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FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 07-05 April 2007

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Predictions of firm-by-firm term structures of credit spreads based on current spot and forward values can be improved upon by exploiting information contained in the shape of the credit-spread curve. However, the current credit-spread curve is not a sufficient statistic for predicting future credit spreads; the explanatory power can be increased further by exploiting information contained in the shape of the riskless-yield curve. In the presence of credit-spread and riskless factors, other macroeconomic, marketwide, and firm-specific risk variables do not significantly improve predictions of credit spreads. Current credit-spread and riskless-yield curves impound essentially all marketwide and firm-specific information necessary for predicting future credit spreads.

Key words: Term structure of credit spreads; forecasting future credit spreads

JEL code: G12

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A vast literature exists that is concerned with predicting future riskless interest rates. Fama and Bliss (1987), Campbell and Shiller (1991), Cochrane and Piazzesi (2005), Diebold and Li (2006), and others show that the current yield curve contains significant information on future yields. More recently, studies have focused on whether auxiliary variables can be used in conjunction with yield curve information to improve forecasts. For example, Ludvigson and Ng (2006) find that macroeconomic variables have predictive power for future government bond yields, over and above what is contained in the riskless yield curve.

In contrast to the many studies concerned with the predictability of riskless yields, much less work has been done on predicting credit spreads at the firm level. Certainly, identifying variables that help in predicting credit spreads has not been well documented. This is surprising because the corporate debt market in the U.S. is huge, estimated at over $5 trillion, making it one of the nation's largest asset classes. It is also surprising because credit risk is present in most financial activities and therefore is important to measure, predict and price accurately.

Our goal in this paper is to better understand the *predictable* nature of credit spreads at the firm level, and to identify variables that assist with the predictions. In this regard, our goal is similar to that of Ludvigson and Ng (2006) for riskless rates. More specifically, our objective is to evaluate whether future credit spreads of a firm can be well predicted by information contained in the current term structure of credit spreads, or if additional firm-specific, industry-specific, and/or macroeconomic information can increase the explanatory power.

To conduct this study, we first construct credit-spread curves at the firm level, using the prices of multiple corporate bonds issued by a firm. Considerable empirical evidence suggests that 3 factors may be necessary for modeling credit spreads of differing maturities. In the riskless market, this is often achieved using a 3-factor model that permits level, slope, and curvature shocks. Our construction of credit-spread curves also permits these types of shocks. Allowing for varied types of shocks permits weaker correlations among credit spreads of different maturities. For example, in our study, we find that the 2-year and the 5-year credit spreads change in the same direction only about 60% of the time, and the correlation between their changes is low enough to warrant more than one factor for credit spreads.

Once credit-spread curves have been constructed firm by firm, we investigate the performances of the current spot and forward credit spreads as predictors of future credit spreads. With risk-neutral investors, credit spreads of longer maturities are roughly equal to the average value of expected short credit spreads. In this setting, the expectations hypothesis holds and forward credit-spread models should provide unbiased forecasts. Forecasts based on the spot and forward credit spreads, referred to as random-walk models, provide the benchmarks against which we compare other models.

We first examine whether random-walk forecasts can be improved upon by taking advantage of the *full shape* of the credit-spread curve. This raises the question of whether the credit-spread curve is sufficient for forecasting future credit spreads or whether incorporating information from additional variables could produce superior forecasts. Including marketwide variables, for example, allows us to incorporate the time-varying nature of credit risk without explicitly modeling it. To this end, we evaluate whether using a block of riskless factors, representing the level, slope, and curvature of the riskless term structure, is informative. It is well known that credit spreads are correlated with interest rates, and it is possible that the block of riskless factors can be used to improve credit spread predictions.

Other blocks of variables could also increase the forecasting power. Since lower-rated firms are more likely to face financial constraints when the business cycle moves toward recession, credit-spread curves constructed for a group of below-investment-grade firms should be sensitive to economic trends and could provide an important window on the future credit spreads of any specific firm. We investigate whether Bloomberg's B-rated-index credit-spread curves contain information about future credit spreads of individual firms, over and above the information contained in a firm's credit spreads and in the riskless term structure. In addition, we explore whether macroeconomic variables, or their forecasts, and firm-specific risk information are informative about the future credit spreads of any specific firm.

We note that credit spreads are largely determined by the likelihood of default as well as by the anticipated recovery given default. These in turn depend on a firm's industry affiliation and credit rating. As a result, the loadings on the explanatory variables may vary from firm to firm. We account for this by using panel regressions on groups of firms double-sorted by industry and credit ratings as well as by running analyses at the firm-by-firm level.

Our results are based on extensive in-sample and out-of-sample tests. It is widely believed that significant in-sample evidence of predictability does not guarantee significant out-of-sample predictability. Indeed, the literature is replete with warnings about using in-sample inferences to show predictability. However, the inclusion of irrelevant variables, while increasing the in-sample fit, does not affect the reliability of in-sample tests of predictability.[1] This point has been emphasized by several authors including Inoue and Kilian (2004), who show that neither data mining nor parameter instability provide plausible explanations for in-sample tests to reject the no-predictability null hypothesis more often than for out-of-sample tests. Indeed, they conclude that in-sample predictability is typically more credible than results of out-of-sample tests, because out-of-sample analysis requires sample splitting, which in turn involves loss of information, and, hence, lower power in small samples. We carefully conduct both in-sample and out-of-sample forecasts using panel and firm-by-firm regressions.

[1]By construction, the F-test of predictability is designed under the hypothesis that the regressor is irrelevant, and, as more and more irrelevant variables are included, the critical value of the F-test will increase to account for this. Thus, the inclusion of irrelevant variables has no effect on the asymptotic size of predictability tests.

Our results from in-sample and out-of-sample tests are consistent, and can be summarized as follows. First, predictions given by either the forward or the spot credit spread (the random walk models) can be substantially improved upon by using a model that incorporates the level, slope, and curvature factors of the credit-spread curve. That is, the shape of the credit-spread curve is informative about the future level of any particular credit spread. Second, we find that the credit-spread curve is not a sufficient statistic for forecasting future credit spreads. Forecasts can be improved upon by incorporating information from the riskless term structure. For example, with such a model we are able to predict future out-of-sample 6-months-ahead 5-year credit spreads with no unconditional bias and an average absolute prediction error of 31 basis points. Third, in the presence of current credit-spread and riskless factors, other information, at the margin is less informative. Aggregated credit-spread curves, constructed from non-investment-grade industrial firms, help for longer forecast horizons. Beyond this, stock-market-wide information, macroeconomic factors, and firm-specific risk variables are not informative. All information from these variables relevant for forecasting is already reflected in firm-specific credit spreads, aggregated credit-spread curves, and riskless yield curves. Our most parsimonious model, which uses information only from the current credit-spread and riskless-yield curves, significantly outperforms the spot model: for example, for forecasting 6-months-ahead 5 year credit spreads this model produced smaller mean-squared prediction errors (MSPEs) for over 80% of our firms compared to the spot model. Finally, given firm credit-spread curves and riskless yield factors, no other sets of variables could be identified that was consistently informative. For example, replacing our macro variables with macro forecasts from the Survey of Professional Forecasters did not improve out-of-sample forecasts of credit spreads.

The remainder of this paper is structured as follows. Section 1 reviews related work. Section 2 describes our use of the modified Diebold-Li 3-factor model for fitting riskless-yield curves and credit-spread curves. Section 3 describes the data and provides descriptive statistics. In section 4, we investigate in-sample measures of predictive content for firm credit spreads, and in section 5 we examine out-of-sample predictions. Section 6 concludes.

1 Related Work

In contrast to the many studies concerned with the predictability of future riskless yields, much less work has been done on predicting future credit spreads and linking time-varying credit risk premia to changing macroeconomic conditions. Rather, the primary focus has been on establishing structural and reduced-form models for credit spreads that either fit an existing set of corporate bond prices or attempt to explain a current term structure, in terms of both *levels* and *shapes*.[2] Empirical tests of early structural models have been somewhat disappointing; however, as more realism has been introduced into models, the potential for explaining credit-spread curves has improved.[3]

A general shortcoming of these early models is that they typically failed to incorporate macroeconomic variables explicitly, or consider factors other than default likelihood and recovery under default. Empirical studies find that riskless rates and credit spreads fluctuate over business cycles, that credit spreads widen when the economy is weak, that spreads can be partly explained by factors used to model risk premia in common stock, and that liquidity effects exist that may vary with industry and over time.[4] Overall, these studies conclude that spreads on corporate bonds are much wider than what would be required to compensate for expected credit losses alone. This credit spread puzzle is often attributed in part to fluctuating credit-risk premia that are more likely to be linked to marketwide forces rather than to firm-specific idiosyncratic factors.

Theoretical models have recently been developed to examine the relationship between credit spreads and the state of the economy in an equilibrium setting. Tang and Yan (2006) develop a structural model that allows credit spreads to be affected by the interaction of macroeconomic conditions and firm characteristics, which appears to improve on existing structural models as that examined by Huang and Huang (2003). Amato and Luisi (2006) develop a reduced-form model where instantaneous credit spreads are assumed to be affine functions of observable macroeconomic variables as well as latent factors. They find that the movements in the risk premia of corporate bonds can be largely attributed to macro factors, especially output and inflation risk. If affine models, such as that of Amato and Luisi (2006) are viable, then from a prediction perspective, forecasts of future credit spreads will depend solely on credit-spread factors, in which case, information on the macroeconomy should not provide any incremental benefit.

Our study is related to empirical studies by Collin-Dufresne, Goldstein, and Martin (2001) and Avramov, Jostova, and Philipov (2006), who explain contemporaneous credit spread changes by firm-specific and marketwide variables. The latter study provides evidence that idiosyncratic volatility and price-to-book ratio, at both the aggregate and firm level, are important deter-

[2]Examples of structural credit-spread models include Black and Cox (1976), Kim, Ramaswamy and Sunderesan (1993), Leland and Toft (1996), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), Acharya and Carpenter (2002), and the references therein.

[3]Empirical studies include Huang and Huang (2003) and Eom, Helwege and Huang (2004) who find that very large pricing errors were the rule. For discussions on the shape of credit-spread curves see Agrawal and Bohn (2006), Helwege and Turner (1999), He, Hu, and Lang (2004) and Krishnan, Ritchken, and Thomson (2006). For more recent approaches, see Zhang, Zhou and Zhu (2006) and Cremers, Driessen, Maenhout and Weinbaum (2005).

[4]See studies by Duffee (1998), Elton, Gruber, Aggrawal and Mann (2001), Driessen (2002), Longstaff, Mithal and Neis (2005) and Chava and Jarrow (2004), for example.

minants of the time-series variation in corporate credit spreads. Our study differs from these studies in that we focus on *forecasting future credit spreads* given the existence of current credit spreads, rather than on identifying the determinants of changes in credit spreads. Moreover, we work with complete credit-spread curves. Most empirical studies in this area define the credit spread as the difference in basis points between the yield of the corporate bond and the yield of an equivalent Treasury security, thereby not addressing the term structure of credit spreads. In contrast, we extract the *full term structure* of credit spreads for each firm, avoiding the implicit assumption that credit spread shocks are parallel.

In a sense, our study is related to the work of Fama and Bliss (1987), Campbell and Shiller (1991) and, more recently, Cochrane and Piazzesi (2005) and Diebold and Li (2006), all of which explore the predictable nature of riskless yields.[5] Their findings provide clear evidence against the expectations hypothesis of the term structure and establish that risk premia in riskless bond yields do vary over time.[6] Recently, Ludvigson and Ng (2006) establish that real and inflation factors have important predictive power for future excess returns of U.S. Treasury bonds, over and above information on the yield curve. Such behavior is ruled out by affine term structure models of the yield curve, where the forecastability of yields can be attributed only to information summarized by yields and forward rates. Unlike these studies, ours is concerned with predicting future credit-spread curves using information on current credit-spread curves, and investigating whether auxiliary variables, whether firm specific, industry specific, or marketwide, would, at the margin, be informative.

Finally, our study is closely related to Diebold and Li (2006) and Diebold, Rudebusch, and Aruoba (2006), who extend the analysis for riskless debt by forecasting future riskless yield curves based on current yield curve information as well as information on additional macroeconomic variables. One of their innovations was to provide a macroeconomic interpretation of the Nelson-Siegel representation of the yield curve by combining it with a VAR representation of the macroeconomy. We adapt their approach to risky corporate credit spreads.

2 A Factor Model for Riskless and Risky Bonds

Let $P^{(n)}(t)$ be the date t price of a zero-coupon riskless bond that pays \$1 in n periods time. Similarly let $\pi_j^{(n)}(t)$ be the date t price of a zero-coupon bond issued by firm j that promises to

[5]We do not review a similar literature on the predictability of exchange rates. For discussions of this literature, see the excellent survey articles by Hodrick (1987) and Engel (1996).

[6]Early yield-curve models ignore macroeconomic linkages and essentially impose a no-arbitrage restriction based on the dynamics of latent factors. Recent models, however, directly link these latent factors to macroeconomic variables. Examples include Ang and Piazzesi (2003) and Ang, Dong, and Piazzesi (2005), among many others.

pay \$1 n periods later. Then

$$P^{(n)}(t) = e^{-y_f^{(n)}(t)n} \tag{1}$$

$$\pi_j^{(n)}(t) = e^{-y_j^{(n)}(t)n}. \tag{2}$$

where $y_f^{(n)}(t)$ is the riskless yield to maturity and $y_j^{(n)}(t)$ is the risky yield to maturity. The date t n-year credit spread is given by, $s_j^{(n)}(t)$, where

$$s_j^{(n)}(t) = y_j^{(n)}(t) - y_f^{(n)}(t) \tag{3}$$

In a series of papers, Diebold and Li (2006) and Diebold, Rudebusch, and Aruoba (2006) explore the predictability of riskless yields. They reconsider the Nelson and Siegel (1987) model for representing the cross-section of yields. In particular, they consider the model

$$y_f^{(n)}(t) = \beta_{1f}(t) + \beta_{2f}(t)F_2^{(n)} + \beta_{3f}(t)F_3^{(n)}, \tag{4}$$

where

$$F_2^{(n)} = \frac{(1 - e^{-\lambda_t n})}{\lambda_t n}$$

$$F_3^{(n)} = \frac{(1 - e^{-\lambda_t n})}{\lambda_t n} - e^{-\lambda_t n}.$$

The Nelson-Siegel model is parsimonious and easy to estimate; it has a discount function that begins from 1 at date 0, and approaches 0 as the horizon extends to infinity. Bliss (1997) shows that this model performs very well in fitting the cross-section of riskless bond prices relative to a large class of alternatives.

Diebold and Li (2006) reinterpret this model as a 3-factor model, with state variables

$$\beta_f(t) = (\beta_{1f}(t), \beta_{2f}(t), \beta_{3f})(t))'.$$

The loading on $\beta_{1f}(t)$ is 1, a constant that can be viewed as a permanent or long-term factor that affects all maturities equally; the loading on $\beta_{2f}(t)$, $F_2^{(n)}$, is a function that rapidly decreases to zero as n increases and hence can be viewed as a short-term factor; the loading on $\beta_{3f}(t)$, $F_3^{(n)}$, a function that begins at zero, increases, and then decreases to zero, can be viewed as a mid-term factor. Diebold and Li point out that these three factors can be viewed as controlling the level, slope, and curvature of the yield curve. Indeed, since $y_{f,t}^{(\infty)} = \beta_{1f}(t)$ and $y_{f,t}^{(\infty)} - y_{f,t}^{(0)} = -\beta_{2f}(t)$, the first two betas correspond to level and slope. Increasing $\beta_{3f}(t)$ has no effect on the short and long rates but does affect the middle rates, so it captures curvature effects.

As a model of the term structure, the Nelson-Siegel parameterization allows yield curves to have increasing, decreasing, humped, and inverted-humped shapes. Moreover, since the short rate equals $\beta_{1f}(t) + \beta_{2f}(t)$, whereas the long rate equals $\beta_{1f}(t)$, the short rate will be more volatile, which is consistent with empirical evidence. Although the model is flexible, one possible disadvantage is that it does not impose no-arbitrage restrictions. Diebold and Li argue that this is not really a severe limitation because the no-arbitrage restriction should be approximately satisfied in the data.

In our analysis, we use the Diebold-Li model, not only to summarize the riskless yield curve but also to summarize credit-spread curves constructed from Bloomberg's fair-market-value corporate yield curves. Let $\beta_I(t)$ represent the vector of the level, slope, and curvature of the credit-spread curve obtained from firms belonging to a certain credit rating. Then

$$\beta_I(t) = (\beta_{1I}(t), \beta_{2I}(t), \beta_{3I}(t)).$$

In addition, and most important, we use the Diebold-Li model to extract the time series of credit spread state variables at the individual-firm level. This is a more difficult task because the credit-spread curve for each firm at each month is not observable but must be inferred through the prices of corporate securities. Specifically, for each firm j, we assume:

$$s_j^{(n)}(t) = \beta_{1j}(t) + \beta_{2j}(t)F_2^{(n)} + \beta_{3j}(t)F_3^{(n)}. \tag{5}$$

Then:

$$\pi_j^{(n)}(t) = e^{-y_f^{(n)}(t)n-(\beta_{1j}(t)+\beta_{2j}(t)F_2^{(n)}+\beta_{3j}(t)F_3^{(n)})n} \tag{6}$$

Let $\beta_j(t)$ represent the credit-spread vector for firm j at date t. Then:

$$\beta_j(t) = (\beta_{1j}(t), \beta_{2j}(t), \beta_{3j}(t)).$$

Given this vector and the observed riskless yield $y_f^{(n)}(t)$, for each maturity n, the price of all corporate zero-coupon bonds can be obtained and then the price of all corporate coupon bonds can be established. Alternatively, given the prices of an array of corporate bonds issued by firm j, we can infer the credit-spread curve's state variables, $\beta_j(t)$. To do this, assume firm j has $N_j(t)$ bonds trading at date t. We look for firms which have 5 or more bond issues outstanding with maturities spanning at least seven years. We choose the credit-spread state variables to minimize the resulting sum of squared errors between theoretical and observed coupon-bond prices. That is, for each date, t, and for each firm, j, we solve:

$$\beta_j^*(t) = argmin_{\beta_j(t)} \sum_{i=1}^{N_j(t)} \epsilon_{i,j}^2(t) \tag{7}$$

where $\epsilon_{i,j}(t)$ is the actual price of bond i of firm j trading at date t less its estimated value.

Our goal in the data preparation phase is to construct a time series of these monthly riskless state variables or factors, $\beta_f(t)$, credit-spread index factors, $\beta_I(t)$, and a panel of firm credit-spread factors, $\beta_j(t)$, $j = 1, ..., N$, where N is the number of firms.

Diebold and Li find that for riskless rates the time series of parameter estimates from the sequence of cross-sectional regressions is highly autocorrelated. They establish a vector autoregressive model that forecasts future beta values, which are then used to estimate future yields. Specifically:

$$\beta_f(t+h) = \eta_{f1} + \eta_{f2}\beta_f(t) + \eta_{f3}X(t) + \epsilon(t+h), \tag{8}$$

where η_{f1} is a 3×1 vector, η_{f2} is a 3×3 matrix, $X(t)$ is a set of control variables, say of size k, η_{f3} is a matrix of size $3 \times k$, and $\epsilon(t+h)$ is the residual vector.

Let $\beta_f(t+h|t)$ be the date t forecast for the beta state values at date $t+h$, and let $y_f^{(n)}(t+h|t)$ be the date t forecast of the yield at date $t+h$, of a riskless bond that matures n years later. Then:

$$y_f^{(n)}(t+h|t) = \beta_{1f}(t+h|t) + \beta_{2f}(t+h|t)F_2^{(n)} + \beta_{3f}(t+h|t)F_3^{(n)} \tag{9}$$

In principle, we could run regressions of the form in equation (8) at the firm level. In practice, we complement the firm-by-firm regressions with panel regressions that exploit commonalities across firms of similar types. For example, we postulate models of the form

$$\beta_j(t+h) = \eta_{j0} + \eta_1\beta_j(t) + \eta_2\beta_f(t) + \eta_3\beta_I(t) + \eta_4 M(t) + \eta_5 F_j(t) + \epsilon_j(t+h), \tag{10}$$

where $M(t)$ is a vector of macroeconomic and marketwide variables and $F_j(t)$ is a vector of firm-specific variables. Once the predicted values of future beta values are obtained, theoretical credit spreads can be computed, and these theoretical values can be compared to the actual future credit spreads. Firms in each of these panel regression models can further be grouped by credit ratings, industry, or along other possible dimensions. Even the simplest case of the above model where $\eta_2 = \eta_3 = \eta_4 = \eta_5 = 0$ is of some interest because it allows us to examine the predictability of credit spreads based on information contained in the shape of today's credit-spread curve alone.

3 Data and Descriptive Statistics

Riskless-Yield-Curve Factors

Our first data set consists of month-end price quotes for Treasury issues for the period 1970-2005 taken from the Center for Research in Security Prices (CRSP) Government Bond Files. We eliminate bonds with option features and bonds with special liquidity problems that arise because their maturities fall within one year. We use the Fama-Bliss (1987) bootstrapping procedure on the riskless-bond data collected from CRSP to compute raw yields from the filtered data. This method establishes forward rates in order to price bonds of successively longer maturities correctly, given the yields fitted to previously included issues. From these forward rates, the averages over increasing maturities are computed to obtain the zero-yield curve. This resulting curve, called the unsmoothed Fama-Bliss curve, prices the included bonds exactly .[7] Once the yield curve is established, we compute the yields to maturity for zero bonds of any maturity. We chose different maturities up to 10 years that are six months apart. For each selected month, therefore, we have 20 yields of maturities ranging from 6 months to 10 years. Using this data, we construct the vector of riskless beta factors, $\beta_f(t)$, for each date.

Figure 1 shows that the three beta factors do indeed correspond closely to level, slope, and curvature effects. The solid lines in figure 1 show the time series of the estimated parameter values over the period 1970-2005, and are based on fixing $\lambda = 0.7308$, the value recommended by Diebold and Li. The dashed lines show the level, slope and curvature of the data-based riskless-yield-curve. The data-based riskless-yield-curve level is taken as the 10-year rate. The slope is the difference between the 10-year and 3-month rate. The curvature is defined as twice the 2-year yield minus the sum of the 3-month and 10-year yield.

Figure 1 Here

B-Rated Credit-Spread-Index Factors

Our second data set consists of the B-credit-rated-Index yield curves for industrial firms taken from Bloomberg. These yield curves are available daily from 1992 and are constructed using prices from new-issue calendars, trading/portfolio systems, dealers, brokers and evaluation services. Option-adjusted spread analysis is employed to construct option-free yield curves.

We choose a below-investment-grade index of industrial firms (the B-rated index) because these credit spreads could be extremely sensitive to prospects of market changes. Further, using an aggregate index eliminates noise from idiosyncratic firm-level shocks. We extract the monthly level, slope, and curvature factors, $\beta_I(t)$, for the B-rated-Index credit spreads from these yield curves. Figure 2 repeats the analysis of figure 1, and shows that the B-Index factors indeed are closely related to the B-rated Index levels (long credit spreads), slopes (long-credit spreads minus short-credit spreads), and credit-spread curvatures.

Figure 2 Here

Thus, the two figures above show that the beta factors correspond very well with the level, slope, and curvature effects for both the riskless and the risky term structures.

[7] We thank Rob Bliss for providing us with the Fortran programs and data that allowed us to make this computation.

Macro-economic Variables

Our third data set consists of macroeconomic information. It includes a Real Activity Index, $RA(t)$, an Inflation Index, $I(t)$, and two aggregate stock market variables: stock market momentum, $R_M(t)$, and stock market volatility, $\sigma_M(t)$.

The Real Activity and the Inflation indices are the first principal components of several observable time-series of macroeconomic variables, following Ang and Piazzesi (2003). Before conducting the principal component analysis, we purge these variables of the riskless factors. They therefore represent variables that are orthogonal to the riskless term-structure information. Increased real activity could spell investor confidence or, alternatively, signal inflationary pressures, both of which affect credit spreads, but differently. As inflation increases, so do the riskless yields, and the credit spread can increase as well. However, the effects of rising inflation on the long and short credit spreads can be different.

Stock market momentum is the 12-month cumulative holding-period return of the Center for Research in Security Prices (CRSP) Value-weighted Index return. Collin-Dufresne, Goldstein, and Martin (2001) find a negative relationship between equity market returns and the level and slope of credit spreads. On the other hand, with stock market momentum, there could be flight of funds to the stock market, as a result of which credit spreads could rise. Stock market volatility is the monthly volatility of the CRSP value-weighted portfolio using the daily returns of the index within each month, following French, Schwert, and Stambaugh (1987). Asset volatility, generally approximated by equity volatility, includes both an idiosyncratic and a market component. Campbell, Lettau, Malkiel, and Xu (2001) demonstrate that these two components could have different impacts on credit spreads. As stock market volatility increases, idiosyncratic risk could increase and credit spreads should rise. On the other hand, as stock market volatility increases, there could be a flight to the perceived relative safety of the bond markets, causing credit spreads to fall.

Let

$$M(t) = (RA(t), I(t), R_M(t), \sigma_M(t))$$

represent our 4-vector of macro-economic variables, each of which is described in detail in the Appendix.

Firm-specific Risk Variables

Our fourth data set consists of firm-specific information. It includes leverage, $L_j(t)$, book-to-market ratio, $BM_j(t)$, stock return momentum, $R_j(t)$, and stock return volatility, $\sigma_j(t)$, the data for all of which are taken from the Compustat and CRSP databases.

As leverage increases, bond risk increases and the credit spreads should increase. As Pastor and Veronesi (2003) show, the book-to-market ratio decreases with expected profitability. Also

Fama and French (1992) show that the book-to-market ratio is a risk factor; as the book-to-market ratio increases, credit spreads should increase. According to structural models, an increase in stock return (stock return momentum) raises the equity holders' option value and reduces the default probability, which, in turn, should decrease credit spreads. Avramov, Jostova and Philipov (2006) found stock market momentum to be a primary driver of credit spreads. As stock return volatility increases, firm value volatility increases, and default risk increases, which in turn should increase credit spreads. Each of these variables is described in detail in the Appendix.

Let

$$F_j(t) = (L_j(t), BM_j(t), MM_j(t), \sigma_j(t))'$$

represent the vector of firm variables for firm j.

We use additional firm-specific information for grouping purposes. These are credit ratings and industry. Credit spreads depend on the likelihood of default and on the recovery rate given default. Credit ratings determine the probability of default. Chava and Jarrow (2004) show that recovery rates vary with industry. We assign firms to either of two credit rating groups, namely, investment-grade and below-investment-grade firms.[8] We assign firms to one of two industry groups, namely, manufacturing and service.

Corporate Bond Data

Our final data set consists of the prices of corporate bonds. We focus on firms that are or were part of the $S\&P500$ index for any of the years in our sample period, January 1990 through December 2005. The S&P 500 Index is maintained by a team of Standard & Poor's economists and index analysts, who ensure that its composition remains a leading indicator of U.S. equities, reflecting the risk and return characteristics of the broader large-cap universe. On average, almost two changes are made to the S&P 500 Index each month, so the number of firms in the index over this period is quite large. Whereas some deletions were caused by mergers and acquisitions or spin-offs, others were deleted because of low share-price or market-capitalization. Indeed, our sample includes a few firms that subsequently defaulted. Our primary source of trade-price data on bonds, Bloomberg, is augmented with data from DataStream. We collect bond prices for all fixed-rate U.S. dollar-denominated bonds that are non-callable, non-putable, non-convertible, not part of an unit (e.g., sold with warrants) and have no sinking fund. We also excluded bonds with asset-backed and credit-enhancement features. This ensures that our credit spreads relate more directly to the creditworthiness of the issuer rather than the collateral. We use only transaction prices. Further, we eliminate all data that have inconsistent or suspicious issue/dates/maturity/coupon, etc., or are otherwise questionable.

[8] Investment grade firms are those that are rated BBB or above according to the $S\&P$ long-term firm rating found in the quarterly Compustat, augmented with credit ratings data from Bloomberg, while the below-investment-grade firms are those that are rated below BBB.

Panel A of table I shows the number of firms and firm-months in our sample, step-by-step through our screening process. The first column shows the data particulars of the initial set of firms. In the first screen, we require a minimum of 5 prices of bonds of different maturities that span at least 7 years for each month to estimate the credit-spread level, slope and curvature parameters. In the second screen, we drop all firm-months that do not have at least 6 consecutive months of reasonable credit-spread level, slope, and curvature parameter estimates. In the third screen, we need data from Compustat to obtain our firm-specific risk measures. Our final sample comprises 241 firms and $11,894$ firm-months of data.

Table I Here

Panel B shows that manufacturing and service-sector firms are well-represented in our final sample. Most of the firms are investment grade, as would be expected from S&P 500 firms. However, we have a sizeable sample of below-investment-grade firms as well as 3 firms that defaulted.

Historically, the corporate bond market has been the main source of credit-risk data. In recent years high-quality data on credit spreads have become available from the Credit Default Swap (CDS) market and from the secondary loan market. We choose bond market price data for this study for a few reasons. First, the bond market has a longer history of data available, which allows us to incorporate macroeconomic variables and establishing behavior over a longer period. Indeed, the quality of credit default swap data before 2000 is questionable, and our corporate bond data extends back a decade beyond 2000. Second, the corporate bond market still has very wide coverage of names, which gives us access to a larger universe. Third, although some authors claim that default swap spreads are less confounded by illiquidity, tax, and various market microstructure effects, trading in the CDS market is infrequent, with each issuer having about one trade or quote per trading day; CDS spreads are often larger than corporate bond spreads, which would be unlikely if CDS spreads contain no liquidity premium.[9]

For each of our eligible firms, and for each month we perform the optimization routine given by equation (7). We drop bonds that we could not price within two dollars, and rerun the optimization routine. Bond prices derived from our optimization routine fit the data extremely well, as shown by the histogram of errors in figure 3.

Figure 3 Here

[9]For example, 19 of the 33 reference entities studied by Blanco, Brennan, and Marsh (2005) have average CDS spreads larger than their corresponding corporate-bond yield spreads. For more discussions on this issue see Berndt, Douglas, Duffie, Ferguson, and Schranz (2005), Ericsson, Reneby, and Wang (2005), Longstaff, Mithal, and Neis (2005), Pan and Singleton (2005) and Tang and Yan (2006).

Over 90% of the bonds could be fitted to within 1.0 dollar of their price, and over 75% (50%) of all bonds were priced within an error of 65 (33) cents. The average absolute error was 45 cents. In sum, our fit of the credit spread curves was very tight given the data.

Figure 4 illustrates the time series of yield curves for a representative firm in our sample. The graph clearly shows that a firm's risky bond yield curve can indeed be upward-sloping, downward-sloping or hump-shaped, and change shape over time.

Figure 4 Here

Furthermore, credit spreads along the maturity spectrum do not always move in the same direction. For example, for our data set, the 3-year and 5-year credit spreads moved in the same direction 77.5% of the time, 3 year and 7-year credit spreads moved in the same direction 67% of the time, and 3 and 10 year credit spreads moved in the same direction 63% of the time. The results confirm that shocks to the credit spread curve need not be parallel; they also suggest that the primary drivers of short-term credit spreads may be quite different from the drivers of longer-dated credit spreads. This is the reason we use the credit spread level, slope, and curvature (beta) factors, which represent the entire term structure of credit spreads, in the analysis in this paper.

3.1 Descriptive Statistics

Panel A of Table II compares firm specific characteristics by our industry and credit ratings groups. Leverage and book-to-market ratio are, on average, significantly higher for the below investment grade firms than for the investment grade firms, and for the service-sector firms than for the manufacturing firms. Stock return momentum is, on average, significantly higher for the investment-grade firms than for the below-investment-grade firms, and for the service-sector firms than for the manufacturing firms.

Table II Here

Panel B of Table II shows the average credit-spread level (β_1), slope ($-\beta_2$), and curvature (β_3) factors across firm-months for firms grouped according to their industry or credit ratings. The level of credit spreads for low grade firms is on average 18 basis points higher than for investment grade bonds, and the difference is significant. The slopes and curvatures of service-sector firms are significantly different from those of manufacturing-sector firms.

Overall this table shows that firm characteristics as well as the credit-spread factors are significantly different both across our 2 credit ratings groups, and across our 2 industry groups.

Thus, it would be meaningful to run analyses separately groups of firms that are double-sorted based on their credit ratings and industry groupings.

Panel A of table III examines the contemporaneous relationship between riskless level, slope and curvature factors and our macro variables. Specifically:

$$\beta_f(t) = \eta_{0f} + \eta_{1f} M(t) + \epsilon_f(t) \tag{11}$$

The table also examines the relationship between B-index credit spreads with riskless factors and macroeconomic variables:

$$\beta_I(t) = \eta_{0I} + \eta_{1I}\beta_f(t) + \eta_{2I} M(t) + \epsilon_I(t) \tag{12}$$

This table reports the adjusted R^2 values for these regressions. The riskless factors are significantly associated with contemporaneous macro-economic information. The B-rated Index credit-spread factors are significantly associated with macroeconomic information, even after controlling for the impact of riskless factors.

By construction, our real activity and inflation indices are uncorrelated with our riskless factors. However, stock market momentum and volatility significantly affect each of the riskless factors. These macro variables account for over 20% of the variation of each of the riskless factors, as measured by the adjusted R^2 values. The 3 riskless factors alone account for 70% of the variation of the slopes of B-rated credit-spread curves, and for 42% of their curvatures. When macro variables are added to the regression the explanatory power increases significantly for all three index factors.

Table III Here

Panel B shows panel regression results, controlling for firm fixed effects, of the contemporaneous determinants of credit spreads for firms double-sorted by credit ratings and industry. Specifically, for firm j in one of the 4 credit ratings-industry groups (high or low rating and service or manufacturing industry), k:

$$s_{jk}^{(n)}(t) = \eta_{0,jk}^{(n)} + \eta_{1,k}^{(n)} M(t) + \eta_{2,k}^{(n)} F(t) + \epsilon_{jk}^{(n)}(t). \tag{13}$$

Controlling for firm fixed effects, the blocks of firm specific and macro variables accounted for around 40% of the variability of 3-year credit spreads, 55% of the variability of 5- year credit spreads and 50% of the variability of 10- year credit spreads, on average, across all groups. The explanatory power of the macro and firm variables, on average, is higher for manufacturing firms than for service firms, and higher for the lower-rated manufacturing firms than for higher-rated manufacturing firms. The explanatory power of macro and firm variables over credit spreads that we find is in line with the results of Avramov et al., who explain 54% (67%) of the variability of credit spreads for medium (low) grade firms using macro and firm variables.

4 In-Sample Measures of Predictive Content

Predicting Riskless Yields

Panel A of Table IV shows the results of the regressions of six-month-ahead riskless yields against the current yield and with two additional yields. Specifically:

$$y_f^{(n)}(t+h) = \gamma_0^{(n)} + \gamma_1^{(n)} y_f^{(3)}(t) + \gamma_2^{(n)} y_f^{(5)}(t) + \gamma_3^{(n)} y_f^{(10)}(t) + \epsilon^{(n)}(t+h) \tag{14}$$

For example, the future 5- year yield is regressed against the current 5- year yield, the 3- year yield and the 10- year yield. The results show that the future level of each of the three yields depends not only on their current level, but also on the shape of the yield curve.

Table IV Here

The shape of the yield curve is captured by the riskless-yield-curve level, slope and curvature factors. So, in panel B, we use the 3-vector of current month riskless factors, and then add successively our blocks of one-month lagged factors, the current-month macro variables, and the one-month lagged macro variables. Specifically:

$$y_f^{(n)}(t+h) = \eta_{0f}^{(n)} + \eta_{1f}^{(n)} \beta_f(t) + \eta_{2f}^{(n)} \beta_f(t-1) + \eta_{3f}^{(n)} M(t) + \eta_{4f}^{(n)}(t-1) M(t-1) + \epsilon^{(n)}(t+h) \tag{15}$$

The impact of incorporating different blocks of variables are assessed for the 3, 5, and 10-year yields. Notice that the current 3-vector of riskless parameters can explain more than 72 percent of the variability of the future riskless yields across the maturity spectrum. The panel also shows that collectively, the lagged riskless parameters do not increase explanatory power. The macro variables, however do add to the explanatory power, as do the lagged macro variables. Although statistically significant, the contribution of macro variables to the R^2 value is small, decreasing from about 5% for the three year yield to about 2% for the ten year yield.

Since the source of predictability of riskless yields stems from the predictability of the beta factors, Panel C of the Table shows the same statistics as Panel B except that the dependent variables are now the 6-month ahead riskless level, slope and curvature factors. More than 77 percent of the variability of the future riskless level and slope factors can be explained by the current level, slope and curvature factors, while 45 percent of the variability of the future riskless curvature can be explained by the current level, slope and curvature parameters. The vector of current-month macro-variables increases the explanatory power.

The implications of the above results are consistent with the findings of Cochrane and Piazzesi (2005), Ludvigson and Ng (2006), and Diebold, Rudebusch and Aruoba (2006), namely that the shape of the yield curve is useful for predicting future levels of yields and that macroeconomic factors can be used to improve the forecasts. We now proceed to investigate whether similar results hold for the predictability of credit spreads.

Predicting B-rated Index Credit Spreads

The six-months-ahead 3, 5, and 10-year credit spreads for the B-rated index are regressed against the current credit-spread-index factors, their lagged values, the riskless factors, their lagged values, the macro variables, and their lagged values in a hierarchical regression:

$$\begin{aligned} s_I^{(n)}(t+h) &= \eta_{0I}^{(n)} + \eta_{1I}^{(n)}\beta_I(t) + \eta_{2I}^{(n)}\beta_I(t-1) + \eta_{3I}^{(n)}\beta_f(t) + \eta_{4I}^{(n)}(t-1)\beta_f(t-1) \\ &+ \eta_{5I}^{(n)}M(t) + \eta_{6I}^{(n)}(t-1)M(t-1) + \epsilon_I^{(n)}(t+h). \end{aligned} \tag{16}$$

The R^2 and partial R^2 values are reported in panel A of table V and the significance of incremental blocks of variables is identified.

Table V Here

We find that the current beta factors explain more than 44% of the variability of future Index credit spreads across the maturity spectrum. The lagged factors contribute a small but significant amount to explanatory power. More important is the role of the riskless beta factors, which explain about 20% of the remaining variability, with the exact amount depending on the credit maturity. Lagged riskless factors play an insignificant role, but current macro variables explain over 30% of the remaining variability, with their lags explaining a small additional amount.

Panel B of Table V reports the results of hierarchical regressions where the future credit spreads in the regression equation (16) are replaced with the credit-spread factors. Results are similar to those of Panel A. Most of the variability of future credit spread factors can be explained by the current period credit-spread beta factors, current riskless-curve beta factors, and the current macro variables. These 3 blocks of explanatory variables explain about 75% of the variability of future credit-spread levels, about 80% of the variability of future credit-spread slopes, and about 65% of the variability of future credit-spread curvature factors.

The results of this table are analogous to those of the previous table on riskless yield predictions. The shape of the current credit-spread curve contains information for predicting future credit-spread curves, and forecasts can be further enhanced using contemporaneous information on the riskless-yield curve and macroeconomic variables.

4.1 Predicting Firm Credit Spreads

The Importance of Current and Lagged Credit-Spread Curve Factors

We forecast the h-month ahead credit spreads, based on their current values, and on other points on the credit-spread curve. Specifically, for $n = 3, 5, 10$ years we consider,

$$s_j^{(n)}(t+h) = \gamma_{0,j}^{(n)} + \gamma_1^{(n)} s_j^{(n)}(t) + \gamma_2^{(n)} s_j^{(short)}(t) + \gamma_3^{(n)} s_j^{(\infty)}(t) + \epsilon_j^{(n)}(t+h), \tag{17}$$

where $h = 6$ months, the long credit spread $s_j^{(\infty)}(t) = \beta_{j1}(t)$, and the short credit spread $s_j^{(short)}(t) = \beta_{j1}(t) + \beta_{j2}(t)$. We use panel regression methodology, with firm fixed effects, run over groups of firms that are double-sorted based on their credit rating and industry. Since the data are overlapping, and the residuals are heteroskedastic, we compute heteroskedastic and autocorrelation-consistent standard errors that are also adjusted for clustering by firms. Since the results for the 3 and 10-year spreads are qualitatively similar to those of the 5-year spreads, we tabulate only the results for the 5-year spreads. The R^2 and partial R^2 values, as well as their significance, are reported in the first two columns of table VI.

Table VI Here

Not surprisingly, the future 5-year credit spread depends on the current 5-year credit spread. However, future credit spreads also depend on the shape of the credit-spread curve. Specifically, future credit spreads depend on the current long and short credit spreads as well. A partial F-test reveals that these two additional points add significantly to the explanatory power of future 5 year credit spreads.

With just the current 5-year credit spread as an independent variable, the coefficient on the spread is significantly different from zero but significantly lower than one, implying that the changes in credit spreads do not follow a random walk. About 35% of the variability of the 5year credit spread is attributable to differences in firms. That is, there is significant within-firm variability (the remaining 65%) that still needs to be explained. We see that once the effects of different firms have been removed, we can account for roughly, 42% of the variance in future 5-year credit spreads with three points on the current credit spread curve. The importance of the shape of the credit-spread curve parallels the findings of Cochrane and Piazzesi (2005) for the riskless term structure, and are consistent with our findings for riskless yield curves and B-Index credit spread curves.

Rather than use the current level of specific points on the credit spread curve as independent variables, we could use the 3 credit spread state variables, namely the level, β_1, the slope, β_2, and the curvature, β_3, as the independent variables. This leads to a panel regression model that gives the same R^2 results as reported in the first column of Table VI, namely, 0.626. All three factors are significant for our three maturities of 3, 5 and 10 years.

We next incorporate information on lagged credit spreads. Specifically, we consider panel regression models of the form:

$$s_j^{(n)}(t+h) \quad = \quad \gamma_{0,j}^{(n)} + \gamma_1^{(n)}(L)\beta_{1j}(t) + \gamma_2^{(n)}(L)\beta_{2j}(t) + \gamma_3^{(n)}(L)\beta_{3j}(t) + \epsilon_j^{(n)}(t+h) \qquad (18)$$

In this autoregressive distributed lag model $\gamma_i^{(n)}(L)\beta_{kj}$ represents a lag polynomial, so that

$$\gamma_i^{(n)}(L)\beta_{kj}(t) = \gamma_{i1}^{(n)}\beta_{kj}(t) + \gamma_{i2}^{(n)}\beta_{kj}(t-1) + ... + \gamma_{ip}^{(n)}\beta_{kj}(t-p),$$

where p is the number of lagged variables.

The middle columns of table VI report on the significance of each block of variables. With firm fixed effects and the current credit spread factors included in the model, the R^2 is 0.626, as reported in the first regression. Adding 1- month lagged state variables increases the R^2 to 0.634. A partial F-test at the 1% level rejects the null hypothesis that the lags are not significant. Incremental additions of 2 and 3 month lags are not statistically significant.

To dig deeper into this, we repeat the analysis, but this time run the above regression model firm by firm. The left columns of panel B of table VI reports the results. The first column shows the average adjusted R^2 values over all firms. The inclusion of all 3 lags, increases the average adjusted R^2 value from 0.435 to 0.462. The next two columns reports the proportion of firms for which the incremental contribution of the lagged variables was significant at the 10% and 5% levels of significance. For 35.8% (28.5%) of our firms incorporating the first lag of credit-spread factors is significant at the 10% (5%) level. The proportions drop as the lag increases.

Overall, the shape of the current credit-spread curve contains significant information for forecasting future credit spreads; incorporating information contained in the lagged-period credit spread curve may modestly enhance the predictive power of future credit spreads.

The Importance of Auxiliary Information

We now evaluate whether the credit spread curve reflects all known information relevant for forecasting future credit spreads, or whether there are other variables that can be used to improve predictability. Beyond our set of current and lagged credit spread factors, other blocks of explanatory variables include the 3 vector of riskless factors, the 3- vector of B-Index credit spread factors, the 4 vector of macro variables, and the 4 vector of firm-specific risk variables.

We establish the sequential importance of our blocks of variables by running a hierarchical panel regression model of the form:

$$\begin{aligned} s_{jk}^{(n)}(t+h) &= \eta_{0,jk} + \eta_{1k}\beta_{jk}(t) + \eta_{2k}\beta_{jk}(t-1) \\ &+ \eta_{3k}\beta_f(t) + \eta_{4k}\beta_I(t) + \eta_{5k}M(t) + \eta_{6k}F_{jk}(t) + \epsilon_{jk}^{(n)}(t+h), \end{aligned} \qquad (19)$$

where j references the firm and $k = 1,2,3,4$ represents the industry-ratings group. Our goal is to investigate the hypothesis that $\eta_{3k} = \eta_{4k} = \eta_{5k} = \eta_{6k} = 0$.

The rightmost columns of panel A show the incremental increase in R^2 as successive blocks are added to the set of explanatory variables. Once the fixed firm effects as well as the current and lagged credit-spread factors are removed, the riskless credit spread factors account for almost 14% of the remaining unexplained variability. And once this has been accounted for, the B-rated index factors, the macro variables, and the firm variables each account for about 2%, which is statistically significant at the 5% level. We also examine the explanatory power of our sets of variables for the 3-, and 10-year credit spreads for all firms as well as firms segregated by industry group and ratings. Collectively, we can explain anywhere from 60% to 80% of the variability of future credit spreads by our set of independent variables, depending on the group.

Panel B shows the results for firm-by-firm regressions. The average adjusted R^2 values increase as additional blocks are added. After the firm's current and lagged credit-spread factors are accounted for, the impact of the block of riskless-yield factors is significant at the 5% level for 70% of all firms. The additional blocks – B-index factors, macro variables, and firm-specific variables – are all incrementally significant in about 50% of the firms. We study those firms for which macro and firm-specific variables are significant at the 10% level, given all other blocks of explanatory variables, and classify them according to industry and ratings. The firms for which macro and firm effects are significant do not concentrate in any of these groups. Moreover, for the firms for which macro variables were significant, the median incremental contribution to adjusted R^2 values is of the order of 10% for each of the future beta factors. For five-year credit spreads, the macroeconomic variable block, when significant, accounts for under 10% of the adjusted R^2 value. The same conclusions can be drawn from the marginal impact of firm-specific risk variables. The firms for which firm-risk variables contribute significantly in the presence of other factors, do not concentrate in any industry or credit-ratings categories, and their contribution to the explanatory power is of a similar magnitude as the macro variables.

The last 2 columns report the average absolute errors and the average root mean square errors of each regression model, averaged over all firm-months. As the table shows, the average absolute prediction error drops to about 25 basis points when the current and lagged 3-vector of beta factors, and the current 3 vector of riskless factors are used to predict 6-month-ahead 5-year credit spreads. In comparison, the average absolute prediction error using the spot (forward) credit spread is 31.47 (44.34) basis points. The table also shows that the root-mean-squared prediction errors drops to about 39 basis points when the credit-spread and riskless factors are used. Beyond this, as the number of independent variables increases, the errors decrease, but at a very slow rate.

The results show that the shape of the current credit-spread curve contains significant information for forecasting future credit spreads, and additional information is contained in the riskless-yield-curve factors. The results also indicate that much smaller incremental contributions could come from any additional factors.

The results of our hierarchical regressions have to be interpreted carefully. The contribution of macro and firm-specific-risk variables to the explanatory power of credit spreads, in the presence of all other factors is small. By themselves, however, macro and firm variables can explain about 48% of the variability of future 5-year credit spreads. However, much of this explanatory power is subsumed by information contained in the credit-spread and riskless factors. To emphasize this point, in table VII, we perform panel regressions of the form in equation (19) over an array of maturities. In the top panel, we report the sequential R^2 values as blocks of variables are added. The bottom panel repeats the analysis, but reverses the order of the blocks so that firm variables are the first block.

Table VII Here

Consider the results for the 3-year credit spread. With credit spread and riskless factors, 40% of the variability is explained. Macroeconomic and firm-specific variable blocks, being the last two, collectively explain an additional amount of less than 1%. In contrast, panel B shows that firm and macro variables explain 28% of the variability. The riskless, B-Index, and credit-spread factors, however, as the last blocks, collectively explain an incremental amount of over 13%. Thus, credit spread and riskless factors are extremely informative, and contain most of the information that is necessary for forecasting credit spreads. This result holds consistently across the maturity spectrum.

Table VII also shows the relative importance of blocks of variables on credit spreads across the maturity spectrum. For example, panel A shows that additional blocks of variables beyond the riskless factors all contain significant incremental information about future credit spreads but only for longer maturities.

5 Out-of-Sample Measures of Predictive Content

We consider rolling out-of-sample predictions. We begin by using information over an initial training period to estimate parameters for our regression models. Then, using all historical information known to the market up to date t, we predict future credit spreads. We repeat this procedure over consecutive months, using all our models and using panel regressions as well as firm-by-firm regressions.

We consider several models for predicting future credit spreads. The first model, the spot model, uses the current credit spread to predict future credit spread. The second model, the forward model, uses the appropriate forward credit spread to predict future credit spread. These two models are the benchmark random-walk models against which the performance of additional prediction models are evaluated. In our first model, M_1, predictions are based on the current credit-spread level, slope, and curvature factors. Successive models include information on additional blocks of variables in a hierarchical fashion. Model M_2 uses information on both current period credit-spread factors and lagged credit-spread factors; Model M_3, includes information on the riskless factors; Model M_4, includes information on the B-Index credit spread factors; Model M_5, includes information on the macro variables; and Model M_6 includes all these variables and adds firm-specific-risk variables as well.

The top panel of table VIII reports the average bias and standard deviation as well as the average absolute error and standard deviation, when panel regression methodology (controlling for firm fixed effects run on groups of firms double sorted on the basis of credit ratings and industry) is used to estimate the 5-year credit spreads six months ahead. Model M_3, has the lowest average bias, the lowest average absolute error, and the lowest standard deviation.

Table VIII Here

For each model, we compute the mean squared prediction errors (MSPE), and then compute the ratio of this value relative to the MSPE for the spot model. The bottom panel shows the quartiles of the ratios, followed by the proportion of firms for which a model produced MSPEs that were smaller than those of the spot model. The forward model underperforms the spot model, as does M_1. Model M_3, again, is the best. Indeed, 58% of the firms had smaller MSPEs using M_3 than using the spot model, which is significantly different from 0.5 at the 1% level of significance. Higher-order models performed worse than model M_3 in the out-of-sample analysis.

Table IX shows the results of firm-by-firm regressions. As in the panel regression results, M_3 has the smallest bias (6 basis points) and the smallest average absolute error (31 basis points) of all the models examined, significantly lower than that of the spot model (that yields an average absolute error of 37 basis points).

Information contained in variables, in addition to the riskless factors, do not improve the predictions of 6-month-ahead credit spreads. The bottom panel shows that M_1, the simple credit-spread model, outperforms the spot model , in terms of MSPE, for 63% of the firms, adding lags does not improve performance, but adding riskless factors results in a model (M_3) that outperforms the spot model for 84% of the firms, and the 75^{th} quartile of the ratio was 0.95, less than 1. Like the panel regression results, adding firm-specific and macro variables does not improve predictions of future credit spreads.

Table IX Here

The relative performance of all the models in the firm-by-firm regression models is summarized in figure 5, which shows the MSPE for each model relative to the MSPE for the spot model in the form of box plots. The leftmost box and whisker plot is for the forward model, and its performance relative to the spot model is poor, with the 25^{th} percentile exceeding 1. Using just the credit-spread factors produces a dramatic improvement, as the second box plot of the figure shows. Incorporating lagged credit spreads does not significantly improve predictions; adding riskless factors results in the best model (whose entire box plot fall below 1). Adding other blocks of variables does not improve the forecasts of future credit spreads.

Figure 5 Here

The fact that the forward credit spread performs so poorly, relative to all the other models, is a result that is routinely obtained elsewhere, in riskless and foreign exchange markets. The fact that the forecasts can be improved using information, not only from the credit-spread curve, but also from the riskless term structure, is a new result, that warrants closer investigation. Working towards this goal, we turn our attention to the time-series properties of the MSPEs. For each firm, and for each year we compute the MSPEs for all our models based on firm-by-firm regressions. In panel A of figure 6, we compare each model's MSPEs normalized by the MSPEs of the spot model.

Figure 6 Here

Panel A shows the time series of box plots of MSPE ratios for models M_1, M_2, M_3, and M_4, in that order, relative to the spot model. There is intertemporal variation, but model M_3 outperforms the spot model in 8 of the 10 years. Panel B shows the time series of MSPE ratios for models M_3, M_5, and M_6 relative to the Spot Model. It is clear that there is no advantage in incorporating macro and firm variables. In particular, in every year except 2002, the model without macro and firm factors had the smallest MSPE ratios. To confirm the result that adding macro and firm variables does not improve out-of-sample prediction performance, we computed, for each firm and for each year, the ratio of the MSPEs for the three models that incorporated information beyond the riskless factors and normalized these values by the MSPEs of the model that incorporated information up to the riskless factors. Panel C shows these time series of MSPE ratios for models M_4, M_5 and M_6 relative to M_3. In all years except 2002, the median MSPE ratio exceeded 1 for the models that incorporated either macro or the macro and firm variables information (M_5 and M_6). The model that also uses information from the B-rated credit spreads (M_4) outperformed model M_3 in 52% of occasions, although this is not significantly different from a tie, at the 1% level of significance. Indeed, models M_3 and M_4 had significantly lower average absolute errors in each year than either the spot or the forward models.

Overall, the results of this section indicate that a parsimonious model that uses the information on the credit-spread and riskless factors known to the market at the time of the prediction yields predictions of future 6-months-ahead credit spreads that are significantly superior to those of the random-walk models. More information does not significantly improve the predictions; in fact, using macro and firm-specific variables only adds noise. Of course macro and firm-specific variables are important determinants of credit spreads. But the credit-spread and riskless curves essentially impound all marketwide and firm-specific information necessary for predicting future credit spreads.

5.1 Out-of-Sample Predictions of Credit Spreads of Different Maturities and Forecast Horizons

To check the robustness of our results, we examine the out-of-sample prediction errors of our various models for maturities other than 5 years and for forecast horizons other than 6-months. In this section we examine forecasts of 3-year and 10-year credit spreads; we also alter the forecast horizon from 6 months, first to 3 months and then to 12 months. Table X reports the average absolute errors by firms, and the proportion of firms for which each Model's MSPE is lower than that of Model M_3 based on firm-by-firm regressions.

Table X Here

The top panel shows that M_3 and M_4 are the best models for predicting 6 month ahead 3-year credit spreads, in terms of average absolute prediction errors as well as MSPE ratios. The best models for predicting 6-months-ahead 10-year credit spreads are M_2 and M_3. The bottom panel shows that M_3 is the best model for predicting 3 month ahead 5-year credit spreads, in terms of average absolute prediction errors as well MSPE ratios, whereas M_4 is the best model for predicting future 12-months ahead 5-year credit spreads. In each case, the proportion of firms for which model M_3 yields a lower MSPE than either the spot or forward model is, at the 5% level, significantly higher than 50%.

These results are shown pictorially in figure 7. The 4 panels, respectively, show box plots of MSPE ratios of different models for predicting 6-months-ahead 3-year credit spread, the 6-month-ahead 10-year credit spread, the 3-month-ahead 5-year credit spread, and the 12-months-ahead 5-year credit spread models. The MSPE-ratio-box-plots in each panel are those of spot, forward, and models M_1, M_2, M_4, M_5, and M_6, all relative to the MSPE of model M_3.

Figure 7 Here

Overall, tables IX and X and figures 5, 6 and 7, make two important points. First, the model that uses information contained in the current and lagged term structures of credit spreads as well as in the current riskless yield curve is a parsimonious model that generally leads to the best predictions for future n-month-ahead credit spreads of different maturities. Such a model leads to significantly better predictions than do the random walk models. Second, macro and firm-specific information, over and above information on credit spread and riskless factors does not improve predictions.

5.2 Using Macroeconomic Forecasts

It is perhaps surprising that macro and firm variables are so efficiently embedded into the current term structures of credit-spread and riskless yields, that, at the margin, they do not improve out-of-sample forecasts of credit spreads. One important consideration is that the market knows the forecasts of future macro variables at the time of the prediction. We need not be constrained to using only past information. Perhaps it might help, in terms of the accuracy of predictions of future credit spreads, if we substituted macroeconomic variables with forecasts of future macroeconomic variables.

We collect quarterly information from the Survey of Professional Forecasters (SPF). The survey's participants forecast several macroeconomic variables, and report their forecasts at the middle of each quarter. Typically, about 40 forecasters participate. The survey data are obtained from the web site of the Federal Reserve Bank of Philadelphia. We use the median 6-months-ahead forecasts of key macro variables and match them with the month in which they are made.

The macro variables we use are the median 6-months-ahead GDP forecast, the median 6-months-ahead CPI Inflation forecast, the median 6-months-ahead Industrial Production forecast, and the median 6-months-ahead forecast of Moody's AAA corporate bond yield. We replace our current 4-vector of macro-variables with this 4 vector of macro-forecasts, and re-estimate the 6-month-ahead forecasts of out-of-sample credit spreads using our firm-by-firm regression models. This estimation uses data from a quarterly database rather than a monthly database because the macro-forecasts are available only once a quarter (in the middle month of the quarter).

We evaluate whether using macro forecasts rather than current macro variables improves forecasts of future credit spreads. The models we compare are the (a) the spot model, (b) the model with credit-spread factors and riskless factors, (M_3) (c) the model with credit-spread factors, riskless factors and Index factors, (M_4) (d) the model with credit-spread factors, lagged factors, and macro-variable forecasts, (e) the model with credit-spread factors, lagged factors, riskless factors, and macro-variable forecasts, and (f) the model with credit-spread factors, lagged factors, riskless factors, index factors, and macro-variable forecasts.

Table XI reports average absolute errors by firms and the proportion of firms for which each out-of-sample prediction model has a lower MSPE relative of relative to MSPE of Model M_3, firm by firm.

Table XI Here

The average absolute prediction errors are significantly lower for models M_3 and M_4 than for those of any of the other model that uses macro forecasts. The proportion of firms that have lower MPSEs is also significantly lower than 0.5 for the other models (except M_4).

Figure 8 shows the box plots of the ratios of Mean Square Prediction Errors (MSPEs) for our different credit-spread prediction models relative to the MSPE of the model that uses only current period credit-spread and riskless-yield factors (M_3), firm by firm and quarter by quarter.

Figure 8 Here

The 5 box plots show that models M_3 or M_4 are better than each of other 4 models that use macro forecasts.

6 Conclusion

This study examines the predictability of credit spreads at the firm level. We construct monthly credit-spread curves for a large representative sample of 241 high- and low-credit-rated firms from the manufacturing and service sectors, over a period of 16 years from 1990 through 2005. Using a 3-factor Diebold-Li model, appropriately modified for credit spreads, we fit a term structure of credit spreads for each firm every month. The fit of the bond prices derived from our optimization routine to the data is extremely good: Over 90% of the bonds fit to within 1 dollar of their price. We document that credit-spread curves can be upward or downward sloping, and can take hump-shaped patterns. Credit spreads of different maturities for the same firm can move in different directions over the same time period. For example, in our data set, the 3-year and 10-year credit spreads move in the same direction only 63% of the time.

Once the firm-by-firm credit-spread curves are constructed, we investigate which blocks of variables are informative for predicting future credit spreads. Benchmark forecasts based on the current spot and forward credit spreads can be substantially improved upon using a model that incorporates the level, slope, and curvature factors of the credit-spread curve. That is, today's credit-spread curve contains significant information on future credit spreads. But the credit-spread curve is not a sufficient statistic for forecasting future credit spreads. Forecasts can be further significantly improved upon by incorporating information contained in the riskless yield curve. B-rated credit-spread curves contain additional information for longer horizon predictions. In the presence of these 3 blocks of factors, aggregate-stock-market and other macroeconomic variables, as well as firm-specific-risk variables do not contain significant incremental information on future credit spreads.

Our results indicate that risk-premia factors that account for the predictability of credit spreads can be traced back to information contained primarily in the firm's own credit-spread curve and in the riskless curve, and that, in their presence, the incremental information contained in other marketwide as well as firm-specific variables is negligible. Our findings that there is significant information contained in the shape of today's credit-spread curve, but it is not, by itself, a sufficient statistic for forecasting future credit spreads, should be considered in establishing theoretical models, in future, for credit spreads.

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Appendix

Descriptions of Blocks of Macro and Firm Variables

Macro-Variables	Description
Real Activity Index	Real Activity Index, RA(t), in month *t* is the first principal component of 4 underlying time series of macro-variables after purging each of them of the riskless level, slope and curvature factors. The 4 underlying monthly series of macro-variables are the Index of Help Wanted Advertising in Newspapers, (HELP), the Unemployment Rate, (UE), the growth rate of Employment, (EMPLOY) and the growth rate of Industrial Production, (GIP). All growth rates are measured as the 12-month difference in the logs of the index.
Inflation Index	Inflation Index, I(t), for month *t* is the first principal component of 3 underlying time series of macro-variables after purging each of them of the riskless level, slope, and curvature factors. The 3 underlying monthly series of macro-variables are the Consumer price Index, (CPI), the Producer price Index of Finished Goods, (PPI), and the Market Commodity Price Index, (PCOM). All these inflation measures are measured as changes in the logs of their indices over a 12 month period.
Stock Market Momentum	Stock market momentum for month *t* is the 12-month cumulative holding period return from month t-13 through month t-2 of the Center for Research in Security Prices (CRSP) value weighted index return following the methodology described in Ken French's web-site.
Stock Market Volatility	Stock market volatility is the monthly volatility of the CRSP value-weighted index return using the daily returns of the index within each month, following the methodology of French, Schwert and Stambaugh (1987).

Firm-Specific Variables	Description
Leverage	Leverage, L(t), for month *t* is the ratio of debt outstanding on the balance sheet of the firm (Compustat Quarterly data item 51) and the market value of its common stock, computed monthly as the product of the number of shares outstanding and the closing share price each month (Compustat Quarterly data items 61 and 14). The book value of debt is the same number for all three months of a quarter.
Book-to-Market Ratio	The book-to-market ratio, BM(t) for month *t* is the ratio of the book value of equity to the market value of equity. The book value of equity is defined as stockholders' equity plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock, which are respectively Compustat Quarterly data items 60, 52, and 55. The market value of equity is defined as the number of shares outstanding multiplied by the end of respective month closing stock price, which are respectively Compustat Quarterly data items, 61 and 14.
Stock Momentum	Stock momentum for month *t* is the 12-month cumulative holding period stock return from month t-13 through month t-2 taken from CRSP.
Stock Volatility	Stock volatility is the monthly volatility using the daily stock returns in each month from CRSP.

Table I
Data Sample

Panel A shows the number of firms and firm×months in our sample, step-by-step through our screening process. Our sample comprises industrial, banking, and services sector firms in the S&P 500 index at any time during the period 1990-2005. Our initial screen eliminates all bonds other than fixed-rate U.S. dollar-denominated bonds that have no derivative features: 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. The first column shows data particulars of the initial set of firms. In the first screen, we require a minimum of 5 prices of bonds of different maturities that span at least 7 years for each month to estimate the credit spread level, slope and curvature factors. In the second screen, we drop all firm-months that do not have at least 6 consecutive months of reasonable credit spread level, slope, and curvature factor estimates. In the third screen, we need data from Compustat to obtain our firm-specific risk measures. Our final sample comprises 241 firms and 11,894 firm months of data. Panel B shows the proportion of firms and firm months in our final dataset falling under different industry and rating cohorts. We obtain bond ratings from Quarterly Compustat (augmented with data from Bloomberg), and assign numerical scores for the ratings starting with a score of 1 for AAA rating, 2 for AA rating and so on. We then segregate all firms into two overall groups: those whose bonds are rated BBB and above based on the average score of all bonds of that firm (the investment grade or “high” rated firms), and those that are rated below BBB (the non-investment grade or “low” rated firms).

PANEL A: The screening process

Initial sample		Sample after 1st screen to obtain firm betas		Sample after 2nd screen after obtaining betas		Sample after 3rd screen of obtaining Compustat/CRSP data	
Firms	**Firm months**	**Firms**	**Firm months**	**Firms**	**Firm months**	**Firms**	**Firm months**
387	14,234	340	14,049	256	13,589	241	11,894

PANEL B: The Final Sample

Industry	Firms	Firm months	Credit Rating	Firms	Firm months
Manufacturing-Sector	92	4034	Investment Grade	194	9709
Service-Sector	149	7860	Below Investment Grade	47	2185

Table II
Firm Characteristics and Credit Spread Factors

Panel A shows the average firm characteristics – the average leverage, book-to-market ratio, monthly stock momentum, and stock volatility (reported on an annualized basis), for firms grouped by credit ratings (high and low), and industry (manufacturing and service). Leverage is the ratio of debt outstanding on the balance sheet of the firm (Compustat Quarterly data item 51) and the market value of its common stock, computed monthly as the product of the number of shares outstanding and the closing share price each month (Compustat Quarterly data items 61 and 14). The book value of equity is defined as stockholders' equity plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock, which are respectively Compustat Quarterly data items 60, 52, and 55. The market value of equity is defined as the number of shares outstanding multiplied by the end of respective month closing stock price, which are respectively Compustat Quarterly data items, 61 and 14. Stock volatility is the sum of the daily squared holding period returns divided by number of observations in a month, from CRSP. The monthly volatility is presented as annualized numbers. Stock momentum is the cumulative 12 monthly holding period returns from end of month t-13 through month t-2 from CRSP. Panel B shows the average credit spread level, slope and curvature factors across firm-months for firms segregated by their industry or credit ratings. The level (beta 1), slope (negative of beta 2) and curvature (beta 3) factors are measured in basis points. Difference of means, along with their *t*-statistics, between manufacturing firms and service-sector firms, and between the below investment grade firms and investment grade firms are shown.

Panel A

Firm Risk Variables	Industry			Credit Rating		
	Service	Manufacturing	Difference	Below Investment Grade	Investment Grade	Difference
Leverage	0.74	0.34	0.40*** (38.14)	0.70	0.58	0.12*** (7.00)
Book-to-Market Ratio	0.72	0.47	0.25*** (29.01)	0.76	0.61	0.15*** (11.32)
Stock Momentum	0.17	0.15	0.02** (2.01)	0.13	0.17	-0.04*** (-6.99)
Stock Volatility (annualized)	0.21	0.20	0.01 (1.70)	0.21	0.21	0.00 (0.85)

Panel B

Credit Spread Factor	Industry			Credit Rating		
	Service	Manufacturing	Difference	Below Investment Grade	Investment Grade	Difference
Level	239.69	244.54	-4.85 (-1.59)	255.79	238.08	17.71*** (4.60)
Slope	28.72	21.79	6.93*** (6.89)	26.50	26.34	0.16 (0.13)
Curvature	-15.20	-28.54	13.34*** (8.03)	-20.18	-17.70	-2.48 (-1.24)

***, **, and * denote significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table III
Contemporaneous Determinants of Riskless Factors, Index Factors, and Credit Spreads

The top half of Panel A reports the adjusted R^2 when each of the riskless factors is regressed on the 4-vector of current month macro-variables. The 4-vector of macro-variables comprises the 1st Principal Component of the Real Activity Variables after each of these variables are purged of the riskless factors, the 1st Principal Component of the Inflation Variables after each of these variables are purged of the factors parameters, stock market momentum, and stock market volatility. The Real Activity variables are (a) the index of Help Wanted Advertising in Newspapers (HELP), (b) the unemployment rate (UE), (c) the growth rate of employment (EMPLOY), and (d) the growth rate of Industrial Production (GIP). The Inflation Variables are the growth rates of (a) the Consumer Price Index (CPI), (b) the Producer price Index (PPI) and (c) of the Commodity Price Index (COMM). The bottom half of Panel A reports the adjusted R^2 when each of the B-Index factors are regressed first on the 3-vector of current month riskless factors, and then when the 4-vector of current month macro-variables is also added as explanatory variables. The B-index factors are constructed from the B-credit-rated-Index term structure curves obtained from Bloomberg. Panel B shows the reports the adjusted R^2 when the 3-year, 5-year and 10-year credit spreads are regressed on the 8-vector of current month macro-variables and firm variables, for 4 groups of firms double-sorted on the basis of their credit ratings and industry. Panel Regressions with firm fixed effects are run over each group of firms. The significance of each block of explanatory variables is based on the *p*-value of the partial *F*-statistic.

Panel A

Dependent Variables	Current Riskless Factors	+ Current Macro Variables
Riskless Beta 1		0.213***
Riskless Beta 2		0.239***
Riskless Beta 3		0.276***
Index Beta 1	0.155***	0.777***
Index Beta 2	0.692***	0.786***
Index Beta 3	0.428***	0.629***

Panel B

		3-year credit Spread	5-year credit Spread	10-year credit Spread
Credit Rating	Industry	Explanatory Variables		
		Current Macro and Firm Variables	Current Macro and Firm Variables	Current Macro and Firm Variables
High	Manufacturing	0.417***	0.595***	0.583***
	Service	0.401***	0.570***	0.498***
Low	Manufacturing	0.582***	0.702***	0.686***
	Service	0.397***	0.430***	0.439***

***, **, and * denote significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table IV
Determinants of 6-Months-Ahead Riskless Yields and Factors

Panel A shows the regression coefficients and, in parentheses, the associated *t*-statistics that are based on standard errors robust to heteroskedasticity and autocorrelation, when the future 6-month ahead 3-, 5- and 10-year riskless yields are regressed on the current month 3-, 5-, and 10-year riskless yields. The sample period is 1970-2005. Panel B shows the R^2 and the partial R^2 values when future 6-month ahead 3-, 5- and 10-year riskless yields are regressed on 4 blocks of variables: the 3-vector of current month level, slope and curvature factors, the one-month lagged 3-vector of level, slope, and curvature factors, the 4-vector of current month macro-variables, and finally, the one-month lagged 4-vector of current month macro-variables. Panel C shows the same statistics as Panel B except that the dependant variables are now the 6-month-ahead riskless level, slope, and curvature factors. The significance of the partial R^2 values is based on the *p*-values of the partial *F*-statistic of the block of variables. The sample period for Panels B and C is 1990-2005.

Panel A: Future Riskless Yield

	6-months-ahead 3-year Yield	6-months-ahead 5-year Yield	6-months-ahead 10-year Yield
Current month 3-year Yield	4.556 (5.61)***	3.937 (5.93)***	3.634 (7.11)***
Current month 5-year Yield	-6.795 (-4.60)***	-6.323 (-5.23)***	-6.531 (-7.00)***
Current month 10-year Yield	3.203 (4.66)***	3.358 (5.95)***	3.871 (8.79)***
Intercept	0.002 (0.96)	0.002 (1.04)	0.003 (1.42)

Panel B: Future Riskless Yield

	6-months-ahead 3-year Yield		6-months-ahead 5-year Yield		6-months-ahead 10-year Yield	
	R^2	Partial R^2	R^2	Partial R^2	R^2	Partial R^2
Current month 3-vector of Beta Factors	0.727		0.726		0.752	
1-month lagged 3-vector of Beta Factors	0.729	0.010	0.728	0.004	0.754	0.010
Current month 4-vector of Macro Variables	0.771	0.153***	0.755	0.100***	0.765	0.045**
1-month lagged 4-vector of Macro Variables	0.781	0.048**	0.767	0.048**	0.776	0.045**

Panel C: Future Riskless Factors

	6-months-ahead Riskless Beta1		6-months-ahead Riskless Beta2		6-months-ahead Riskless Beta3	
	R^2	Partial R^2	R^2	Partial R^2	R^2	Partial R^2
Current month 3-vector of Beta Factors	0.781		0.773		0.456	
1-month lagged 3-vector of Beta Factors	0.790	0.040*	0.803	0.133***	0.465	0.017
Current month 4-vector of Macro Variables	0.799	0.044**	0.865	0.316***	0.574	0.203***
1-month lagged 4-vector of Macro Variables	0.807	0.036*	0.871	0.042*	0.603	0.068**

***, **, and * denote significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table V
Determinants of 6-Months-Ahead B-Rated-Index Credit Spreads and Factors

The top Panel shows the R^2 and the partial R^2 values when future 6-months-ahead 3-, 5- and 10-year B-index credit spreads are regressed on 6 blocks of variables: the 3-vector of current month level, slope, and curvature factors, the one-month lagged 3-vector of level, slope, and curvature factors, the 3-vector of current month riskless factors, their 1-month lagged values, the 4-vector of current month macro-variables, and finally their one-month lagged values. The bottom panel shows the same statistics except that the dependant variables are now the 6-months-ahead B-rated credit spread level, slope and curvature factors. The significance of the partial R^2 values is based on the *p*-values of the partial *F*-statistic of the block of variables. The sample period is 1990-2005.

	6-months-ahead 3-year credit spread		6-months-ahead 5-year credit spread		6-months-ahead 10-year credit spread	
	R^2	Partial R^2	R^2	Partial R^2	R^2	Partial R^2
Current month Betas	0.481		0.449		0.452	
1-month Lagged Betas	0.505	0.046*	0.474	0.047*	0.478	0.047*
Current month Riskless Betas	0.596	0.184***	0.582	0.204***	0.603	0.240***
1-month Lagged Riskless Betas	0.597	0.003	0.582	0.001	0.603	0.000
Current month Macro-variables	0.734	0.341***	0.735	0.366***	0.759	0.393***
1-month Lagged Macro-variables	0.758	0.087**	0.757	0.083**	0.776	0.071**

	6-months-ahead Beta 1		6-months-ahead Beta 2		6-months-ahead Beta 3	
	R^2	Partial R^2	R^2	Partial R^2	R^2	Partial R^2
Current month Betas	0.508		0.737		0.564	
1-month Lagged Betas	0.531	0.047*	0.760	0.088***	0.577	0.031
Current month Riskless Betas	0.666	0.287***	0.821	0.252***	0.659	0.192***
1-month Lagged Riskless Betas	0.666	0.002	0.825	0.025	0.663	0.013
Current month Macro-variables	0.799	0.398***	0.839	0.081***	0.682	0.056**
1-month Lagged Macro-variables	0.809	0.048*	0.846	0.043*	0.688	0.019

***, **, and * denote significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table VI
Determinants of 6-Months-Ahead 5-Year Credit Spreads

Panel A reports the R^2 values and the partial R^2 values of explanatory variables for 3 different specifications when the 6-months-ahead 5-year credit spreads are regressed on blocks of explanatory variables. Panel regressions (after controlling for firm fixed effects) are run over groups of firms double-sorted by credit ratings and industry. The standard errors are corrected for heteroskedasticity and autocorrelation, and for clustering by firms. The significance of the partial R^2 values is based on the *p*-values of the partial *F*-statistic of the block of variables. Panel B shows the average R^2 and the average adjusted R^2 when the regressions, with the future 6-month-ahead 5-year credit spread as the dependent variable, are run firm-by-firm. Also shown are the proportion of firms for which each block of variables was significant at the 10 and 5 percent levels, the average absolute error, and the average Root Mean Square Error (RMSE).

Panel A: Panel Regressions

Block of Variables	R^2	Partial R^2	R^2	Partial R^2	R^2	Partial R^2
Firm Fixed effects	0.351		0.351		0.351	
Current month same-maturity credit spread	0.579	0.359***				
Current month long credit spread	0.601	0.052***				
Current month short credit spread	0.626	0.063***				
Current month Betas			0.626	0.424***	0.626	0.424***
1-month Lagged Betas			0.634	0.021**	0.634	0.021***
2-month Lagged Betas			0.636	0.008		
3-month Lagged Betas			0.638	0.005		
Riskless Betas					0.685	0.139***
B-Rated Index Betas					0.691	0.019**
Macro Variables					0.697	0.019**
Firm Variables					0.704	0.023**

***, **, and * denote significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel B: Firm-by-Firm Regressions

Block of Variables	Average Adjusted R^2	Proportion of firms that are significant at the 10% level	5% level	Average Adjusted R^2	Percentage of firms that are significant at 10% level	5% level	Average Absolute Error	Average RMSE
Current month Betas	0.435	81.7	77.9	0.435	81.7	77.9	28.82	43.19
1-month Lagged Betas	0.460	35.8	28.5	0.460	35.8	28.5	28.48	42.49
2-month Lagged Betas	0.477	21.9	14.0					
3-month Lagged Betas	0.462	16.3	10.6					
Riskless Betas				0.595	74.5	69.6	25.77	39.30
B-Rated Index Betas				0.675	55.6	47.7	25.31	38.96
Macro Variables				0.702	60.5	52.6	25.02	38.63
Firm Variables				0.731	56.9	52.7	25.02	38.46

Table VII
Relative Importance of Explanatory Variables For Predicting Credit Spreads

This table reports the R^2 values when future 6-months-ahead credit spreads of different maturities are regressed sequentially on the successive blocks of explanatory variables. The sequence of the blocks of explanatory variables is reversed for Panel B as compared to Panel A. Panel regression controlling for firm fixed effects are run by groups that are based on ratings and industry. The standard errors are corrected for heteroskedasticity and autocorrelation, and for clustering by firms. The significance of the explanatory variables is based on the *p*-values of the partial *F*-statistics.

Panel A

	Short Credit Spread	0.5 yr	1 yr	3 yr	5 yr	7 yr	10 yr	20 yr	Long Credit Spread
Firm fixed effects	0.198	0.203	0.209	0.261	0.351	0.327	0.307*	0.237***	0.194***
3-vector of Current Credit Spread Factors	0.321***	0.336***	0.357***	0.513***	0.626***	0.594***	0.520***	0.375***	0.302***
3-vector of Lagged Credit Spread Factors	0.345***	0.361***	0.383***	0.536***	0.634***	0.607***	0.537***	0.392***	0.318***
3-vector of Riskless Factors	0.357***	0.378***	0.405***	0.595***	0.685***	0.627***	0.545***	0.401***	0.333***
3-Vector of Index Factors	0.357	0.378	0.406*	0.599**	0.691**	0.632**	0.555***	0.425***	0.358***
4-vector of Macro Variables	0.362**	0.384**	0.412**	0.605**	0.697**	0.639***	0.565***	0.434***	0.365***
4-vector of Firm Variables	0.364	0.386	0.414	0.609*	0.704**	0.647**	0.572**	0.440**	0.370**

Panel B

	Short Credit Spread	0.5 yr	1 yr	3 yr	5 yr	7 yr	10 yr	20 yr	Long Credit Spread
Firm fixed effects	0.198	0.203	0.209	0.261	0.351	0.327	0.307*	0.237***	0.194***
4-vector of Firm Variables	0.200	0.206	0.214	0.294***	0.388***	0.400***	0.367***	0.271***	0.214***
4-vector of Macro Variables	0.249***	0.264***	0.281***	0.398***	0.481***	0.491***	0.470***	0.358***	0.276***
3-Vector of Index Factors	0.268***	0.289***	0.316***	0.488***	0.555***	0.516***	0.478***	0.385***	0.318***
3-vector of Riskless Factors	0.281***	0.304***	0.335***	0.527***	0.586***	0.532***	0.489***	0.395***	0.327***
3-vector of Lagged Credit Spread Factors	0.337***	0.359***	0.388***	0.588***	0.680***	0.625***	0.554***	0.424***	0.353***
3-vector of Current Credit Spread Factors	0.364***	0.386***	0.414***	0.609***	0.704***	0.647***	0.572***	0.440***	0.370***

***, **, and * denote significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table VIII
Out-of-Sample 6-Months-Ahead 5-year-Credit-Spread Prediction Errors Using Panel Regressions

The table shows the statistics of 6-months-ahead Out-of-sample prediction errors of 5-year credit spreads (where prediction error is defined as the actual 5-year credit spread minus predicted 5-year credit spreads in basis points). Panel regression methodology with firm fixed effects is used where the panel regressions are run by groups that are based on ratings and industry. The standard errors are corrected for heteroskedasticity and autocorrelation, and for clustering by firms. Panel A shows the average out-of-sample 6-month-ahead prediction errors (the average bias) and the average of the absolute errors, along with standard deviations by firms. Panel B reports statistics of the distribution of the ratio of Mean Square Prediction Errors (MSPE) for each model relative to that of the Spot Model by firms, and the proportion of firms for which each Model has a lower MSPE relative of that of the Spot Model. Our credit spread prediction models include successively more blocks of variables. Model M_1 uses just the current credit spread betas, M_2 adds the lagged beta factors, M_3 adds the riskless factors, M_4 adds the B-index factors, M_5 adds the macro-variables, and finally, M_6 adds the firm variables on top of all the aforementioned blocks of variables.

Panel A

	Errors		Absolute Errors	
	Average	Standard Deviation	Average	Standard Deviation
Spot	7.96	30.84	37.34	30.61
Forward	-6.26	37.57	46.97	34.48
M_1	6.34	31.63	40.06	29.85
M_2	6.75	31.84	39.52	29.51
M_3	5.40	29.17	35.86	28.30
M_4	6.39	29.16	36.01	28.74
M_5	6.32	29.98	36.82	29.65
M_6	10.42	29.84	37.27	30.43

Panel B

	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile	Proportion of firms, for which model has lower MSPE than Spot Model
Forward	1.05	1.51	2.39	0.22
M_1	0.88	1.12	1.51	0.40
M_2	0.91	1.10	1.45	0.36
M_3	0.70	0.92	1.24	0.58
M_4	0.72	0.94	1.22	0.56
M_5	0.79	1.01	1.41	0.48
M_6	0.82	1.04	1.44	0.42

Table IX
Out-of-Sample 6-Months-Ahead 5-year-Credit-Spread Prediction Errors Using Firm-by-Firm Regressions

The table shows the statistics of the 6-months-ahead Out-of-sample prediction errors of 5-year credit spreads (where prediction error is defined as the actual 5-year credit spread minus predicted 5-year credit spreads in basis points). Firm-by-firm regressions are used. Panel A shows the average out-of-sample 6-months-ahead prediction errors (the average bias) and the average of the absolute errors, along with standard deviations by firms. Panel B reports statistics of the distribution of the ratio of Mean Square Prediction Errors (MSPE) for each model relative to that of the Spot Model by firms, and the proportion of firms for which each Model has a lower MSPE relative of that of the Spot Model. Our credit spread prediction models include successively more blocks of variables. Model M_1 uses just the current credit spread betas, M_2 adds the lagged beta factors, M_3 adds the riskless factors, M_4 adds the B-index factors, M_5 adds the macro-variables, and finally, M_6 adds the firm variables on top of all the aforementioned blocks of variables.

Panel A

	Errors		Absolute Errors	
	Average	Standard Deviation	Average	Standard Deviation
Spot	7.96	30.84	37.34	30.61
Forward	-6.26	37.57	46.97	34.48
M_1	10.65	27.87	34.75	27.70
M_2	11.50	28.19	34.74	26.86
M_3	5.98	25.39	31.63	24.74
M_4	7.05	25.74	31.87	25.61
M_5	6.93	26.90	33.61	26.85
M_6	7.14	26.47	32.90	26.44

Panel B

	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile	Proportion of firms, for which model has lower MSPE than Spot Model
Forward	1.05	1.51	2.39	0.20
M_1	0.74	0.92	1.08	0.63
M_2	0.70	0.92	1.08	0.60
M_3	0.63	0.79	0.95	0.84
M_4	0.59	0.77	0.96	0.79
M_5	0.66	0.89	1.04	0.73
M_6	0.67	0.88	1.07	0.69

Table X
Robustness Checks of Out-of-Sample Credit-Spread Predictions Using Firm-by-Firm Regressions

This table reports the average absolute errors by firms, and the proportion of firms for which each Model has a lower MSPE relative of that of Model$_3$. Our credit spread prediction models include successively more blocks of variables. Model M_1 uses just the current credit spread betas, M_2 adds the lagged beta factors, M_3 adds the riskless factors, M_4 adds the B-index factors, M_5 adds the macro-variables, and finally M_6 adds the firm variables on top of all the aforementioned blocks of variables. Firm-by-firm regressions are used. Panel A shows these statistics for the 6-months-ahead 3- and 10-year credit spreads, while Panel B shows these statistics for 3- and 12-months-ahead 5-year credit spreads.

Panel A

	6-Months-Ahead 3-year Credit Spread		6-Months-Ahead 10-year Credit Spread	
	Average Absolute Prediction Error across firms	Proportion of firms, for which model has lower average MSPE than Model$_3$	Average Absolute Prediction Error across firms	Proportion of firms, for which model has lower average MSPE than Model$_3$
Spot	60.05	0.15	44.16	0.25
Forward	61.05	0.17	51.67	0.15
M_1	54.67	0.11	40.93	0.46
M_2	54.08	0.10	40.08	0.51
M_3	48.27	N/A	40.98	N/A
M_4	48.30	0.60	41.58	0.45
M_5	52.40	0.28	42.89	0.26
M_6	51.05	0.28	44.45	0.31

Panel B

	3-Months-Ahead 5-year Credit Spread		12-Months-Ahead 5-year Credit Spread	
	Average Absolute Prediction Error across firms	Proportion of firms, for which model has lower average MSPE than Model M_3	Average Absolute Prediction Error across firms	Proportion of firms, for which model has lower average MSPE than Model M_3
Spot	26.15	0.18	53.16	0.19
Forward	32.40	0.05	73.60	0.13
M_1	25.19	0.17	52.04	0.22
M_2	24.72	0.26	52.14	0.22
M_3	23.94	N/A	47.31	N/A
M_4	24.86	0.18	42.75	0.54
M_5	26.07	0.05	47.95	0.36
M_6	25.75	0.17	49.33	0.35

Table XI
Out-of-Sample 6-Months-Ahead 5-year-Credit-Spread Prediction Using Macro Forecasts

This table reports the average absolute errors by firms, and the proportion of firms for which each out-of-sample prediction Model has a lower MSPE relative of relative to MSPE of a model with just the credit spread factors, lagged factors, and the riskless factors (Model M_3), firm by firm. The models compared are the (a) Spot Model, (b) the model with the credit spread factors, riskless factors and Index factors, Model M_4 (c) the model with credit spread factors, lagged factors, and predicted macro-variables, (d) the model with credit spread factors, lagged factors, riskless factors, and predicted macro-variables, and (e) the model with credit spread factors, lagged factors, riskless factors, index factors, and predicted macro-variables. The 4-vecator of macro variable forecasts used are the median 6-month ahead GDP forecast, the median 6-month ahead CPI Inflation forecast, the median 6-month ahead Industrial Production forecast, and the median 6-month ahead Moody's AAA corporate bond yield forecast from the Survey of Professional Forecasters (SPF). We obtain these quarterly forecasts from the web site of the Federal Reserve Bank of Philadelphia. Firm by firm regressions are run.

	6-Months-Ahead 5-year Credit Spread	
	Average Absolute Prediction Error across Firms	Proportion of firms for which model has lower average MSPE than $Model_3$
Spot	36.23	0.26
M_3	31.94	N/A
M_4	32.08	0.50
M_2 + macro-forecasts	40.75	0.23
M_3 + macro-forecasts	37.46	0.20
M_4 + macro-forecasts	45.97	0.14
M_5 + macro-forecasts	53.19	0.10

Figure 1
Riskless Term Structure: Beta Values As Level, Slope, and Curvature Factors

The plots compare the time series of riskless yield curve level, slope, and curvature parameter estimates with the corresponding actual long rates, slopes, and curvatures. The time series of beta values are obtained using the Nelsen-Siegel model as discussed in the text. The data consists of the unsmoothed monthly Fama-Bliss riskless yields over the period January 1970 to December 2005.

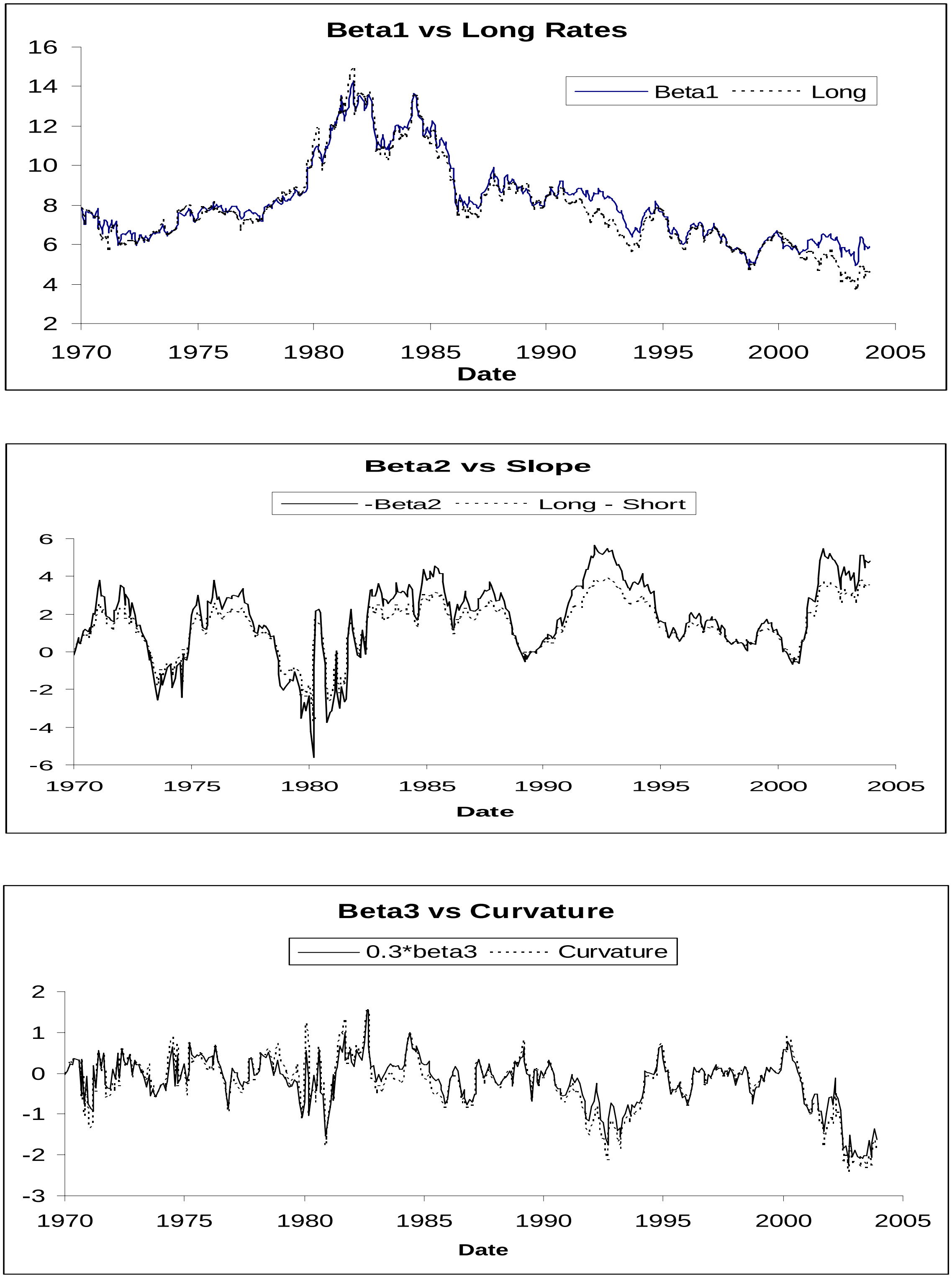
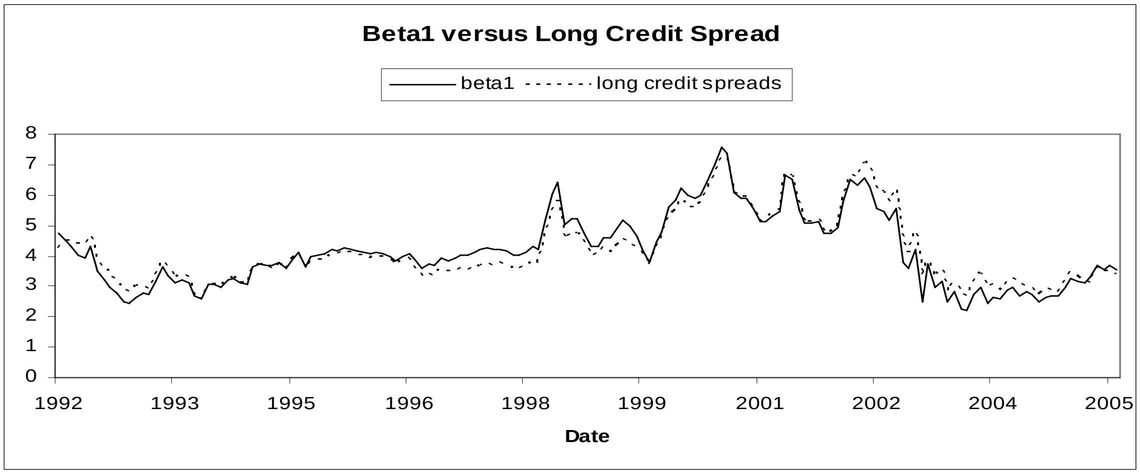
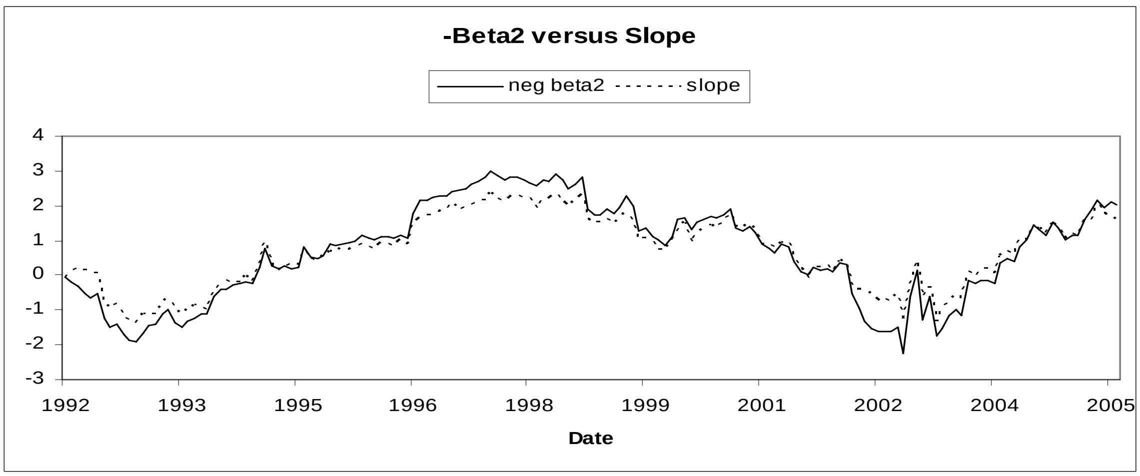


Figure 2
B-Rated Index Term Structure of Credit Spreads: Beta Values as Level, Slope, and Curvature Factors

The plots compare the time series of riskless yield curve level, slope, and curvature factor estimates with the corresponding actual long rates, slopes, and curvatures. The data consists of the B-rated Index term structure curves obtained from Bloomberg for the period January 1992 to December 2005.





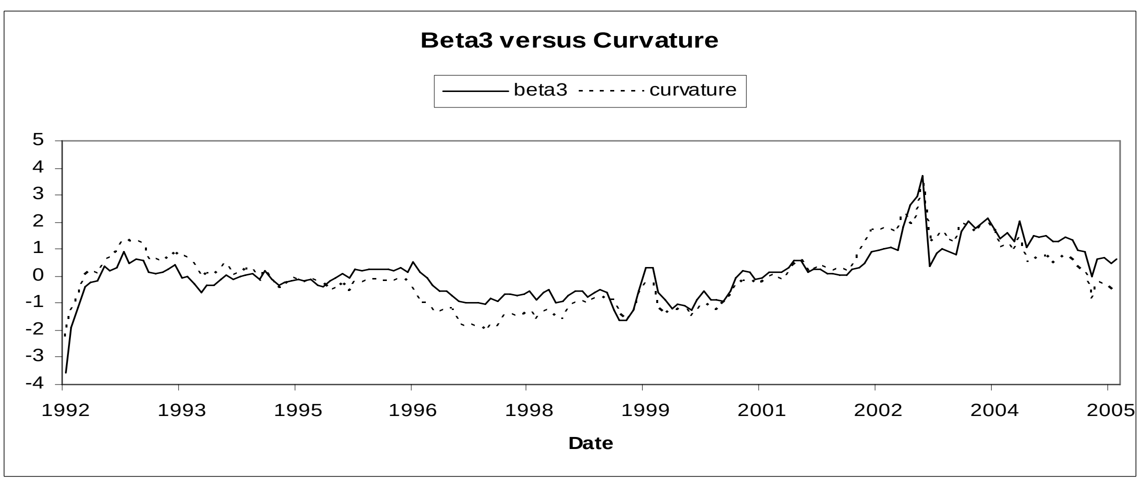


Figure 3
Histogram of Pricing Errors

This figure shows the histogram of bond pricing errors obtained from our optimization routines for each firm-month combination. The bond pricing errors (calculated as the bond trade price from Bloomberg minus the fitted bond price obtained from our Model) are in dollars.

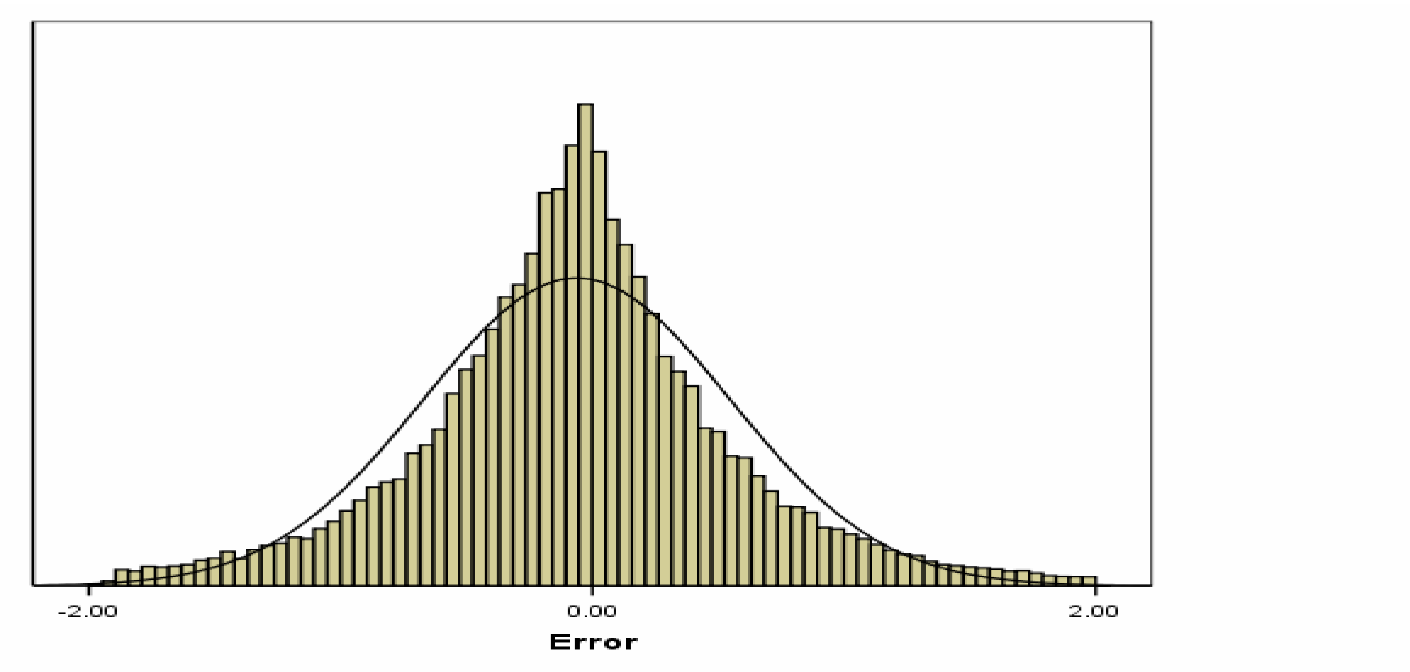


Figure 4
Corporate Bond Yield Curves for An Illustrative Firm

This figure shows the time series of risky yield curves for a representative firm, the Altria Group, constructed using the estimated credit spread level, slope, and curvature parameters.

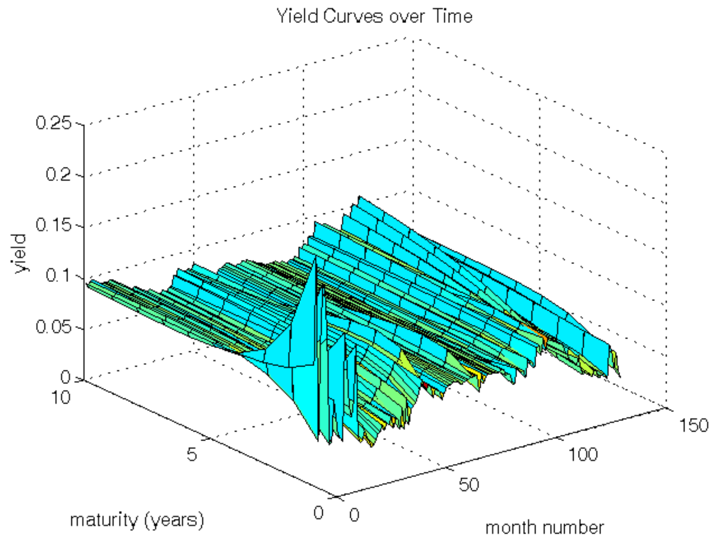


Figure 5
Out-Of-Sample Prediction Errors of 5-year Credit Spreads: Comparison of Models

This figure shows the box plots of the ratios of Mean Square prediction Errors (MSPE) for our different credit spread prediction models relative to the MSPE of the Spot Model, firm by firm, over all time periods. Our credit spread prediction models include successively more blocks of variables. The models shown are the Forward Model, Model M_1 that uses just the current credit spread betas, Model M_2 that adds the lagged beta factors, Model M_3 that adds the riskless factors, Model M_4 that adds the B-index factors, Model M_5 that adds the macro-variables, and finally, Model M_6 that adds the firm variables on top of all the aforementioned blocks of variables.

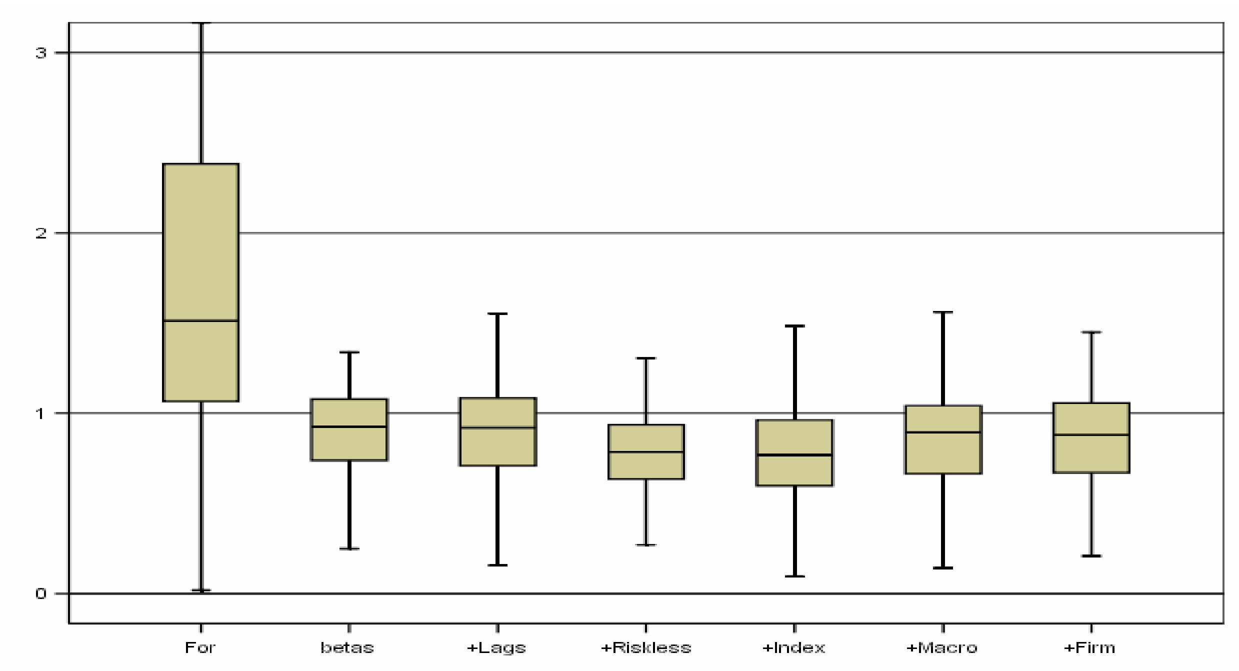


Figure 6
Out-Of-Sample Prediction Errors of 5-year Credit Spreads: Time Series Comparison of Models

Panel A shows the time series of box plots of Mean Square prediction Errors (MSPE) ratios for Models M_1, M_2, M_3, and M_4, in that order, relative to the Spot model. Panel B shows the time series of MSPE ratios for Models M_3, M_5, and M_6 relative to the Spot Model. Panel C shows the time series of MSPE ratios for Models M_4, M_5, and M_6 models relative to that of Model M_3. Our credit spread prediction models include successively more blocks of variables. Model M_1 uses just the current credit spread betas, M_2 adds the lagged beta factors, M_3 adds the riskless factors, M_4 adds the B-rated index factors, M_5 adds the macro-variables, and finally, M_6 adds the firm variables on top of all the aforementioned blocks of variables.

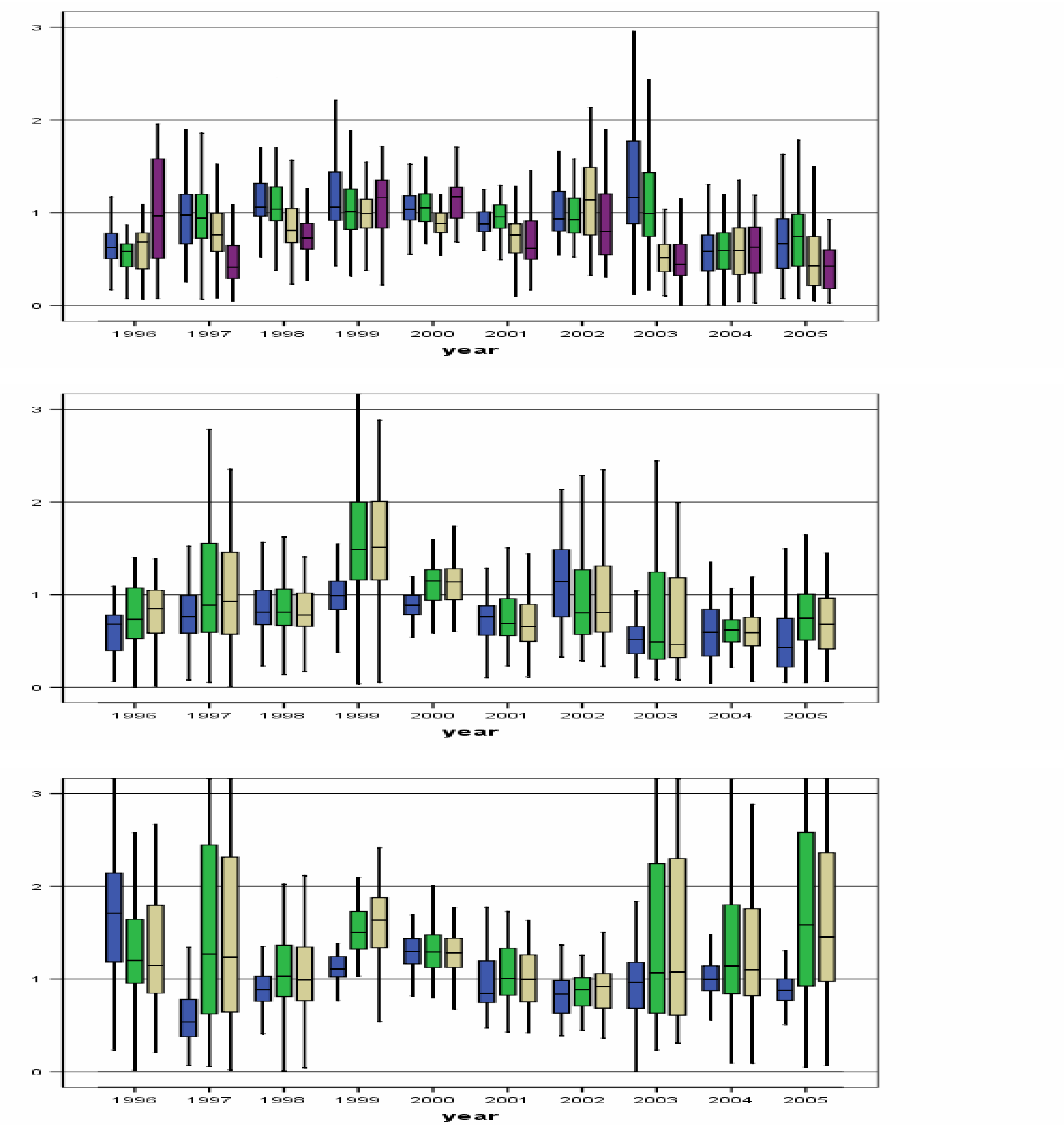


Figure 7
Out-Of-Sample Prediction Errors: Comparison of Models for Different Credit Spread Predictions

The panels from top to bottom show box plots of Mean Square prediction Errors (MSPE) ratios for 6-Months-Ahead 3-year-Credit-Spread forecasting Models, 6-Months-Ahead 10-year-Credit-Spread forecasting Models, 3-Months-Ahead 5-year credit spread forecasting Models, and 12-Months-Ahead 5-year credit spread forecasting Models. The MSPE ratios plots in sequence in each Panel are those of Spot, Forward, and of Models M_1, M_2, M_4, M_5, and M_6, all relative to the MSPE of a model with just the credit spread factors, lagged factors, and riskless factors (Model M_3), firm by firm.

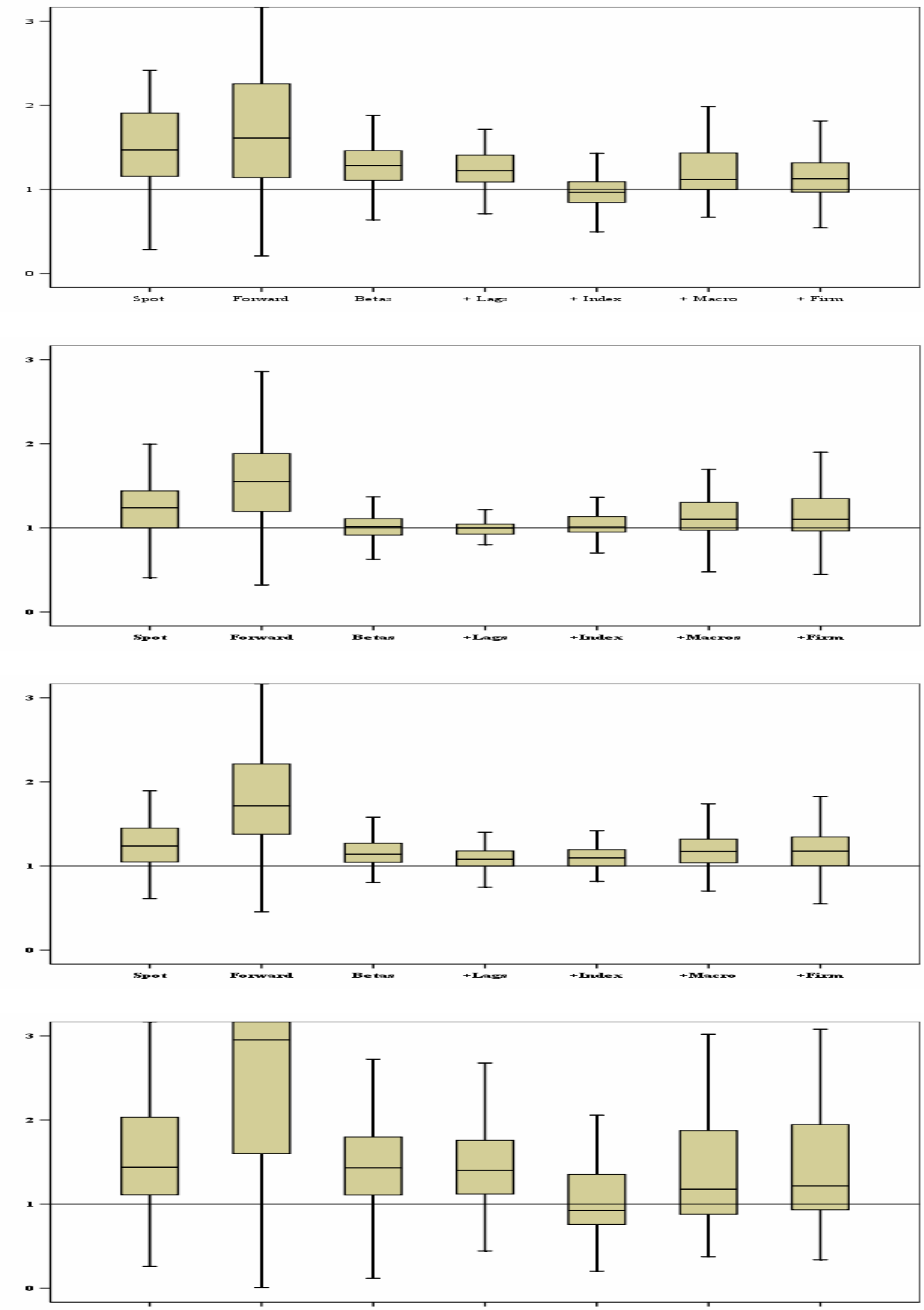


Figure 8
Out-Of-Sample Prediction Errors of 5-year Credit Spreads: Comparison of Models Using Macro-Forecasts

This figure shows the box plots of the ratios of Mean Square prediction Errors (MSPE) for different credit spread prediction models relative to the MSPE of a model with just the credit spread factors, lagged factors, and riskless factors (Model M_3), firm by firm. The models compared are the (a) Spot Model, (b) the model with the credit spread factors, riskless factors, and Index factors, Model M_4 (c) the model with credit spread factors, lagged factors, and predicted macro-variables, (d) the model with credit spread factors, lagged factors, riskless factors, and predicted macro-variables, and (e) the model with credit spread factors, lagged factors, riskless factors, index factors, and predicted macro-variables. The 4-vector of macro variable forecasts used are the median 6-months-ahead GDP forecast, the median 6-month ahead CPI Inflation forecast, the median 6-months-ahead Industrial Production forecast, and the median 6-months-ahead Moody's AAA corporate bond yield forecast from the Survey of Professional Forecasters (SPF). We obtain these quarterly forecasts from the web site of the Federal Reserve Bank of Philadelphia.