Monitoring and Controlling Bank Risk: Does Risky Debt Help?*

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ABSTRACT

We examine whether mandating banks to issue subordinated debt would 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 do not find strong and consistent evidence that they do. To evaluate whether subordinated debt controls risk taking, we examine whether the first issue of 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.

Policymakers are actively considering requiring banks to issue subordinated notes and debentures (SND). A mandatory SND requirement appears to be an important part of the market oriented reforms contained in the consultative paper issued by the Basel Committee on Banking Supervision (1999).The U.S Shadow Regulatory Committee has come out strongly in favor of mandatory SND as a mechanism for realizing enhanced market discipline of banks. Moreover, the Gramm-Leach-Bliley Act of 1999 mandated a joint Federal Reserve and U. S. Treasury study of bank SND requirements. This legislation also requires all large banking firms to have at least one issue of SND outstanding at all times.

Proponents of mandatory SND 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 risk 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. Moreover, banks would face increased costs of funding should they adopt riskier strategies. As a result, banks with SND may be less likely to adopt risky strategies in the first place. This is the preventative influence role of risky debt.

The purpose of this paper is to examine whether SND issued by banks and bank holding companies (BHCs) (together referred to as banking firms) enhances risk monitoring and 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 and liquidity factors. To evaluate preventative influence, we examine changes in the risk characteristics of banking firms around the time they *first* issued SND.

A lengthy literature exists that addresses the question of whether the market prices of liabilities respond to risk taking by individual banks. 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 period, yields on SND were affected by accounting measures of risk. Jagtiani, Kaufman and Lemieux (2002) confirm this result for the post-1991 period; a period that follows the passage of the Federal Deposit Insurance Corporation Improvement Act (FDICIA), which supposedly reduced the breadth of the safety net for banks.[2] A related literature concerns 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 (2000) indicate that neither the market nor 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 of the issue and the yield of an equivalent Treasury security.

For example, Flannery and Sorescu (1996) calculate the default risk premium as the SND yield minus the yield of a Treasury bond with approximately the same maturity date.[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, which we are aware of, attempt to extract the *term structure* of credit-spreads for each bank. The importance of this is 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 move upward, downward, or reflect humped-shaped shocks.

We carefully extract an entire credit-spread curve for each of our firms for each quarter. Then we examine whether firm-specific risk variables influence credit spread *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 an 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 changes in market-wide and liquidity factors, and we do not find any consistent evidence that they do. 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, and find similar results.[5]

Next, we examine how bank risk changes around the time a banking firm first issues SND. We use both the raw risk changes of each SND-issuing banking firm and the matched-adjusted risk changes (computed as the risk changes of each SND-issuing banking firm over and above that of a portfolio of size, leverage and profitability matched non SND-issuing banking firms). We do not find any significant change in the firm-specific risk characteristics. Thus, we fail to find evidence consistent with the preventative influence effect for SND.

We conclude that mandating banking firms to issue SND is unlikely to provide the purported benefits of enhanced risk monitoring or preventative influence, as envisioned by its proponents.

The remainder of the paper is organized as follows. Section I describes how we construct our risky and riskless bond databases. Section II describes the model we use to construct the credit spread curves for each firm and discusses the fit to bond prices. Section III describes our sets of firm-specific, market and liquidity variables. Section IV examines whether risky debt facilitates market monitoring of bank risk. We perform several additional analyses in section V that include examining whether credit spread changes reflect firm risk changes better when we consider only the recent issuers of SND; checking whether changes in credit spreads predict future rating migrations; and examining whether our results are bank specific or whether they apply more generally. Section VI examines the preventative influence benefits of SND and section VII concludes.

I. Data

Our first task is to construct credit-spread curves at the end of each quarter for as many different banking firms as possible, and then to repeat this exercise for a control sample of non-banking firms. The reason we use quarters for our time increments is that we want to relate changes in credit spreads to changes in firm specific information, which is reported only quarterly. Moreover, bank supervisors need to act quickly (e.g., within a quarter) in response to any signals that a bank's financial condition may deteriorate.

The data for our analysis comes from the Fixed Income Securities Database (FISD) on corporate bond characteristics matched to the National Association of Insurance 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). The NAIC database has an advantage over the Warga database since the former contains transaction prices rather than quotes.

We record the transaction prices and all the characteristics of each traded bond. We separate all data into two broad categories: trades by banking and trades by 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 $3,265$ 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. 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, 608 transactions from 245 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.[6]

Our second screen eliminates all those firm-quarter combinations for which we had fewer than 7 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 210 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 and 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 of firms for which we could not collect firm-specific risk measures. The firm-specific risk data are collected from the Federal Reserve Y-9 reports and Federal Financial Examination Council's Reports of Income and Condition (Call reports) for BHCs and banks, 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, our final database consists of 6, 590 transactions from 535 issues made by 50 banking firms. Of these, 17 are banks and 33 are bank holding companies. For non-banks, we have 9, 703 transactions from 2335 issues made by 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. This is the first of the three databases we use in this paper. Panel B of Table I 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, 33% of SND issues have maturities between 1 and 5 years, and 26% have maturities between 5 and 10 years. 8% of all banking firms issues were rated AA and above, 62% were rated A, and 17% had lower ratings. The descriptive statistics of bonds issued by non-banking firms in our final control sample are roughly similar to those issued by the banking firms with the exception of ratings; we were unable to find the credit ratings for many issues of non-banking firms.

We use the final sample of banking and non-banking firms to construct credit spread curves for each firm. The average number of issues (transactions) per firm-quarter used to construct credit spread curves for banking firms was 5.01 (13.67). A little over 23% of these bonds have between 1 and 5 years remaining to maturity, and a little over 52% have a time to maturity between 5 and 10 years. Thus, the number of transactions and issues and their range of maturities allow us to be confident that meaningful quarterly credit spread curves at the firm level can be derived.

Our second dataset comprises daily estimates of the zero riskless yield curve. Unlike corporate bonds, there is much information on Treasury rates. To set this up, for each day we use the weekly 3-month, 6-month, one, two, three, five, seven, ten, twenty and thirty year Constant Maturity Treasury rate data from January 1993 to December 2000 obtained from the web site of the Federal Reserve Bank of St. Louis. We use a cubic spline smoothing procedure to extract the par rates for 3 and 6-month maturities, and then for all remaining maturities at 6 month intervals. From this par curve, we then extract the zero-coupon rates for 3 and 6-month maturities and for all maturities thereafter at intervals of 6 months. The final saved output for each day is the annualized continuously compounded zero coupon yields for the three and six month rates, and for the one, two, three, five, seven, ten, twenty and thirty year maturities.

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 III.

II. Extracting Credit Spreads

Our goal is to use actual price information on all bonds for 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. However, 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 establish our 3-factor model for pricing risky debt, describe the estimation process for the parameters of the riskless and risky term structure, and present the results.

A. Pricing Risky Bonds

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,

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

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

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

$$s_p(t;m) = -\frac{1}{m} log \left[\frac{G(t,t+m)}{P(t,t+m)} \right], \tag{3}$$

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

Establishing 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,

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

$$du(t) = -bu(t)dt + \sigma_u dw_u(t). \tag{5}$$

$\theta(t)$ 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 (1994) who develop analytical solutions for the price of a zero coupon riskless bond at any future date t in terms of the state variables $r(t)$ and $u(t)$. This model has been well studied. For example, Jegadeesh and Pennacchi (1996) evaluate how well this model performs for pricing Eurodollar Futures contracts. Further, the model implies 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.[7]

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, given by equations (4) and (5), together with:

$$ds(t) = [\alpha_0 - \alpha_1 s(t)]dt + \sigma_s dw_s(t), \tag{6}$$

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

$$G(t,T) = P(t,T)e^{-D(t,T)s(t)-K(t,T)}, \tag{7}$$

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

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

Using equation (3), the date t credit spread over the time $[t, t+m]$, $s_p(t;m)$, reduces to:

$$s_p(t;m) = \overline{D}(m)s(t) + \overline{K}(m), \tag{8}$$

where:

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

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.

B. Estimation Technique

Our state variables (r_t, u_t, s_t) are not directly observable. We do have rich riskless term structure data, which allows us to measure, with error, functions of (r_t, u_t). To facilitate estimation using discretely observed data, we separate the estimation problem into two phases. In the first phase, we estimate the riskless term structure parameters using a time series of cross sections of riskless bond prices, imposing both cross-sectional model restrictions and conditional time-series restrictions. We accomplish this using a Kalman filter approach. However, given the relative paucity of risky bond price data, our approach for estimating the remaining credit related parameters for each firm is modified. In particular, we adopt an empirical Bayes estimation procedure used in non-linear mixed effects models. This approach produces consistent estimators, and is very close in intent to the Kalman filtering approach, where the underlying process is not observable. The details of the estimation techniques are summarized in the Appendix.

C. 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 the prediction errors for each maturity.

Figure 1 Here

The model displays almost no bias in estimating yields, and the majority of predictions provided by our 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 are 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 inter-quartile ranges for percentage errors are symmetrically distributed about zero for all maturity buckets. The inter-quartile range extends for about 2.5%. In aggregate, the mean (median) pricing error was 0.22% (0.16%). The mean of the absolute percentage errors was 2.2%, while the median of the absolute percentage errors was 1.2%. These results indicate that the model is fitting actual data remarkably well with no obvious biases along the maturity spectrum. The bottom panel of Figure 2 shows the box whisker plots for our sample of non-banks.

The average percentage pricing error per bank is almost 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.

Given the distribution of maturities (see Panel B of Table I), we have chosen to focus on representative maturities for credit spreads of 3 and 7 years in all our analysis. Interestingly, the 3 and 7 year credit spreads often move in opposite directions. For our bank data, 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.

III. 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. As evidenced by Figure 2, the 3-factor model fits our data remarkably well with no obvious biases along the maturity spectrum. However, the credit spreads may be capturing default probability, anticipated recovery rates given default, liquidity effects or risk aversion effects. The magnitude of credit spreads could fluctuate according to changes in market and business cycle conditions, changes in bond liquidity factors and firm risk 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 is not possible to include additional state variables into the dynamics of the instantaneous credit spread. Indeed, even those papers that parameterize credit spreads as a function of candidate state variables limit themselves to considering only a few state variables. Jarrow and Yildirim (2002) use only interest rates as the state variable while Bakshi, Madan and Zhang (2001), consider a variety of models with no more than two state variables.

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 per firm-quarter. These explanatory variables are firm specific risk characteristics, market wide factors, and liquidity factors.

A. 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	

	Variable	Description	As Variable Increases, Spreads	Source of Data
Non-Banks				
	ROA	Operating Income Before Depreciation/ Total Assets	decreases	Compustat
	Interest Coverage	Operating Income Before Depreciation/ Interest Expense	decreases	
	Profit Margin	Operating Income Before Depreciation / Sales	decreases	
	Leverage	(Total Assets- Stockholder Equity)/ Stockholder Equity	increases	
	Market to Book Ratio	(Total Shares $\times$ Closing Share Price)/ Stockholder Equity	decreases	

On the last day of a quarter, the firm specific variables are not yet publicly released. The final Call Report (bank level) data are released to the public around 65 days after the end of the quarter, and the final Y9 (BHC level) data are released to the public around 80 days after the end of the quarter. Thus, at date t, the firm variables pertaining to firm i in the current quarter, t, denoted by a 5 vector $F_i(t)$, are not yet publicly known. However, the firm variables pertaining to the previous quarter, $F_i(t-1)$, are publicly known at time t.

B. 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 (GIP) is measured as the change in the industrial production number from the beginning to the end of the current quarter. Ceteris paribus, higher growth should translate into lower credit spreads. Similarly, if the $S\&P$ 500 return (measured over a quarter) is high, individual firms are likely to be prospering. 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 an increase in the slope of the 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. Finally, as firm volatility increases, the probability of default increases, and the credit spread increases. Since many of the firms we investigate do not have publicly traded options, we cannot observe their implied volatilities. We therefore use the VIX index, which is a weighted average of eight implied volatilities of near the money options on the $S\&P$ 100 index.

Let $M(t)$ represent a vector of these 5 market variables at the end of quarter t, and $\Delta M(t)$ a vector that contains the change in these variables over the t^{th} quarter. The second entry of $\Delta M(t)$ is the same as the second entry of $M(t)$: the $S\&P$ 500 return over the quarter. One element of $M(t)$, Growth in Industrial Production, becomes known to the market around 15 days after the end of a quarter. Let $M^P(t)$ represent the vector of the 5 market variables, of which all except GIP pertain to the current quarter, and all of which are known precisely to the market at date t.

C. 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. A wider TED 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. Finally, the Relative Trade Size variable controls for the fact that a few large trades could impact spreads differently compared to a number of smaller trades.

Let $L(t)$ represent a 4 vector of these liquidity variables for firm i at the end of quarter t, and $\Delta L(t)$ a 4 vector of their changes. Notice that the third entry of $\Delta L(t)$ 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.

D. Control Variables

Regulators often have other indicators of bank risk changes, in addition to credit spreads changes. These include stock returns, changes in the examiner rating (the CAMELS and BOPEC ratings), and changes in the credit ratings of outstanding debt issues. Unfortunately, stock returns from CRSP are available only for a subset of our sample of banking firms. In particular, they are available for almost all BHCs but only for a small fraction of our banks. Also, a full scope bank/BHC examination is, typically, conducted once a year, and, in our sample, 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. Therefore, we will only use these variables later as a check for the robustness of our results.

These 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 CAMEL ratings for banks	Federal Reserve System 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.)	

With regard to the examiner ratings, 50% of our banking firms had the highest ratings and 45% had the second highest ratings. With regard to credit ratings, we established a single numeric credit score for each firm-quarter as follows. First, we translated the letter ratings from each agency for each issue on each firm into numeric scores, with 1 representing the lowest rating and 15 the highest rating. The most common ratings for the banking firms in our sample, using Standard & Poor's notation, are $BBB+$, $A-$ and A, which correspond to scores of 9, 10 and 11 respectively. We then took the average values of all the agency ratings each firm-quarter, to obtain a single numeric credit score for each banking firm each quarter. As Table I shows, we have data on credit ratings for 87% of all our banking firms.

Ratings by credit agencies make much finer distinctions between banks than do examiner ratings. The examiner ratings for our sample of banking firms were 1, 2, or 3, with 1 representing the highest quality. The average credit-rating scores corresponding to an examiner rating of 1, 2 and 3 were 10.98, 10.63 and 9.40 respectively.

IV. Market Monitoring

A. Determinants of Credit Spread Levels

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

On the last day of a quarter, the market variables, $M(t)$, and liquidity variables, $L(t)$, are known. However, firm specific variables are not yet publicly released; so $F_i(t)$ may be known with error. We correct for this "error in variables" problem using the standard two-stage least squares procedure. Specifically, let $S_i^k(t)$ represent a particular k-year credit spread, and $S_i(t-1)$ a 4-vector of the 3, 5, 7, and 10 year spread levels of the previous quarter. Then, pooling all firms together, we have the following system of equations:

$$S_i^k(t) \quad = \quad \beta_0 + \beta_F^{k\prime} F_i(t) + \beta_L^{k\prime} L(t) + \beta_M^{k\prime} M(t) + e_i^k(t) \tag{9}$$

$$
\begin{aligned}
F_i(t) &= \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \epsilon_i(t) \\
GIP(t) &= \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t),
\end{aligned}
$$

where the beta coefficients measure the sensitivity to firm, liquidity and market variables, $A_j, j = 1..,4$ and $B_j, j = 1..,4$, represent appropriately sized matrices or vectors of coefficients for the instrumental variables, $\epsilon_i(t)$ is the vector of residuals for firm specific variables, and $\eta_i(t)$ is the residual for GIP.

The 3 and 7-year credit spreads are regressed 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, credit ratings, size (measured in terms of total assets), and leverage.

The reason for looking at banks and BHCs separately is that bank issued debt may be riskier than BHC-issued debt because the holders of SND issued by BHCs typically have recourse to assets owned by other banks in the same holding company. Segregation based on size takes into account the possible "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 (FDICIA) in 1991, although Covitz, Hancock and Kwast (2002) argue that FDICIA may not have induced as large an increase in market discipline as previously thought. The market may still perceive the largest banking firms to be TBTF, particularly when there are complex derivative books with master netting agreements to contend with. Segregation by credit ratings takes into account the possibility that higher rated banks may not feel the same pressure from regulators to control risk taking. Furthermore, investors in the debt market have the incentive to monitor bank risk more closely for the lower rated banks. Hence, bank specific risks, and any changes thereof, may get reflected more in credit spreads for the lower rated banking firms. 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 non-banking 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, credit rating, size and leverage. For size and leverage, high refers to firms with values above the median. For credit rating, high refers to those firms with a credit rating of $A-$ and above.[8]

The above analysis replicates previously well-known results using levels of credit spreads. However, 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.

B. 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. Again to account for the "errors in variables" problem in the changes in firm-specific risk variables, $F_i(t)$ is instrumented by $M(t)$, $L(t)$, and $F_i(t-1)$. The system of equations is then given by:

$$\begin{aligned} \Delta S_i^k(t) &= \beta_0 + \beta_S^{k'} S_i^k(t-1) + \beta_F^{k'} \Delta F_i(t) + \beta_L^{k'} \Delta L(t) + \beta_M^{k'} \Delta M(t) + e_i^k(t) \quad (10) \\ F_i(t) &= \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \epsilon_i(t) \\ GIP(t) &= \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t), \end{aligned}$$

where $\Delta S_i^k(t)$ represents the change in a particular k-year credit spread over the t^{th} quarter for firm i, and $\Delta F_i(t) = F_i(t) - F_i(t-1)$.

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. Panel A of 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

For the full sample, changes in 3-year credit spreads do not significantly reflect changes in firm specific risks, after controlling for changes in market-wide variables and liquidity variables. However, when we examine the results for our different sub-samples, we find that changes in 3-year credit spreads do significantly reflect changes in firm specific risks for banks, lower credit-rated banking firms, high levered banking firms, and, surprisingly, for the larger firms. Nevertheless, of the total sums of squares that can be explained by the regression equations, firm-specific variables explain around 1% for the full sample. Even for the firm subgroups where firm variables mattered the most, the contribution of firm risk variables to the explainable sums of squares was less than 9%.

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. The resulting system of equations is given by:

$$\begin{aligned} \Delta S_i^k(t) &= \beta_S^{k'} S_i^k(t-1) + \beta_F^{k'} \Delta F_i(t) + \beta_L^{k'} \Delta L(t) + \beta_M^k T + \epsilon_i^k(t) \\ F_i(t) &= \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \epsilon_i(t) \\ GIP(t) &= \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t), \end{aligned} \tag{11}$$

where T is a vector of size 24 (one for each quarter that our data spans), which 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 re-estimate the model controlling for fixed effects, our results are unchanged: changes in credit spreads reflect changes in firm risks for banks, banking firms that are rated below $A-$, for banking firms that have total assets more than the sample median, and leverage more than the sample median.

The results are similar when we examine the 7-year credit-spread changes (see Table IV). For the full sample, changes in firm specific variables do not significantly influence changes in credit spreads, even when we re-estimate the model controlling for time fixed-effects. However, for banks, lower rated banks and larger banks, firm specific variables do influence changes in credit spreads.

Table IV Here

We also considered a regression model in which the dependent variable was the change in 10-year credit spreads. Using 10-year credit spread changes is reasonable since 29% of bank issues have maturities exceeding 10 years. Again, we find that changes in firm specific risk variables do not significantly influence credit-spread changes for the full sample.

We do however, find a strong statistically significant relationship between changes in the market variables and changes in credit spreads. To determine which specific market variables affect changes in credit spreads, we 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 (10) is estimated over all the data and over the various subgroups.

Table V Here

In general, for both changes in the 3 and the 7-year credit-spreads, changes in the 5-year Treasury yields is an important variable. The signs of all significant market variable coefficients are as expected.

V. Additional Checks

A. Including Control Variables

As a robustness check, we examine whether changes in credit spreads reflect changes in firm risk after controlling for not only market and liquidity variables but also other variables that can reflect changing firm risk. In particular, we include stock returns, credit rating changes and examiner rating changes as additional independent variables for changes in credit spreads. We use the time fixed-effects regression specification because in this regression specification, credit spread changes tended to reflect firm risk changes marginally better (see tables III and IV). The results do not change. The partial F-statistic (p-value) for the vector of firm risk variables changes is 1.604 (0.161) for the 3-year credit spread changes, and 1.515 (0.187) for the 7-year credit spread changes. Thus, changes in firm risk variables are not reflected in changes in credit spreads after controlling for other sources of information on firm risk changes.

B. Common Factors among Residuals

Next, we analyze the residuals of the model specification in which changes in the 3-year credit spreads are regressed on changes in market, liquidity and firm risk variables (see table III). The adjusted R^2 for this specification was 49.6 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-quarter into one of four bins, determined by two leverage groups and two size groups. For each bin, we computed an average residual for each quarter, and then extract the principal components from the resulting covariance matrix. The first principal component accounted for 40% of the variation, the second an additional 25%, and the third, a further 19%. 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, it unlikely that we have missed accounting for certain firm-specific risk variables that may have had explanatory power over changes in credit spreads.

C. Recent Debt Issuances

We have found that credit spread levels reflect information on bank specific risks, but credit spread changes do not reflect information on changes in bank specific risks as well. Since the model explaining credit spread levels is linear, at first glance it may seem surprising that the first difference model does not work as well. In this section, we provide one possible explanation for this result based on Covitz and Harrison's (2003) conclusion that banks with good information attract market scrutiny by issuing debt. The increased focus on firm risk around debt issuances improves the likelihood that favorable firm-specific risk information is accurately digested by the marketplace, and subsequently reflected in credit rating upgrades. If it is true that around debt issuances market scrutiny of firm-specific is high, then the relationship between credit spread levels (credit spread changes) should be more tightly connected to firm specific risk levels (firm-specific risk changes) for firms that frequently issue debt than for firms that had not issued SND in some time. For the latter category of firms, it is possible that over time, when no new SND issues are being made, changes in market conditions, rather than in firm specific conditions become the primary drivers for changes in credit spreads.

To test this theory, we divide our bank data into two groups, namely, those banking firms that never made an issue over our sample period, and those banking firms that made issues over the sample period. There were 26 banking firms in the first category and 24 in the second. Let I be an indicator variable that is 1 if a firm has issued debt during our sample period, and 0 otherwise. We now consider the systems of equations:

$$\begin{aligned} S_i^k(t) &= \beta_0 + \beta_1^k I + \beta_F^{k'} F_i(t) + \beta_L^{k'} L(t) + \beta_M^{k'} M(t) + \beta_{is}^{k'} I F_i(t) + \epsilon_i^k(t) \\ F_i(t) &= \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \epsilon_i(t) \\ GIP(t) &= \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t), \end{aligned} \tag{12}$$

and

$$\begin{aligned} \Delta S_i^k(t) &= \beta_0 + \beta_1^k I + \beta_S^{k'} S_i^k(t-1) + \beta_F^{k'} \Delta F_i(t) + \beta_L^{k'} \Delta L(t) + \beta_M^{k'} \Delta M(t) \\ &\quad + \beta_{is}^{k'} I \Delta F_i(t) + \epsilon_i^k(t) \\ F_i(t) &= \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \epsilon_i(t) \\ GIP(t) &= \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t), \end{aligned} \tag{13}$$

where the interaction terms, $IF_i(t)$ and $I\Delta F_i(t)$ are vectors obtained by multiplying point-wise the dummy variable with the vector $F_i(t)$ and $\Delta F_i(t)$ respectively.

Table VI Here

The first 3 columns of Table VI report the results for the levels of the 3, 7 and 10 year credit spreads. The significance of the interaction term shows the additional explanatory power of the block of firm specific risk variables for banking firms that have recently issued debt, over and above all other variables. For all three credit-spread levels, the role of firm specific risk variables is more important for firms that have recently issued debt. In particular, the partial F test of the interaction effects of firm variables with the issue dummy variable is significant at the 5% level.

The last 3 columns report the results for changes in credit spreads. At the 5% significance level, the 3, 7 and 10 year credit spread changes are all significantly influenced by the changes in risk variables for firms that have recently issued debt. Note, however, that the partial R^2 values are low. For example, for the changes in the 7-year credit spread, the value is 0.025, indicating that 2.5% of the variability remaining among the residuals without the interaction variable, can now be explained. Since the unadjusted R^2 for the seven year change regression was over 50%, this implies that the interaction variable accounts for less than 1% of the total variation. In other words, credit spread changes, for the most part, are still explained by market forces rather than by changes in firm specific variables, even for firms that have recently issued debt.

D. What if Strong-Form Market Efficiency Held?

While it is most realistic to assume, as we have done throughout the paper, that investors do not know the precise values of $F_i(t)$ at date t, in this section we examine how our results would change if strong form efficiency held. That is, what if the market knew firm information before their public release? The actions of bank officers could allow the information regarding $F_i(t)$ to be revealed to the public at or around time t. If we make this assumption, the actual values of $F_i(t)$ rather than their instrumented values must be used in equations (9) and (10). To be consistent with the notion of strong form efficiency, we also assume, in this section, that GIP(t) is also known to the market on date t.

The results do not change. Bank risk variables still strongly influence credit spread *levels*, but *changes* in credit spreads do not reflect changes in bank risk variables for the overall sample. Bank risk variable changes affect changes in the 3 year credit spreads only for the lower rated banking firms, while bank risk variable changes affect changes in the 7 year credit spreads only for the high leveraged banking firms. Thus, our finding that changes in bank risk variables are not reflected in changes in credit spreads become stronger when we assume strong-form market efficiency.

E. Do Credit Spread Changes Anticipate Credit Rating Changes?

Even if credit spread changes are not informative of firm risk changes, SND can still be useful if changes in credit spread are informative about the direction of future credit rating changes. In this section, we test for this potential benefit of SND.

We begin by confirming that credit ratings do indeed migrate when firm specific risk variables change. Let $\Delta R_i(t+1)$ represent the change in the average credit rating score for a firm from quarter t to quarter $t+1$. Let $\Delta IR_i(t+1)$ be 1 if firm i was upgraded in quarter $t+1$, -1, if it was downgraded, and 0 if there was no change. We run the following OLS as well as Ordered

Logit regression equations:

$$\Delta R_i(t+1) = \beta' T + \beta'_F \Delta F_i^L(t+1) + \epsilon_i(t) \tag{14}$$
$$\Delta IR_i(t+1) = \beta' T + \beta'_F \Delta F_i^L(t+1) + \epsilon_i(t). \tag{15}$$

where $\Delta F_i^L(t+1)$ is the vector of the difference between the firm-specific variables pertaining to date t (that are publicly released some time after date t) and the firm-specific variables pertaining to date $t-1$ (that are publicly released some time after date $t-1$). In these equations, we also have a block of time dummy variables, one for each quarter, that capture all the time fixed effects, including changes in market conditions from quarter to quarter.

The results, shown in Panel A of Table VII, indicate that credit ratings do indeed migrate based on firm-specific risk changes. Next we test whether changes in credit spreads can predict credit rating changes.

We again consider the following OLS and Ordered Logit regression models:

$$\Delta R_i(t+1) = \beta' T + \beta'_F \Delta S_i^k(t) + \epsilon_i(t) \tag{16}$$
$$\Delta IR_i(t+1) = \beta' T + \beta'_F \Delta S_i^k(t) + \epsilon_i(t). \tag{17}$$

In Panel B of Table VII we report the results when the independent variable is the change in 3 and 7 year credit spreads.

Table VII Here

Panel B results show that credit-spread changes cannot be used to predict future changes in credit rating. When analyzed in the context of our earlier results, the results of Table VII are not surprising. While changes in credit ratings do reflect previous changes in firm risk variables, changes in credit spreads, in general, do not significantly and consistently reflect changes in risk variables. As a result, changes in credit ratings do not reflect previous changes in credit spreads. Thus, we find that changes in credit spreads are not useful signals of credit-rating migrations.

F. Are our Results Specific to Banking Firms?

Our results could be due to the fact that we have examined only banking firms that are highly regulated. We have found that credit-spread changes are influenced by market variables to such an extent that we are unable to find any consistent dominant relationship between changes in credit spreads and changes in firm risk variables. To investigate whether this is true for all firms, we regress changes in credit spreads on changes in firm specific risks, changes in liquidity and changes in market variables, for non-banking firms using equation (10). Table VIII 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.

Table VIII Here

The results for our sample of non-banking firms are consistent with those for banking firms: for the full sample, changes in credit spreads do not reflect changes in firm specific risk variables, after controlling for changes in market-wide and liquidity variables. The 7 year credit spread changes reflect firm risk changes for the lower rated firms and the more levered firms. The result that firm risk changes do not get significantly reflected in credit-spread changes for non-banking firms complements that of Collin-Dufresne, Goldstein and Martin (2001). Although their study did not explore the relative role of firm-specific, liquidity, market, and control variables, they concluded that structural models based on firm specific variables were unable to capture changes in credit spreads, and that a significant proportion of the moves could be attributable to unidentified common factors.

VI. Preventative Influence

Banks with SND may be less likely to adopt risky strategies in the first place. This is because if investors are able to accurately price risky debt, then a banking firm would incur increased costs of funding if it were to adopt riskier strategies, after it has issued SND. This is the preventative influence benefit of SND. We investigate this effect by examining whether firm-specific risks change significantly after a banking firm issues its first SND. Panels A and B of Table IX 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, which first issued SND in or after 1988, because changes in the data reported on the Y-9 and Call Reports make construction of comparable BHC and bank risk proxies prior to that time problematic. 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 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 which are matched to the issuer in terms of Total Assets and leverage. Next, from these 50 banks (BHCs), we find the closest 10 firms based on Return on Assets, 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 IX Here

Table IX 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, we fail to find evidence consistent with any preventative influence benefit of SND.

VII. Conclusion

The purpose of this paper is to examine whether risky debt issued by banks and bank holding companies enhances risk monitoring and helps 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 firm-specific risks have changed. In this way, risky debt enhances risk monitoring. Moreover, banks holding 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.

Bank specific information is strongly revealed in the *levels* of credit spreads but *quarterly changes* in bank risk variables bear only a weak relationship to contemporaneous changes in credit spreads. We find that bank specific influences on credit spreads are overwhelmed by shocks due to movements in the market variables for banks (and liquidity variables for non-banks). It is difficult to separate the change in the credit spread into a signal of a change in bank risk versus other components reflecting the "noise" of market and liquidity shocks. Therefore, the "signal to noise" ratio is too small for bank supervisors to accurately estimate changes in bank risks with any degree of confidence. Further, credit spread changes do not act as signals for future rating changes, although credit ratings do respond to changes in firm risk. Finally, we find no evidence that SND can control risk taking: neither the raw risk characteristics nor the risk-matched-firm adjusted characteristics change significantly after a banking firm first issues SND.

Our results question the efficacy of mandating subordinated debt for banking firms as we find little evidence of a risk- change-signaling benefit or preventative influence benefit. Nevertheless, we must temper our conclusion by noting the following: First, 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 find, consistent with the evidence of Covitz and Harrison (2003), credit spreads tend to reflect firm-specific risk factors more for banking firms that regularly issue SND than for firms that do not. Nevertheless, changes in market variables remain the most dominant explanatory variables for changes in credit spreads. Finally, although we find that subordinated debt does not significantly facilitate monitoring of firm risk taking, and does not significantly change the risk-taking behavior of banking firms, it can still have the benefit of providing an additional cushion from banking losses for the depositors and, consequently, the FDIC.

Appendix: Estimation Methodology

We first describe the process for estimating the riskless parameters, and then describe our approach to estimating the risky credit spread parameters.

A. 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:

$$dr(t) = [\theta(t) + u(t) - \overline{a}r(t)]dt + \sigma_r dw_r(t) \tag{A.1}$$

$$du(t) = -bu(t)dt + \sigma_u dw_u(t) \tag{A.2}$$

$$ds(t) = [\alpha_0 - \overline{\alpha}_1 s(t)]dt + \sigma_s dw_s(t), \tag{A.3}$$

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. The ensuing state space system's parameters can be estimated by maximum likelihood. The likelihood function is estimated recursively using a standard Kalman filter.

B. 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. 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:

$$\hat{A}' = (\hat{a_1}, \hat{a}_2, \ldots, \hat{a}_K)$$

$$A' = (a_1, a_2, \ldots, a_K).$$

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:

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

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Endnotes

[1] Examples include Avery, Belton and Goldberg (1988) and Gorton and Santomero (1990). For excellent reviews of this literature see Flannery (1998) and Bliss (2000).

[2] Other recent studies include De Young, Flannery, Lang, and Sorescu (2001), Morgan and Stiroh (2001) and Sironi (2002,2003).

[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 where the relationship of large uninsured liabilities is described by a non-linear function of risk variables.

[5] This result for non-banking firms is in line with that of Collin-Dufresne, Goldstein and Martin (2001) and Huang and Huang (2002).

[6] 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 can explain the higher proportion of straight debt issued by banks, who clearly have more experience with derivative products.

[7] Examples include Ritchken and Chuang (1999), and Babbs and Nowman (1999).

[8] We also divided our sample according to examiner ratings, where high refers to those banking firms that obtained a 1 rating. Since the results with examiner ratings were similar to those with credit ratings we do not report them.

Table I
Descriptive Statistics of Subordinated Debt 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 National Association of Insurance Commissioners (NAIC) database from 1994 through 1999. The first screen eliminates all debt instruments other than fixed-rate U.S. dollar denominated debt that is non-callable, non-puttable, non-convertible, not part of an unit (e.g., sold with warrants) and has no sinking fund provisions. We also exclude debt with asset-backed and credit enhancement features. We use only trade prices. Further, we eliminate all data that have inconsistent or suspicious issue/dates/maturity/coupon or otherwise does not look reasonable. The second screen eliminates all those firm-quarter combinations for which we had less than 7 trades for the quarter, to ensure that we could obtain reliable estimates for the credit-spread curve for a firm at the end of each quarter. The third and final screen removes transactions from firms for which 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.

Panel B shows the frequency distribution of issues falling under different maturity, coupon and rating buckets 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 1st screen		Sample after 2nd screen		Sample after 3rd 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: The Final Sample

Maturity in years	Banking Firms	Non-banking firms	Coupon	Banking Firms	Non-banking firms	Credit Rating	Banking Firms	Non-banking firms
≤ 1	12%	13%	≤ 3%	3%	0%	AA and above	8%	11%
1 to 5	33%	45%	3% to 6%	7%	19%	A	62%	31%
5 to 10	26%	26%	6% to 7%	45%	37%	BBB	14%	14%
10 to 25	25%	11%	7% to 8%	27%	25%	BB and below	3%	3%
> 25	4%	5%	> 8%	18%	19%	Rating not found	13%	41%

Table II
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 the 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 system of regression equations:

$$S_i^k(t) = \beta_0 + \beta_F^k F_i(t) + \beta_L^k L(t) + \beta_M^k M(t) + e_i^k(t)$$
$$F_i(t) = \alpha_0 + A_1 F_i(t\text{-}1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t\text{-}1) + \varepsilon_i(t)$$
$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t\text{-}1) + B_3 L(t) + B_4 S_i(t\text{-}1) + \eta_i(t),$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3 or 7. $F_i(t\text{-}1)$ is the 5-vector of firm-specific variables pertaining to the previous quarter, and publicly known at time t. $M^P(t)$ is the 5-vector of market variables, of which all except GIP pertain to the current quarter, and all of which are publicly known at time t. S_i is a 4-vector of the 3, 5, 7 and 10 year credit spread levels. High Credit Rating category comprises banking firms with credit ratings of A- and above, and low Credit Rating category the remaining banking firms. High and low categories based on size (total assets) and leverage are defined in terms of being above and below the sample median respectively.

3 year credit spreads

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
F	33.181 (0.000)*	18.845 (0.000)*	8.927 (0.000)*	10.844 (0.000)*	10.229 (0.000)*	19.557 (0.000)*	16.272 (0.000)*	13.983 (0.000)*	22.677 (0.000)*
L	2.244 (0.064)	0.490 (0.743)	2.593 (0.037)*	3.795 (0.005)*	1.934 (0.117)	6.987 (0.000)*	0.865 (0.486)	4.364 (0.002)*	0.602 (0.661)
M	19.092 (0.000)*	4.179 (0.002)*	14.725 (0.000)*	22.256 (0.000)*	9.384 (0.000)*	14.515 (0.000)*	10.340 (0.000)*	16.877 (0.000)*	6.141 (0.000)*
Adjusted R^2	0.377	0.464	0.285	0.381	0.622	0.498	0.382	0.429	0.416

7 year credit spreads

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
F	29.058 (0.000)*	17.151 (0.000)*	6.222 (0.000)*	6.126 (0.000)*	9.688 (0.000)*	36.741 (0.000)*	13.874 (0.000)*	14.574 (0.000)*	16.364 (0.000)*
L	1.172 (0.322)	0.249 (0.910)	2.579 (0.038)*	0.281 (0.890)	1.556 (0.199)	7.168 (0.000)*	0.446 (0.775)	2.033 (0.091)	0.729 (0.573)
M	18.294 (0.000)*	4.363 (0.001)*	12.615 (0.000)*	22.912 (0.000)*	7.885 (0.000)*	31.943 (0.000)*	6.377 (0.000)*	18.295 (0.000)*	5.007 (0.000)*
Adjusted R^2	0.348	0.443	0.223	0.340	0.606	0.643	0.309	0.433	0.354

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

Table III
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, (k =3), are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, using the following system of regression equations:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k \; S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + e_i^k(t)$$
$$F_i(t) = \alpha_0 + A_1 F_i(t\text{-}1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t\text{-}1) + \varepsilon_i(t)$$
$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t\text{-}1) + B_3 L(t) + B_4 S_i(t\text{-}1) + \eta_i(t).$$

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, (k =3) 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 system of regression equations:

$$\Delta S_i^k(t) = \beta_S^k \; S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \, \mathrm{T} + e_i^k(t)$$
$$F_i(t) = \alpha_0 + A_1 F_i(t\text{-}1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t\text{-}1) + \varepsilon_i(t)$$
$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t\text{-}1) + B_3 L(t) + B_4 S_i(t\text{-}1) + \eta_i(t),$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t). $F_i(t\text{-}1)$ is the 5-vector of firm-specific variables pertaining to the previous quarter, and publicly known at time t. $M^P(t)$ is the 5-vector of market variables, of which all except GIP pertain to the current quarter, and all of which are publicly known at time t. S_i is a 4-vector of the 3, 5, 7 and 10 year credit spread levels. High Credit Rating category comprises banking firms with credit ratings of A- and above, and low Credit Rating category the remaining banking firms. High and low categories based on size (total assets) and leverage are defined in terms of being above and below the sample median respectively.

PANEL A

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
ΔF	0.563 (0.729)	3.164 (0.009)*	1.228 (0.300)	1.099 (0.371)	3.783 (0.002)*	7.283 (0.000)*	1.771 (0.120)	4.700 (0.000)*	0.871 (0.502)
ΔL	0.354 (0.842)	0.015 (0.999)	0.307 (0.873)	0.152 (0.962)	0.850 (0.500)	0.041 (0.997)	1.248 (0.292)	0.235 (0.918)	0.356 (0.840)
ΔM	6.577 (0.000)*	2.526 (0.032)*	5.197 (0.000)*	4.784 (0.000)*	2.679 (0.031)*	2.907 (0.015)*	3.386 (0.006)*	2.894 (0.015)*	3.358 (0.006)*
Adjusted R^2	0.487	0.442	0.556	0.667	0.497	0.704	0.411	0.595	0.450

PANEL B

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
ΔF	1.423 (0.215)	3.504 (0.004)*	0.648 (0.663)	1.074 (0.388)	5.400 (0.000)*	7.038 (0.000)*	1.901 (0.096)	4.079 (0.002)*	1.472 (0.201)
Adjusted R^2	0.451	0.424	0.521	0.658	0.488	0.698	0.390	0.554	0.434

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

Table IV
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, (k =7) are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM, using the following system of regression equations:

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

$$F_i(t) = \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \varepsilon_i(t)$$

$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t).$$

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, (k =7) 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 system of regression equations:

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

$$F_i(t) = \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \varepsilon_i(t)$$

$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t),$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t). $F_i(t-1)$ is the 5-vector of firm-specific variables pertaining to the previous quarter, and publicly known at time t. $M^P(t)$ is the 5-vector of market variables, of which all except GIP pertain to the current quarter, and all of which are publicly known at time t. S_i is a 4-vector of the 3, 5, 7 and 10 year credit spread levels. High Credit Rating category comprises banking firms with credit ratings of A- and above, and low Credit Rating category the remaining banking firms. High and low categories based on size (total assets) and leverage are defined in terms of being above and below the sample median respectively.

PANEL A

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
ΔF	1.115 (0.352)	3.044 (0.011)*	2.656 (0.026)*	1.693 (0.151)	2.501 (0.031)*	8.054 (0.000)*	1.528 (0.183)	1.786 (0.117)	1.109 (0.357)
ΔL	0.617 (0.651)	0.191 (0.943)	0.475 (0.754)	0.275 (0.894)	0.756 (0.558)	0.093 (0.985)	0.736 (0.568)	0.732 (0.571)	0.336 (0.854)
ΔM	4.830 (0.000)*	1.829 (0.112)	4.836 (0.000)*	5.421 (0.000)*	2.359 (0.052)	3.380 (0.006)*	1.956 (0.087)	2.288 (0.047)*	2.845 (0.017)*
Adjusted R^2	0.449	0.476	0.466	0.640	0.548	0.648	0.409	0.391	0.470

PANEL B

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
ΔF	1.344 (0.245)	2.558 (0.028)*	1.538 (0.184)	0.961 (0.452)	4.880 (0.000)*	9.746 (0.000)*	1.371 (0.237)	2.910 (0.015)*	0.784 (0.562)
Adjusted R^2	0.422	0.439	0.416	0.613	0.506	0.642	0.392	0.352	0.460

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

Table V
Market Variables that Influence 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 system of regression equations:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + e_i^k(t)$$
$$F_i(t) = \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \varepsilon_i(t)$$
$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t),$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3 or 7. $F_i(t-1)$ is the 5-vector of firm-specific variables pertaining to the previous quarter, and publicly known at time t. $M^P(t)$ is the 5-vector of market variables, of which all except GIP pertain to the current quarter, and all of which are publicly known at time t. S_i is a 4-vector of the 3, 5, 7 and 10 year credit spread levels. High Credit Rating category comprises banking firms with credit ratings of A- and above, and low Credit Rating category the remaining banking firms. High and low categories based on size and leverage are defined in terms of being above and below the sample median respectively.

Changes in 3 year Credit Spreads

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
ΔGIP	-0.088 (-1.538)	-0.031 (-0.282)	-0.117 (-1.784)	-0.118 (-2.236)*	-0.140 (-0.855)	-0.067 (-1.160)	-0.095 (-0.942)	-0.079 (-1.156)	-0.158 (-1.680)
ΔS&P	-0.026 (-0.448)	-0.188 (-1.661)	-0.027 (-0.396)	-0.099 (-1.757)	0.062 (0.407)	-0.130 (-2.133)*	0.109 (1.080)	-0.114 (-1.553)	0.023 (0.251)
Δ 5 Year Treasury Yields	-0.200 (-3.860)*	-0.153 (-1.577)	-0.216 (-3.560)*	-0.116 (-2.280) *	-0.356 (-2.546)*	-0.061 (-1.108)	-0.133 (-1.473)	-0.124 (-1.940)*	-0.190 (-2.949)*
Δ Slope of Yield Curve	-0.065 (-1.622)	-0.126 (-1.704)	-0.046 (-0.984)	-0.009 (-0.245)	-0.153 (-1.463)	-0.043 (-0.996)	-0.150 (-2.319)*	-0.055 (-1.040)	-0.048 (-0.803)
ΔVIX	0.146 (1.580)	0.028 (0.163)	0.178 (1.668)	0.041 (0.469)	0.316 (1.225)	-0.067 (-0.755)	0.304 (1.864)	0.000 (0.000)	0.275 (1.847)

Changes in 7 year Credit Spreads

Explanatory power of the variable block given everything else	All	Type of firm		Credit Rating		Size		Leverage	
		Bank	BHC	High	Low	High	Low	High	Low
ΔGIP	-0.103 (-1.729)	-0.084 (-0.790)	-0.113 (-1.568)	-0.150 (-2.719)*	-0.195 (-1.254)	-0.126 (-2.024)*	-0.050 (-0.496)	-0.082 (-0.982)	-0.150 (-1.627)
ΔS&P	0.002 (0.035)	-0.158 (-1.439)	0.091 (1.187)	-0.055 (-0.921)	0.029 (0.202)	-0.091 (-1.350)	0.008 (0.079)	-0.043 (-0.473)	0.038 (0.424)
Δ 5 Year Treasury Yields	-0.172 (-3.208)*	-0.095 (-1.009)	-0.255 (-3.820)*	-0.158 (-2.987)*	-0.210 (-1.576)	-0.104 (-1.701)	-0.091 (-1.022)	-0.188 (-2.362)*	-0.163 (-1.979)*
Δ Slope of Yield Curve	-0.046 (-1.124)	-0.067 (-0.948)	-0.018 (-0.360)	0.050 (1.247)	-0.144 (-1.470)	-0.001 (-0.006)	-0.119 (-1.866)	-0.049 (-0.782)	-0.053 (-0.910)
ΔVIX	0.105 (1.097)	-0.072 (-0.428)	0.202 (1.720)	0.064 (0.704)	0.160 (0.658)	-0.032 (-0.325)	0.027 (0.163)	0.051 (0.376)	0.175 (1.200)

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

Table VI
Credit Spread Changes and Firm-Specific Risk Changes: Recent Issuance(s) Effect

This Table shows the partial F statistics, associated p values, and the partial R^2 statistics of the block of the interaction of firm-specific risk variables with an indicator variable, I, that is defined below, (the block of the interaction of *changes* in firm-specific risk variables with a dummy variable) when the k-year credit spread, S^k, (*changes* in the k-year credit spread, ΔS^k), where k = 3, 7 or 10, are regressed on vectors of firm-specific risk characteristics, F, liquidity variables, L, and market variables, M (*changes* in firm-specific risk characteristics, ΔF, liquidity variables, ΔL, and market variables, ΔM), using the following system of regression equations:

$$S_i^k(t) = \beta_0 + \beta_1 I + \beta_F^k F_i(t) + \beta_L^k L_i(t) + \beta_M^k M(t) + \beta_I^k IF_i(t) + e_i^k(t)$$
$$F_i(t) = \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \varepsilon_i(t)$$
$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t)$$

and

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k S_i^k(t-1) + \beta_1 I + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + \beta_I^k I\Delta F_i(t) + e_i^k(t)$$
$$F_i(t) = \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \varepsilon_i(t)$$
$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t),$$

where I is an indicator variable that is 1 for banking firms that made an SND issue in one or more quarters in our data sample of firm-quarters and 0 otherwise. $F_i^L(t)$ is the 5-vector of firm-specific variables pertaining to the previous quarter, and precisely known at time t. $M^L(t)$ is the 5-vector of market variables, of which all except GIP pertain to the current quarter, and all of which are precisely known at time t. S_i is a 4-vector of the 3, 5, 7 and 10 year credit spread levels. There are 24 banking firms for which I =1 and 26 banking firms for which I = 0.

Explanatory power of the variable block given everything else	Dependant Variable: S^3	Dependant Variable: S^7	Dependant Variable: S^{10}	Dependant Variable: ΔS^3	Dependant Variable: ΔS^7	Dependant Variable: ΔS^{10}
IF	6.859 (0.000)*	2.930 (0.013)*	2.258 (0.048)*			
IΔF				2.724 (0.020)*	3.986 (0.002)*	5.264 (0.000)*
partial R^2	0.047	0.022	0.018	0.016	0.025	0.031

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

Table VII
Do Credit Spread Changes Predict Credit Rating Changes?

PANEL A shows the partial F statistics (chi square statistics) and the p values of the block of firm-specific risk variables when changes in credit rating in the next period are regressed on the vectors of changes in firm-specific risk characteristics, ΔF, and the time dummy variables, T, using the following regression equations:

Linear Regression Equation: $\Delta R_i\ (t+1) = \beta\,\mathrm{T} + \beta_F\,\Delta F_i^L\ (t+1) + \mathrm{e}_i\ (t)$

Ordered Logit Regression Equation: $\Delta IR_i\ (t+1) = \beta\,\mathrm{T} + \beta_F\,\Delta F_i^L\ (t+1) + \mathrm{e}_i\ (t)$

where $\Delta R_i\ (t+1)$ is the change in the average credit rating the next quarter,

$\Delta IR_i\ (t+1)$ is –1, 0 or +1 to denote rating upgrade, no change and rating downgrade in the next quarter,

and $\Delta F_i^L\ (t+1)$ is the vector of the difference between the firm-specific variables pertaining to date t (that are publicly released some time after date t) and the firm-specific variables pertaining to date t-1 (that are publicly released some time after date t-1).

PANEL B shows the partial F statistics (chi square statistics) and the p values of the k-year credit spread, ΔS^k (where k =3, 7) when changes in credit rating in the next period are regressed on ΔS^k and the time dummy variables, T, using the following regression equations:

Linear Regression Equation: $\Delta R_i\ (t+1) = \beta\,\mathrm{T} + \beta_S\ \Delta S_i^k(t) + \mathrm{e}_i\ (t)$

Ordered Logit Regression Equation: $\Delta IR_i\ (t+1) = \beta\,\mathrm{T} + \beta_S\ \Delta S_i^k(t) + \mathrm{e}_i\ (t)$

PANEL A

Explanatory power of the variable block given everything else	**Linear Regression Dependant Variable: ΔR**	**Ordered Logit Regression Dependant Variable: ΔIR**
ΔF	2.891 (0.014)*	44.416 (0.019)*
R^2 (Nagelkerke R^2)	0.095	0.122

PANEL B

Explanatory power of the variable block given everything else	**Linear Regression Dependant Variable: ΔR**	**Ordered Logit Regression Dependant Variable: ΔIR**
ΔS^3	0.004 (0.953)	0.300 (0.584)
R^2 (Nagelkerke R^2)	0.064	0.088
ΔS^7	1.674 (0.196)	0.452 (0.501)
R^2 (Nagelkerke R^2)	0.068	0.086

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

Table VIII
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 system of regression equations:

$$\Delta S_i^k(t) = \beta_0 + \beta_S^k \; S_i^k(t-1) + \beta_F^k \Delta F_i(t) + \beta_L^k \Delta L_i(t) + \beta_M^k \Delta M(t) + e_i^k(t)$$
$$F_i(t) = \alpha_0 + A_1 F_i(t-1) + A_2 L(t) + A_3 M(t) + A_4 S_i(t-1) + \varepsilon_i(t)$$
$$GIP(t) = \gamma_0 + B_1 M^P(t) + B_2 F_i(t-1) + B_3 L(t) + B_4 S_i(t-1) + \eta_i(t),$$

across all firms (each firm denoted by i) and all quarters (each quarter denoted by t), where k is 3 or 7. $F_i(t-1)$ is the 5-vector of firm-specific variables pertaining to the previous quarter, and publicly known at time t. $M^P(t)$ is the 5-vector of market variables, of which all except GIP pertain to the current quarter, and all of which are publicly known at time t. S_i is a 4-vector of the 3, 5, 7 and 10 year credit spread levels. High Rating category comprises firms that have credit ratings of A- and above, and low rating category the remaining firms. High and low categories based on size (total assets) and leverage are defined in terms of being above and below the sample median respectively.

3 year credit spread changes

Explanatory power of the variable block given everything else	**All**	**Type of firm**		**Credit Rating**		**Size**		**Leverage**	
		Manu-facturing	Service	High	Low	High	Low	High	Low
ΔF	1.284 (0.269)	2.072 (0.069)	0.238 (0.946)	1.690 (0.137)	1.083 (0.369)	2.129 (0.062)	0.542 (0.745)	1.206 (0.306)	0.815 (0.540)
ΔL	8.317 (0.000)*	1.803 (0.128)	8.229 (0.000)*	1.866 (0.116)	17.153 (0.000)*	6.309 (0.000)*	1.509 (0.200)	7.155 (0.000)*	2.451 (0.046)*
ΔM	2.121 (0.061)	0.759 (0.580)	1.406 (0.222)	0.684 (0.636)	5.249 (0.000)*	1.672 (0.141)	1.547 (0.175)	3.416 (0.005)*	0.782 (0.563)
Adjusted R^2	0.193	0.094	0.273	0.095	0.380	0.277	0.087	0.297	0.092

7 year credit spread changes

Explanatory power of the variable block given everything else	**All**	**Type of firm**		**Credit Rating**		**Size**		**Leverage**	
		Manu-facturing	Service	High	Low	High	Low	High	Low
ΔF	1.120 (0.348)	1.915 (0.091)	0.332 (0.893)	1.497 (0.190)	2.277 (0.047)*	1.830 (0.106)	0.308 (0.908)	3.362 (0.006)*	0.814 (0.540)
ΔL	15.061 (0.000)*	2.615 (0.035)*	12.023 (0.000)*	1.888 (0.112)	38.857 (0.000)*	10.230 (0.000)*	1.388 (0.238)	12.255 (0.000)*	3.628 (0.007)*
ΔM	0.833 (0.526)	1.580 (0.165)	0.225 (0.952)	0.987 (0.426)	3.045 (0.011)*	0.673 (0.644)	0.888 (0.490)	1.321 (0.255)	1.205 (0.307)
Adjusted R^2	0.245	0.081	0.334	0.087	0.512	0.323	0.059	0.358	0.096

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

Table IX
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 Return on Assets, 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 25^{th} to 75^{th} 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.

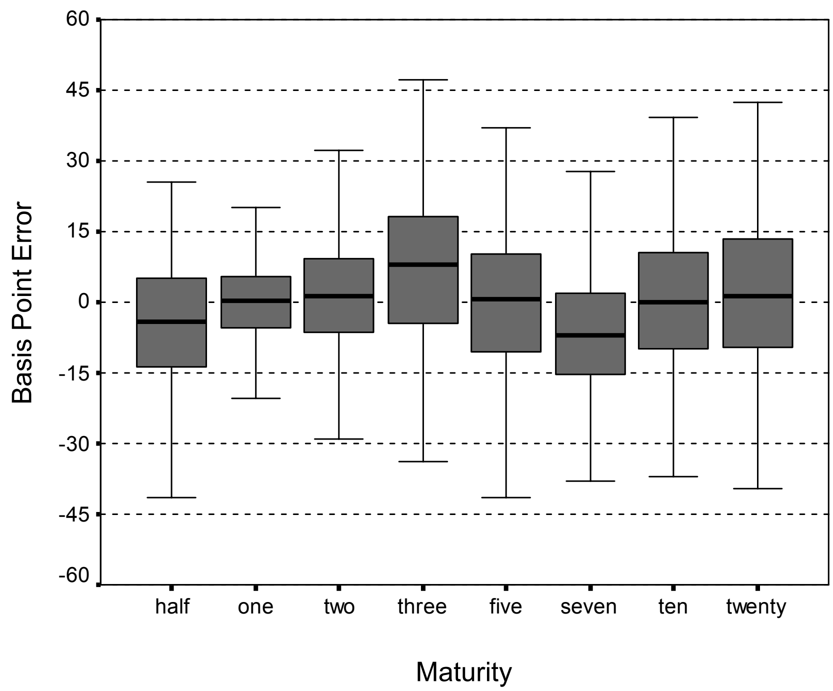

Figure 2
Pricing Errors of Risky Debt

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.