text{-}1)\Delta F_i(t) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + e_i^k(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3 or 7. High Rating category comprises banking firms with examination rating of 1, and low rating category the remaining banking firms. High and low categories based on total assets, leverage and Return on Assets (ROA) are defined in terms of being above the sample median or below the sample median respectively.

Changes in 3 year credit spreads

Explanatory power of the variable blocks given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔF and FΔF	0.674 (0.749)	1.397 (0.188)	0.880 (0.553)	0.627 (0.790)	1.271 (0.248)	1.319 (0.222)	1.775 (0.067)	1.074 (0.384)	1.227 (0.275)	1.287 (0.239)	1.252 (0.260)
Adjusted R^2	0.490	0.517	0.541	0.569	0.510	0.712	0.412	0.588	0.462	0.554	0.441

Changes in 7 year credit spreads

Explanatory power of the variable blocks given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Bank	BHC	High	Low	High	Low	High	Low	High	Low
ΔF and FΔF	0.844 (0.587)	1.068 (0.391)	1.048 (0.403)	0.953 (0.485)	1.624 (0.101)	1.589 (0.111)	2.203 (0.019)*	1.570 (0.117)	1.510 (0.137)	2.118 (0.024)*	2.632 (0.005)*
Adjusted R^2	0.453	0.510	0.467	0.563	0.484	0.684	0.413	0.466	0.475	0.553	0.375

* denotes significantly different from zero at the 5% significance level.

Table VIII.
The importance of changes in firm variables, stock returns and changes in ratings in explaining changes in credit spreads for banking firms: The control variables effect

The table shows the partial F statistics and the p values of the blocks of firm-specific risk variables, stock returns and changes in examiner ratings given everything else, when changes in the k-year credit spread, ΔS^k, are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, market variables, ΔM, and control variables, ΔC, using the following regression equations, with k =3, 7.

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + \beta_C^k \Delta C_i(t) + e_i^k(t)$$

The table also shows the results when changes in the 7 year minus 3 year credit spread slope, ΔSL, is regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, market variables, ΔM, and control variables, ΔC, using the following regression equation:

$$\Delta SL_i(t) = \beta_0 + \beta_1 SL_i(t-1) + \beta_F \Delta F_i(t) + \beta_L \Delta L_i(t) + \beta_M \Delta M(t) + \beta_C \Delta C_i(t) + e_i(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t). The control variables comprise stock returns and change in examiner ratings.

Explanatory power of the variable block given everything else	Changes in 3 year credit spreads	Changes in 7 year credit spreads	Changes in the 7 year minus 3 year credit spread slope
Partial F of ΔF **(p value)**	1.373 (0.234)	0.780 (0.558)	0.436 (0.823)
Partial F of Stock Return **(p value)**	4.741 (0.030)*	1.633 (0.202)	3.265 (0.072)
Partial F of Rating change **(p value)**	0.001 (0.981)	0.752 (0.386)	0.766 (0.382)
Adjusted R^2	0.480	0.426	0.543

* denotes significantly different from zero at the 5% significance level.

Table IX.
The determinants of credit spread changes for non-banking firms

The table shows the partial F statistic and the p value of each block of explanatory variables *given everything else*, when changes in the k-year credit spread, ΔS^k, are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, using the following regression equation:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + e_i^k(t)$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3 or 7. High Rating category comprises firms that have 'A' rating or above, and low rating category the remaining firms. High and low categories based on total assets, leverage and Return on Assets (ROA) are defined in terms of being above the sample median or below the sample median respectively.

3 year credit spread changes

Explanatory power of the variable block given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Manufacturing	Service	High	Low	High	Low	High	Low	High	Low
ΔF	1.205 (0.305)	1.879 (0.097)	0.080 (0.995)	1.514 (0.184)	0.821 (0.535)	0.953 (0.443)	0.807 (0.545)	0.704 (0.623)	1.114 (0.352)	1.179 (0.319)	0.580 (0.716)
ΔL	7.133 (0.000)*	2.519 (0.041)*	6.581 (0.000)*	2.084 (0.082)	16.129 (0.000)*	5.085 (0.001)*	1.437 (0.221)	5.069 (0.001)*	3.022 (0.018)*	2.217 (0.067)	5.226 (0.000)*
ΔM	2.532 (0.028)*	0.989 (0.424)	1.648 (0.146)	1.216 (0.300)	4.411 (0.001)*	1.771 (0.118)	1.898 (0.094)	2.767 (0.018)*	1.650 (0.146)	1.192 (0.312)	1.881 (0.096)
Adjusted R^2	0.166	0.108	0.214	0.101	0.284	0.241	0.073	0.253	0.095	0.091	0.241

7 year credit spread changes

Explanatory power of the variable block given everything else	All	Type of firm		Rating		Size: Total Assets		Leverage		Profitability: ROA	
		Manufacturing	Service	High	Low	High	Low	High	Low	High	Low
ΔF	0.810 (0.543)	2.078 (0.067)	0.157 (0.978)	1.505 (0.187)	0.437 (0.822)	0.550 (0.738)	1.515 (0.184)	0.456 (0.809)	1.940 (0.087)	0.851 (0.514)	0.683 (0.636)
ΔL	13.568 (0.000)*	3.822 (0.005)*	10.101 (0.000)*	3.053 (0.017)*	36.458 (0.000)*	10.049 (0.000)*	1.504 (0.200)	9.593 (0.000)*	5.422 (0.000)*	6.175 (0.000)*	4.849 (0.001)*
ΔM	1.441 (0.207)	2.150 (0.059)	0.833 (0.527)	1.480 (0.195)	2.092 (0.065)	0.946 (0.451)	2.401 (0.037)*	1.429 (0.213)	2.557 (0.027)*	0.821 (0.535)	1.565 (0.169)
Adjusted R^2	0.219	0.119	0.283	0.104	0.415	0.293	0.087	0.304	0.124	0.047	0.450

* denotes significantly different from zero at the 5% significance level.

Table X.
Preventative influence of subordinated debt for Banking Firms

Panels A and B respectively show the average change in the raw and the matched-adjusted firm-specific risk characteristics from before it first issued any subordinated debt to after it did, and the corresponding t statistics. For this exercise we are limited to 14 banks and 14 BHCs that first issued SND in or after 1988 because all data from the Y-9 and call reports are available only after 1988. For each bank (BHC) that issues subordinated debt for the first time, a matched portfolio of 10 non-issuing banks (BHCs) is constructed as follows. For each bank (BHC), we find the closest 250 non-issuing banks (BHCs) based on Total Assets (size). From out of these 250 banks (BHCs), we find the closest 50 firms based on leverage. At this stage, we have a set of 50 non-issuing banks or BHCs for each issuing bank or BHC that are matched to the issuer in terms of Total Assets and leverage. Next, from out of these 50 banks (BHCs), we find the closest 10 firms based on ROA. This set of 10 non-issuers (that are closest to the issuer in terms of Total Assets, Leverage, and ROA in addition to being the same type of firm (bank or BHC) and having the same examiner rating in the issuing quarter) form our matched portfolio for that issuer. We find such a set of matched non-issuing firms for each issuer in our sample.

PANEL A: Raw changes

	Average change from the quarter before the first issue of SND to the quarter after the first issue of SND (t statistic: H_0=0)	Average change from the half year before the first issue of SND to the half year after the first issue of SND (t statistic: H_0=0)	Average change from the year before the first issue of SND to the year after the first issue of SND (t statistic: H_0=0)
ROA	0.0023 (1.425)	0.0021 (1.167)	0.0006 (0.322)
Loan assets to total assets ratio	0.0023 (0.343)	0.0107 (1.269)	-0.0160 (-1.071)
NPA to loan assets ratio	-0.0026 (-1.871)	-0.0044 (-1.816)	-0.0054 (-1.636)
Net Charge-offs to Loan assets ratio	-0.0003 (-0.256)	0.0029 (1.067)	-0.0012 (0.706)
Leverage	-0.1458 (-0.451)	-0.5655 (-0.879)	-0.9214 (-1.817)

PANEL B: Matched-Adjusted changes

	Average change from the quarter before the first issue of SND to the quarter after the first issue of SND (t statistic: H_0=0)	Average change from the half year before the first issue of SND to the half year after the first issue of SND (t statistic: H_0=0)	Average change from the year before the first issue of SND to the year after the first issue of SND (t statistic: H_0=0)
ROA	0.0019 (1.259)	0.0019 (1.079)	-0.0010 (-0.475)
Loan assets to total assets ratio	0.0031 (0.394)	0.0299 (1.195)	-0.0226 (-1.316)
NPA to loan assets ratio	-0.0004 (-0.313)	-0.0004 (-0.207)	-0.0009 (-0.354)
Net Charge-offs to Loan assets ratio	0.0004 (0.324)	0.0041 (1.730)	0.0025 (1.178)
Leverage	0.1336 (0.406)	-0.0618 (-0.188)	0.5790 (0.884)

* denotes significantly different from zero at the 5% significance level.

Figure 1.
Riskless Interest rates: Pricing Errors

This figure shows the one-week ahead prediction errors (in basis points) for several maturities when our model is used to estimate riskless yields, using the Kalman-Filter procedure. The errors are presented in the form of box-and-whiskers plots. The darkened box covers the 25th to 75th percentiles, and the whiskers the reminder. The weekly data used in the analysis covers the period from January 1993 through December 2000, and comprises Constant Maturity Treasury rates of different maturities downloaded from the web site of Federal Reserve Bank of St. Louis.

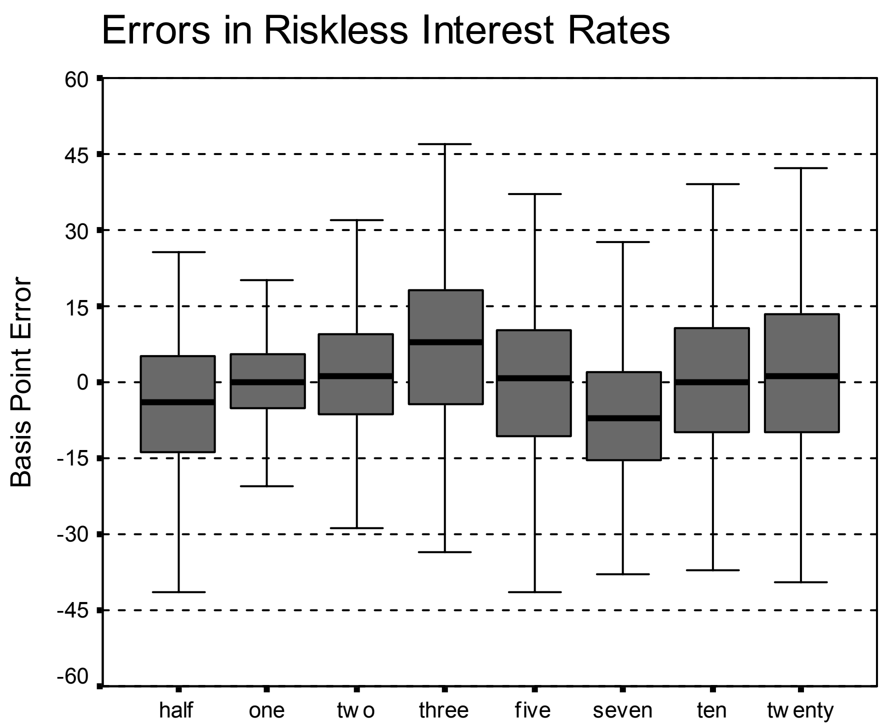
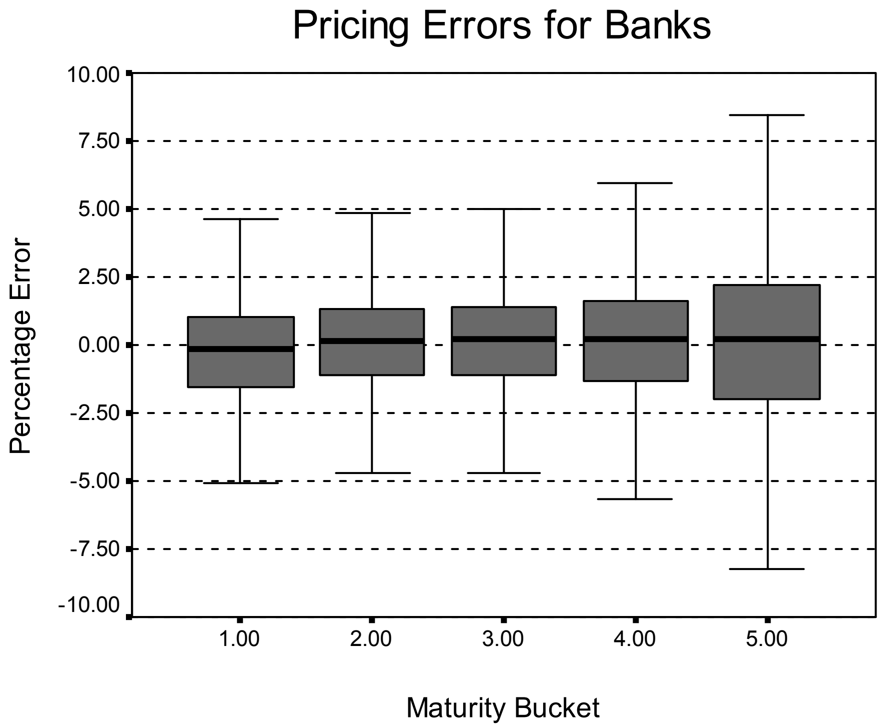


Figure 2.
Pricing Errors of Risky Debt

This Figure shows the percentage errors when our model is used to price subordinated debt issued by banking and non-banking firms across different maturity buckets: defined as 0-2 years, 2-5 years, 5-10 years, 10-20 years and > 20 years.



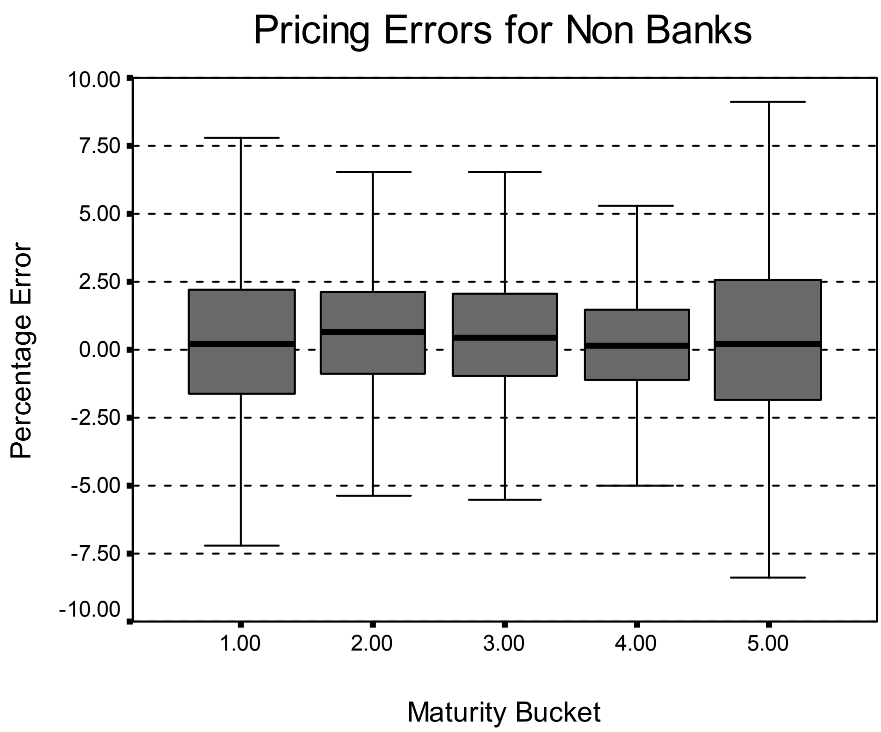


Figure 3.
Pricing errors across Banking Firms

This figure shows the histogram of average percentage errors in bond prices by bank across all banking firms when our model is used to price subordinated debt. The average error is close to zero, and the figure reveals no significant bias, positive or negative.

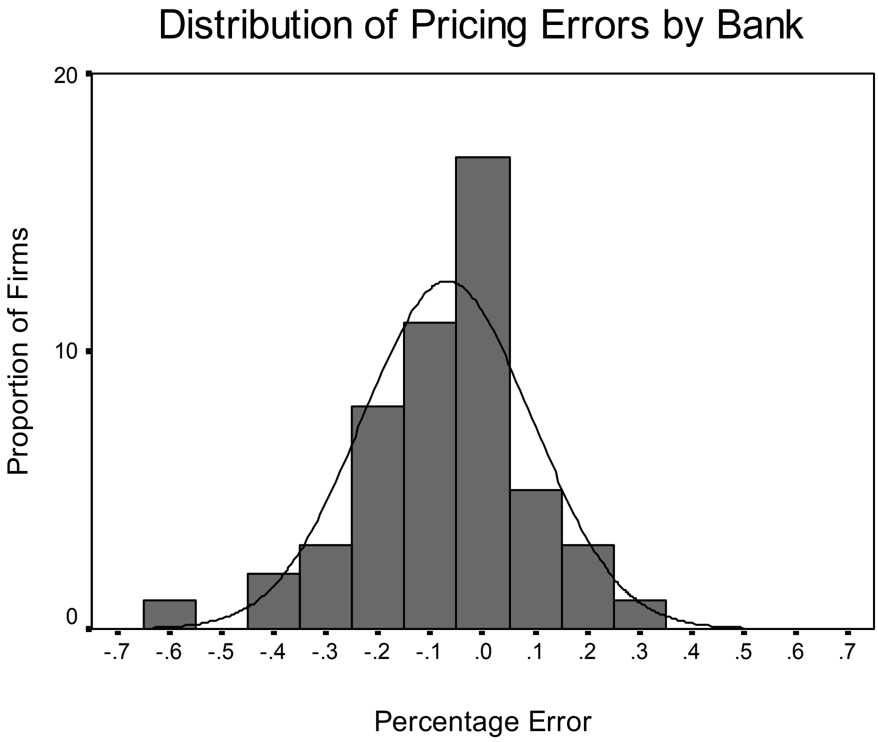


Figure 4.
Time Series fluctuations of Credit Spreads for Banking Firms and Non-Banking Firms

The Figure shows the time series of quarterly 3-year credit spreads for a random sample of banks and non-banks. Not all the time series are complete for all 24 quarters. The credit spreads are reported in basis points. The right hand panels show the quarterly changes in credit spreads.