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Jing-zhi Huang and Weipeng Kong

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Jing-zhi Huang[2]
Penn State University and New York University

Weipeng Kong[3]
Penn State University

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[2]Assistant Professor of Finance, Smeal College of Business, Pennsylvania State University, University Park, PA 16802; Tel: (814) 863-3566; jxh56@psu.edu; www.personal.psu.edu/jxh56; and Visiting Assistant Professor of Finance, Stern School of Business, New York University, New York, NY 10012; (212) 998-0925; jhuang0@stern.nyu.edu.

[3]Doctoral student, Smeal College of Business, Pennsylvania State University, University Park, PA 16802; Tel: (814) 865-0618; wxk140@psu.edu.

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Abstract

We examine the question of the determinants of corporate bond credit spreads using both weekly and monthly option-adjusted spreads for nine corporate bond indexes from Merrill Lynch from January 1997 to July 2002. We find that the Russell 2000 index historical return volatility and the Conference Board composite leading and coincident economic indicators have significant power in explaining credit spread changes, especially for high yield indexes. Furthermore, these three variables plus the interest rate level, the historical interest rate volatility, the yield curve slope, the Russell 2000 index return, and the Fama-French [1996] high-minus-low factor can explain more than 40% of credit spread changes for five bond indexes. In particular, these eight variables can explain 67.68% and 60.82% of credit spread changes for the B- and the BB-rated indexes, respectively. Our analysis confirms that credit spread changes for high-yield bonds are more closely related to equity market factors and also provides evidence in favor of incorporating macroeconomic factors into credit risk models.

1 Introduction

Accessing and managing credit risk of corporate bonds has been a major area of interest and concern to academics, practitioners and regulators.[1] One important issue related to credit risk is to identify factors that affect credit yield spreads of corporate bonds.

In a recent study, Elton, Gruber, Agrawal and Mann [2001] find that expected default losses and state tax are insufficient to explain the corporate bond yield spreads, and the former in fact can account for no more than 25% of the observed spreads. Collin-Dufresne, Goldstein and Martin [2001] consider determinants of spreads in structural models of corporate bond pricing[2] and find that these variables can explain only a small portion of credit spread changes. Campbell and Taksler [2002] document that idiosyncratic equity volatility can explain about one third of the variation in yield spreads. All of the three studies use individual bond prices and focus on investment-grade bonds. Brown [2001] examines the explanatory power of the 10-year Treasury yield, consumer confidence, the VIX index and a Treasury bond liquidity measure on credit spread changes for Salomon Brothers bond indexes. He finds that these variables can explain up to 32.79% of spread changes. Kao [2000] documents that the interest rate level and the yield curve slope, implied volatility of OTC interest rate options and the Russell 2000 index return have significant explanatory power for changes in the credit spread index level.

In this paper, we investigate some possible determinants of credit spread changes using credit spread data from Merrill Lynch. We consider five sets of explanatory variables that characterize different aspects of credit risk: (1) realized default rates, (2) the interest rate level, slope and volatility, (3) equity market factors such as return and volatility, (4) supply/demand for liquidity from corporate bond mutual funds, and (5) macroeconomic indicators. We examine the explanatory power of these variables using option-adjusted credit spreads for nine corporate bond indexes from Merrill Lynch from January 1997 to July 2002.

Our main findings are as follows. Among the variables that have not been used in the literature, the Russell 2000 historical return volatility and the Conference Board leading and

[1] See, for example, Caouette, Altman, and Narayanan [1998], Saunders and Allen [2002], Duffie and Singleton [2003] and references therein.

[2] See, for example, Merton [1974], Geske [1977], Kim, Ramaswamy and Sundaresan [1993], Longstaff and Schwartz [1995], Leland and Toft [1996], and Collin-Dufresne and Goldstein [2001]. Examples of reduced-form models, which use a different approach, include Jarrow and Turnbull [1995], Das and Tufano [1996], Jarrow, Lando and Turnbull [1997], Madan and Unal [1998], and Duffie and Singleton [1999].

coincident indicator indexes have significant power in explaining credit spread changes, especially for high-yield bond indexes. These three variables plus the interest rate level, the historical interest rate volatility, the yield curve slope, the Russell 2000 index return, and the Fama-French [1996] high-minus-low factor can explain more than 60% of credit spread changes for both the BB- and the B-rated indexes. Also, these 8 variables account for respectively 55.54%, 51.4%, and 41.58% of spread changes for the C-rated index, the BBB-A 15+ year index, and the BBB-A 1-10 year index. The explanatory power of these 8 variables is around 30% for other 4 Merrill Lynch bond series analyzed in the analysis.

Our results confirm that credit spread changes for high yield bonds are mainly driven by equity related factors, consistent with predictions from structural models of corporate bond pricing. Our results also suggest that in addition to equity market variables and interest rate variables, macroeconomic factors may also have power in explaining credit spread changes at least at the aggregate level.

The remainder of this article is organized as follows. Section 2 describes the Merrill Lynch credit spread data and the explanatory variables used in our empirical study. Section 3 reports results from our empirical tests including robustness tests. Section 4 concludes the paper.

2 Data

In this section, we first describe our credit spread data and provide some basic summary statistics of credit spread changes. We then discuss explanatory variables used in our empirical analysis.

2.1 The Merrill Lynch Credit Spread Data

Credit spread data used in this study are weekly and monthly option-adjusted spreads (OAS) for nine corporate bond indexes from Merrill Lynch from January 1997 to July 2002. These spreads are purged of any embedded options, coupon effects and index rebalancing effects. The use of option-adjusted spread is of importance for empirical analysis at index level.[3] Each index is a market value weighted average of credit spreads of individual bonds in a given maturity, industry, and credit rating portfolio. The sample includes six OAS series for investment-grade

[3]For instance, Duffee [1998] demonstrates how the callability of corporate bonds and the coupon effects will strongly influence the relationship between Treasury term structure changes and corporate credit spread changes.

corporate bonds: AA-AAA and BBB-A rated series with maturity of 1-10 years, 10-15 years, and 15+ years. These indexes track the performance of US dollar-denominated investment-grade public debt of industrial sector corporate issuers, issued in the US domestic bond market. Our sample also includes three series for high-yield corporate bonds with rating of BB, B and C, respectively. We do not know the industry composition of the high-yield credit spread indexes.[4]

We use mainly monthly credit spread changes in this analysis because many explanatory variables under consideration are only available at monthly frequency. We construct monthly credit spread changes from the corresponding daily credit spread series. The Merrill Lynch daily option-adjusted credit spread indexes start from December 31, 1996 and are rebalanced on the last calendar day of each month. To avoid potential bias due to index rebalancing, we use start-to-end month (excluding the rebalancing day) spread changes to construct our monthly series. For example, consider the monthly spread change for January 1997. January 30 of 1997 is the last observation in that month before index rebalancing on the 31st. The monthly credit spread change for January 1997 is then measured as the difference between the credit spread on January 30, 1997 and the spread on December 31, 1996. Under this method, monthly credit spread changes are measured on the same portfolio. Each monthly series consists of 67 observations from January 1997 to July 2002.

Table 1 presents summary statistics on credit spread changes, denoted ΔCS, for each of the nine monthly credit spread series. As can be seen from the table, the standard deviation of credit spread changes increases as the rating deteriorates and maturity gets longer except for the AA-AAA rated 10-15 years index (which has higher standard deviation than AA-AAA rated 15+ years index). Over the sample period, the standard deviation of credit spread changes ranges from 5.07 to 12.21 basis points for the six investment-grade indexes and from 44.82 to 105.91 basis points for the 3 high-yield indexes. Distribution of spread changes seems to have fatter tails than those of a normal distribution. Extreme movements in spread changes are observed in some months as indicated by the maximum, minimum, 10% percentile and 90% percentile of the distribution of spread changes. In addition, spread changes are positively serially correlated, albeit insignificant in most cases.

The last row of Table 1 shows the average number of bonds included in a given index over

[4]Detailed discussion of the various Merrill Lynch bond indexes can be found in *Bond Index Rules & Definitions*, October 2000, Merrill Lynch & Co., Global Securities Research & Economic Group, Fixed Income Analytics.

the sample period. The Merrill Lynch bond indexes used here are generally constructed based on a large group of bonds except for the AA-AAA rated 10-15 year index. The fact that the three high-yield indexes are each based on a large group of high-yield bonds is particularly important. Corporate bond databases available to academics such as the Lehman Fixed Income Database mainly cover investment-grade bonds.

2.2 Explanatory Variables

The credit spread on corporate bonds (without imbedded options) is the extra yield offered to compensate investors for a variety of risks: (1) expected default loss - the risk that in the event of default, investors will not receive the full amount of the promised cash flows. This component of credit spread is directly related to the default probability of the firm and the recovery rate in the event of default; (2) credit risk premium, due to the uncertainty of default losses ; and (3) liquidity and tax premia, which result from the difference in liquidity and tax status of corporate bonds and Treasury bonds.

We will focus on financial markets and macroeconomic variables that are related to different components of credit spreads. Specifically, we select sets of explanatory variables that characterize (1) the realized overall default rate in the U.S. corporate bond market, (2) the dynamics of the risk free interest rate, (3) the U.S. equity market factors such as return and volatility, (4) liquidity indicators from corporate bond mutual funds, and (5) the state of economy in the US. The first three sets of variables are our proxies for changes in aggregate default risk. The realized overall default rate is directly related to the expected default loss. Interest rate variables and equity return variables are explicit in the structural approach risky bonds pricing models. The supply/demand for liquidity from corporate bond mutual funds is intended to capture one aspect of the liquidity condition in the corporate bond market. The economic state variables are based on the perception that the default risk of corporate bonds is correlated with the aggregate economic activity.

2.2.1 Realized Default Rates

If historical default rates of corporate issuers predict future default risk in the corporate bond market, we would expect a close positive relationship between changes in realized default rates and changes in credit spreads. We obtain Moody's monthly trailing 12-month default rates for all corporate U.S. issuers as well as for speculative grade U.S. issuers over our sample period. Because the effective date of the monthly default rate is on the first day of each month, we take the month t release as the month $t-1$ trailing 12-month default rates. Changes in trailing 12-month default rates for all corporate U.S. issuers, denoted $\Delta df_{a,t}$, will be used in regression analysis of investment-grade index credit spread changes. Changes in trailing 12-month default rate for corporate speculative grade U.S. issuers, denoted $\Delta df_{s,t}$, will be used in regression analysis of high-yield index credit spreads.

2.2.2 Interest Rate Variables

Most empirical studies have used either changes in the short-end (3-month) or changes in the long-end (10-year) of the Treasury yield curve, as measures of changes in the general interest rate level. However, a Treasury yield index may be a more appropriate proxy for the level. We use the monthly changes in the Merrill Lynch Treasury Master Index yields, $\Delta level$, as the measure of changes in the general interest rate. We use the difference between the Merrill Lynch 15+ year Treasury Index yield and the 1-3 year yield as the measure of the yield curve slope. The change in the yield curve slope is denoted as $\Delta slope$.

Interest rate volatility has been incorporated in some credit risk models (e.g. Longstaff and Schwartz [1995] and Das and Tufano [1997]). Higher interest rate volatility should be associated with wider credit spreads. However, the literature on the empirical relationship of interest rate volatility and credit spread changes is relatively thin. Kao [2000] considers the implied volatility of the 3-month OTC option on a 10-year rate and documents that changes in this implied volatility play an important role in explaining monthly credit spread changes for both investment-grade and high-yield bond indexes from March 1991 to December 1998. However, the implied volatility of OTC interest rate options is not easily available for investors and researchers. In this paper, we examine two alternative proxies for interest rate volatility that are based on accessible market data. The first one is the monthly change in the implied volatility of 30-year Treasury bond futures options traded on the Chicago Board of Trade (CBOT), denoted $\Delta\sigma^r_{iv,t}$. However, we have observations for this volatility series only from January 1997 to August 2001. The second measure is the monthly change in the historical volatility of Merrill Lynch Treasury Master Index yields, denoted $\Delta\sigma^r_{hv,t}$. These two volatility measures expect to capture anticipated and realized changes in interest rate volatility, respectively.

2.2.3 Equity Market Variables

Structural models of risky debts pricing indicate that higher asset and equity returns would be associated with narrowing credit spreads. Empirically, it may be interesting to find out which particular equity market index is more closely correlated with credit spread changes and thus more suitable for hedging. So far most studies have examined the S&P 500 index, which is dominated by large-cap stocks. Kao [2000] shows that credit spread changes are significantly related to returns of a small-cap stocks index such as the Russell 2000 index. We consider both the S&P 500 index return (sp_t) and the Russell 2000 index return (rus_t).

Structural models also imply that credit spreads usually increase in equity return volatility. We consider two measures of equity market volatility: the option implied volatility on the Russell 2000 index, and the historical volatility of the Russell 2000 index returns. The monthly changes of these two volatility series are denoted as $\Delta\sigma_{iv,t}^{rus}$ and $\Delta\sigma_{hv,t}^{rus}$, respectively. For comparison, we also consider two other proxies for the equity volatility: the CBOE VIX index (based on the implied volatility of the S&P 100 index options) and the S&P 500 historical return volatility denoted by $\sigma_{hv,t}^{sp}$.

Elton, Gruber, Agrawal and Mann [2001] show that the Fama-French [1996] three factors – the market, the small-minus-big (SMB), and the high-minus-low (HML) – are closely related to the portion of credit spreads that are not explained by the expected default loss and tax. Collin-Dufresne, Goldstein and Martin [2001] also report that the SMB and HML factors are important determinants of credit spread changes of individual corporate bonds. The intuition of this result is that the two factors might be closely correlated with changes in the credit risk premium component of credit spreads. We will examine the incremental explanatory power of these two variables in the presence of equity index returns and equity index volatility.

2.2.4 Liquidity Indicators

Institutional investors are the major owners of corporate bonds. Fridson and Jonsson [1995] find that flows of capital into high-yield bond mutual funds, measured as a percentage of total assets, are negatively correlated with high-yield bond credit spreads and that cash positions, as a percentage of fund assets, are positively correlated with high-yield credit spreads. They argue that these two variables strongly influence the market liquidity, as cash flows into and out from bond mutual funds. Barnhill, Joutz and Maxwell [2000] also find that mutual fund flows play a dominant role in explaining the yield on high-yield bond indexes.

We obtain monthly statistics of the aggregate dollar amount of total net assets, net new cash flow, and liquid assets for all corporate bond mutual funds as well as for all high-yield mutual funds from June 1997 through July 2002. These statistics are released by the Investment Company Institute (ICI). We then calculate the ratio of net new cash flow to total net assets and the ratio of liquid assets to total net assets for all corporate bond mutual funds as well as for all high-yield mutual funds. The monthly changes in these two ratios are denoted as ΔNCF_t and $\Delta liquid_t$, respectively and expected to capture the liquidity risk in corporate bond markets. We use the series for all bond funds in the analysis of the investment-grade credit spread indexes, and the series for all high-yield funds in the analysis of high-yield credit spread indexes.

2.2.5 Macroeconomic Indicators

Empirical evidence indicates that credit spreads behave cyclically over time [see, e.g., Van Horne, 1998]. During periods of economic downturn, credit spreads are expected to increase as investors become more risk averse and firms have lower asset returns. Fridson and Jonsson [1995] find that an index of lagging economic indicators has significant impact on credit spread changes for high yield bond indexes. Helwege and Kleim [1997] find that the GDP growth rate and recession indicators are important in explaining the aggregate default rates of high yield bonds. Jarrow and Turnbull [2000] also suggest that incorporating macroeconomic variables may improve a reduced-form model.

The Conference Board publishes the composite indexes of leading, coincident, and lagged indicators as gauges of the state of the U.S. economy. The leading index is an average of 10 leading indicators; the coincident index is an average of 4 coincident indicators; and the lagged index is an average of 7 lagged indicators.[5] The leading indicator index indicates the future direction of aggregate economic activity. The coincident indicator index measures the current health of the economy. And the lagged indicator index usually reaches its cyclical peaks in the middle of a recession. We use the month-to-month percentage changes in the three indicator indexes as measures of the general economic condition. The changes in these three economic indexes are denoted as $\Delta lead_t$, Δci_t, and Δlg_t, respectively. Although the S&P 500 index and the yield curve slope are both common measures of the economic condition (in

[5] Detailed information about the three indexes is available at www.tcb-indicators.org.

fact, both are indicators in the leading index),[6] we believe that the leading index - an average of 10 leading indicators - should be a better barometer of future economic conditions. The correlation between $\Delta lead_t$ and $\Delta slope_t$ is indeed -0.32 over our sample period even though the weight of the yield curve slope is 0.3274 in the leading index.

Table 2 summarizes the explanatory variables under consideration and the predicted sign of the correlation between these variables and credit spread changes.

3 Empirical Results

To compare the explanatory power of the above mentioned factors that may influence credit spread spreads, we run OLS regressions with each set of explanatory variables separately, and then examine the interaction of these variables in explaining spread changes.

Regression models with financial time series often encounter errors that have serial correlation or heteroskedasticity of unknown form. A preliminary analysis reveals certain degrees of autocorrelations and non-normality in the regression errors of certain models. To correct for the potential bias due to these problems, we use the Newey-West [1987] heteroskedasticity and autocorrelation consistent covariance matrix estimator of the estimated coefficients when calculating the associated t-statistics. In addition, we choose the optimal lag parameter using the method of Newey and West [1994].

3.1 Group Level Regressions

3.1.1 Realized Default Rates

To examine the explanatory power of realized default rates, we estimate the following regression model:

$$\Delta CS_t = \alpha + \beta\, \Delta df_t + \epsilon_t, \tag{1}$$

where Δdf_t represents changes in Moody's trailing 12-month default rates. We use default rates of all U.S. corporate issuers ($df_{a,t}$) in the analysis of the investment-grade credit spread series and use those of U.S. speculative grade issuers ($df_{s,t}$) in the analysis of the high-yield spread series.

[6] The yield curve slope is defined as the difference between the 10-year Treasury bond rate and the federal fund rate in the leading index.

The estimation results are reported in Table 3. As can be seen from the table, the coefficients on changes in realized default rate are all negative, which is counter intuitive, but are statistically insignificant in most cases. The adjusted R^2 is below 5% in all the regressions. These results indicate that realized default rates contain little information on the future prospect of default risk. This reinforces the intuition that realized default rates are, by construction, lagging variables.

3.1.2 Interest Rate Variables

To capture the impact of interest rate dynamics on credit spreads, we consider the interest rate level, the yield curve slope, and the interest rate volatility. First, we use the historical volatility as a proxy for the interest rate volatility and estimate the following model:

$$\Delta CS_t = \alpha + \beta_1 \, \Delta level_t + \beta_2 \, \Delta slope_t + \beta_3 \, \Delta \sigma^r_{hv,t} + \epsilon_t. \tag{2}$$

The estimation results are presented in Panels A of Table 4. As can be seen from the table, the interest rate variables can account for only a small portion of the credit spread changes for the investment-grade indexes. The adjusted R^2 ranges from 1.29% for the BBB-A 10-15 year series to 15.81% for the AA-AAA 10-15 year series. The signs of the coefficients on the interest rate variables are consistent with intuition. High interest rates and steep yield curves are usually associated with expanding economy and low credit spreads. Higher interest rate volatility is usually associated with widen credit spreads. Nonetheless, the impacts of changes in the yield curve slope and changes in historical interest rate volatility are largely insignificant as indicated by their t-values.

However, the same set of the interest rate variables performs much better for the high-yield credit spread series. The adjusted R^2 is respectively 32.84%, 34.08%, and 25.21% for the BB-, B-, and C-rated series. The coefficients on the interest rate level are significantly negative at the 1% level for all the three series. The coefficients on the yield curve slope are positive but insignificant for the three high-yield series. The coefficients on the historical interest rate volatility are also all positive and have a t-value slightly below the 10% critical value.

Next, we use the option implied interest rate volatility as a proxy for the interest rate volatility and estimate the following model:

$$\Delta CS_t = \alpha + \beta_1 \, \Delta level_t + \beta_2 \, \Delta slope_t + \beta_3 \, \Delta\sigma^r_{iv,t} + \epsilon_t. \tag{3}$$

The implied volatility is forward-looking and expected to have a higher correlation with credit spreads than the historical volatility does. In our estimation, we use the implied volatility of 30-year Treasury bond futures options traded on the CBOT over the period January 1997 through August 2001 (after which the data on the implied volatility are not available).

Estimation results, reported in Panel B of Table 4, actually show that the implied interest rate volatility has in fact a less impact than the historical yield volatility. This conclusion still holds after we re-estimated the model (2) over the shorter January 1997 through August 2001 period. However, Kao [2000] documents that the implied interest rate volatility (from the OTC three-month option on a 10-year yield) has strong impact on credit spreads over the period from March 1991 to December 1998. This difference between our result and his may result from a time-varying relationship between the interest rate volatility and credit spreads. Another reason may be due to how the implied interest rate volatility from the CBOT is computed. This implied volatility is based on the price of the nearby interest rate future options traded on the CBOT. When one contract expires, the new nearby contract is selected to derive the implied interest rate volatility series. The switch of contract may bring significant noise into the derived implied volatility series.

So far the interest rate level and the yield curve slope have been estimated using the Merrill Treasury Master Index yields. Alternatively, the constant maturity Treasury (CMT) yields can be also used for the estimation. In an analysis not reported there, we use the CMT 10-year yield to estimate the level and the difference between the 10-year yield and the 2-year yield to estimate the slope. The regression results show that the adjusted R^2 is below 11% for all three high-yield credit spread series over the whole sample period. Namely, the term structure variables based on the CMT yields are much less correlated than those based on the Merrill Treasury indexes with credit spread changes for the Merrill corporate bond indexes. As a result, we use only the Merrill Treasury Master Index yields to estimate the term structure variables in this analysis.

Overall, the interest rate variables considered here can explain a small portion of credit spread changes for the investment-grade series but can do a much better job for the high-yield series.

3.1.3 Equity Market Variables

To capture the impact of equity market on credit spreads, we consider variables such as the equity index return, the index return volatility, and the Fama and French [1996] factors in the analysis that follows.

First, we estimate the following model:

$$\Delta CS_t = \alpha + \beta_1 \, rus_t + \beta_2 \, \sigma_{hv,t}^{rus} + \epsilon_t, \tag{4}$$

where rus_t and $\sigma_{hv,t}^{rus}$ denote the Russell 2000 index return and the index historical return volatility, respectively. Using the implied volatility from options on the Russell 2000 would yield similar results. We use the historical volatility here due to concern of a high correlation between the index return and the implied volatility. Estimation results, reported in Table 5, indicate that the Russell 2000 variables can explain a significant portion of credit spread changes for both investment-grade and high-yield series over the sample period. The adjusted R^2 ranges from 9.27% for the AA-AAA 10-15 year series to 38.25% for the BBB-A 15+ year series for the investment-grade indexes. The adjusted R^2 is respectively 41.12%, 47.09%, and 39.66% for the BB-, B-, and C-rated portfolios. The coefficient on the equity volatility is positive and significant at the 10% level for all the portfolios except for the AA-AAA 10-15 year series.

In an analysis not reported here, we also estimate (4) by replacing the Russell 2000 index variables by the corresponding S&P 500 index variables. The results are similar. Namely, a higher equity market index return will lower credit spreads, and a higher equity volatility will significantly widen credit spreads. However, the adjusted R^2 with the Russell 2000 index variables is at least 10% higher than that with the S&P 500 index variables for most of the nine credit spread series analyzed here.

Next, we add the Fama and French [1996] factors to the regression model in (4). Given the close correlation between the Russell index variables and credit spread changes that is shown in Table 5, other determinants of the equity market risk premium, such as the Fama and French SMB and HML factors, may also closely co-vary with credit spreads. Elton et al. [2001] document that the SMB and HML factors explain a significant portion of credit spreads in their sample of investment-grade bonds from 1987 to 1996 from the Lehman Fixed Income

Database. Vassalou and Xing [2002] also find that the SMB and HML factors contain some default-related information. In an analysis not reported here, we find that the Fama-French 3 factors have roughly the same magnitude of explanatory power on credit spread changes as the Russell index return and volatility variables. In fact, the correlation of the Fama-French market and SMB factors with the Russell index return is over 0.68 during our sample period. However, the correlation of the Russell index return with the HML factor is -0.42 over the sample period. As a result, we estimate the following model:

$$\Delta CS_t = \alpha + \beta_1 \, rus_t + \beta_2 \, \sigma_{hv,t}^{rus} + \beta_3 \, \mathrm{HML}_t + \epsilon_t. \tag{5}$$

The estimated results are reported in Table 6. As can be seen from the table, the HML factor is more closely related with credit spread changes for the high-yield portfolios and only marginally related with those for the investment-grade portfolios. The adjusted R-squared is 47.93%, 54.94%, and 49.45% for the BB-, B-, and C-rated portfolios, respectively. The estimated coefficient on the HML is significant at the 1% level for all three high-yield portfolios but is insignificant for all the investment-grade portfolios except the BBB-A 1-10 year one. The findings here reinforce the notion that credit spread changes for high-yield bonds are more closely related to equity market factors.

In summary, the results in this subsection indicate that, about 30% of credit spread changes for the investment-grade portfolios and about 50% of those for the high-yield portfolios over our sample period are associated with returns, the return volatility and the Fama-French HML factor in the equity market.

3.1.4 Liquidity Indicators

To examine the impact of buying and selling pressure from corporate bond mutual funds on credit spreads, we consider the following regression model:

$$\Delta CS_t = \alpha + \beta_1 \, \Delta liquid_t + \beta_2 \, \Delta NCF_t + \epsilon_t. \tag{6}$$

The estimation results, reported in Table 7, indicate that as expected, the coefficient on the liquid asset ratio is positive for all the credit spread series and the coefficient on the net cash flow ratio is negative for all the spread series (except the AA-AAA 15+ year portfolio). However, the adjusted R-squared is below 2% for all the investment-grade series. The two ratios have some explanatory power for the high-yield series as the adjusted R-squared is respectively 4.47%, 10.15%, and 11.31% for the BB-, B-, and C-rated indexes. Notice that the coefficient on the net cash flow ratio is also significant for the high-yield indexes. In a word, consistent with Fridson and Jonsson [1995], the results here show that the net cash flow (to high-yield mutual funds) ratio has a significant negative correlation with credit spread changes for the high-yield portfolios.

3.1.5 Macroeconomic Indicators

To study the relation between macroeconomic indicators and credit spreads, we run the following regression:

$$\Delta CS_t = \alpha + \beta_1 \, \Delta lead_t + \beta_2 \, \Delta ci_t + \beta_3 \, \Delta \lg_t + \epsilon_t. \tag{7}$$

Estimation results are reported in Table 8. The adjusted R^2 is over 20% for three credit spread series with an maximum of 27% for the BBB-A rated 15+ year index. As expected, increases in the leading index lead to narrowing credit spreads. But surprisingly, the coincident index, which measures the current health of the economy, has positive coefficients that are significant at the 5% significant level for four out of nice credit spread series. The sign on the lagged index is mixed and is insignificant in all cases.

Given the significance of macroeconomic indicator indexes in explaining credit spreads, it may be interesting to investigate the explanatory power of individual macroeconomic indicators. In an analysis not reported here, we examine the relation between credit spread changes and the following individual macroeconomic indicators: the growth rate of money supply (M2), the inflation expectation from the University of Michigan's Survey Research Center, the industrial production index growth rate and unemployment rate. M2 has a standardized factor of 0.3034 in the leading index and the industrial production has a standardized factor of 0.1292 in the coincident index. The explanatory power of these three individual macroeconomic indicators is generally very weak. This seems to justify the purpose of constructing these indicator indexes, which is to effectively smooth out part of the volatility in the individual indicator series and serve a better gauge of the whole economy. The regression coefficient on the industrial production growth rate is all positive, albeit mostly insignificant. Thus one plausible explanation for the positive sign on the coincident index is that the real productivity of the economy has been growing over the past few years, but so has been the volatility in the market. (The correlation between the industrial growth rate and changes in the CBOE VIX index level is 0.26 over the sample period.)

3.2 Combined Regressions

Results in the preceding subsection indicate that credit spread movements can largely be explained by the interest rate dynamics, equity market returns and volatility, and the general state of the economy. Realized default rates and the supply/demand pressures from corporate bond mutual funds are not closely related with credit spread changes. We now examine how much of credit spread changes can be explained by these three sets of variables together:

$$\begin{aligned}\Delta CS_t &= \alpha + \beta_1 \, \Delta level_t + \beta_2 \, \Delta slope_t + \beta_3 \, \Delta\sigma^r_{hv,t} + \beta_4 \, rus_t \\ &\quad + \beta_5 \, \sigma^{rus}_{hv,t} + \beta_6 \, \mathrm{HML}_t + \beta_7 \, \Delta lead_t + \beta_8 \, \Delta ci_t + \epsilon_t. \end{aligned} \quad (8)$$

The overall explanatory power of these variables is quite strong, as shown in Panel A of Table 9. The adjusted R-squared is 67.68% for the B-rated index and 60.82% for the BB-rated index. It reaches 55.54%, 51.4%, and 41.58% for the C-rated, BBB-A 15+ year, and BBB-A 1-10 year portfolios, respectively. The adjusted R-squared is around 30% for the remaining four of the nine credit spread series analyzed here. Notice that the overall explanatory power of the three sets of variables is a notable improvement over the previous studies using spread changes for corporate bond portfolios. More importantly, our findings confirm that credit spread changes for high yield indexes are closely related to equity market factors. These results provide some support of the structural models of credit risk.

To summerize, the Russell 2000 index return, its historical volatility, and the Conference Board leading index are the most significant explanatory variables in the combined regression.

3.3 Robustness Tests

We now address the robustness of our findings. First, we examine how stable the empirical relations estimated earlier with the whole sample. In order to do this, we split our monthly sample in the middle and re-estimate the regression model in Eq. (8) separately with subsamples. The estimation results are reported in Panels B and C of Table 9, respectively. As can be seen from the table, the overall explanatory power of the independent variables is fairly stable through the two sub-sample periods for the high-yield portfolios. However, the adjusted R^2 with the bottom sub-sample is much higher than that with the top sub-sample for most investment-grade portfolios. As indicated by the t-values shown in the table, the main reason for this sharp increase is that equity market variables and the leading economic indicator are much more significantly over the second-half of the whole sample. We also examine the stability of regression coefficients estimated over the two sub-periods. We perform the Chow test of the statistical difference between the vectors of regression coefficients estimated with two sub-samples. The test results (not shown) indicate that the null hypothesis that the two coefficient vectors are the same is rejected at the 5% significance level only for the AA-AAA 15+ year portfolio. This implies that the regression model of credit spreads given in Eq. (8) is fairly stable over our entire sample period.

Next, we examine the sensitivity of the results to the frequency of data used in regression by analyzing weekly changes of credit spreads. Since weekly data are not available on the Fama-French HML factor and the Conference Board leading indicators, we estimate the following regression model:

$$\Delta CS_t = \alpha + \beta_1 \, \Delta level_t + \beta_2 \, \Delta slope_t + \beta_3 \, \Delta\sigma^{r}_{hv,t} + \beta_4 \, rus_t + \beta_5 \, \sigma^{rus}_{hv,t} + \epsilon_t. \tag{9}$$

To construct weekly data, we select the Tuesday observation of each week to avoid any possible weekend effect. (There is only one Monday observation in the week of the September 11 event.) When a Tuesday observation is missing, we use the Wednesday observation. The final sample includes a total of 295 observations, one for each week through the period from December 31, 1996 to August 30, 2002. We note that credit spread changes over those weeks that include a rebalancing day may be affected by rebalancing. The interest rate historical volatility and the Russell 2000 historical return volatility are estimated using the daily data over the past one month. (We also used two alternative volatility estimates: the 3-month historical volatility and the RiskMetrics^{TM}volatility with an exponentially weighted moving average over the prior 3 months. Regression results are robust to the alternative measures of historical volatility and not shown here for brevity.)

Results from the regression model (9), reported in Table 10, show that the interest rate and the equity market factors perform much better in explaining credit spread changes for the high-yield portfolios than those for the investment-grade portfolios. More specifically, the adjusted

R-squared is below 20% for all the investment-grade series but is 28.91%, 42.19%, and 23.22% for the three high-yield series, respectively. We note that the potential problems due to the market microstructure and index rebalancing effects are more severe when the data frequency gets higher and thus may result in a lower adjusted R-squared. Nonetheless, as shown in the table, the interest rate factors and the Russell 2000 return and its volatility are still significant in most of the regressions with weekly data.

Finally, we repeat our analysis using daily option-adjusted credit spreads from the S&P from December 31, 1998 to July 31, 2002. The S&P provides two such series within the U.S. industrial sector: the U.S. industrial investment-grade credit spread index and the U.S. industrial speculative-grade credit spread index. The inception date of the two indexes is December 31, 1998. Composite market prices used to calculate the option-adjusted spread are based on the average bid and ask prices from a number of sources including brokers and dealers. Whenever there is a change in the index issue, the index level is adjusted by a divisor. This mitigates the potential effect due to index rebalancing.[7] We re-estimate the model (9) with weekly data and the model (8) with monthly data, and report results in Table 11. As shown in the table, the interest rate and equity market factors can explain 31.2% of spread changes for the S&P investment-grade series and 62.41% of spread changes for the high-yield series with the weekly sample. Results from the model (8) using the monthly sample show that the adjusted R-squared is 63.37% and 72.95% for the investment-grade and the high-yield series, respectively.

To summarize, our robustness analysis provides evidence that the interest rate and equity market factors are important determinants of credit spread changes for high-yield portfolios even at the weekly frequency. In addition, the interest rate, equity market, and economic indicator factors can also explain much of spread changes for the S&P credit spread portfolios.

4 Conclusions

We analyze determinants of corporate bond credit spreads using the Merrill Lynch option-adjusted credit spread data from January 1997 through July 2002. We focus on the following explanatory variables: Moody's realized default rates, the historical volatility of interest rates,

[7] More detailed information is available in *S&P Credit Indices: Overview and Methodology*, 1999, the McGraw-Hill companies, Inc.

the Russell 2000 historical return volatility, and the Conference Board indexes of leading, coincident and lagged indicators. We find that among these variables, the Russell 2000 historical return volatility, and the Conference Board composite leading and coincident indicators have significant impact on the contemporaneous changes in credit spreads, especially for high-yield corporate bonds.

We also find that the above-mentioned three variables plus the historical volatility of interest rates, the interest rate level, the yield curve slope, the Russell 2000 index return, and the Fama-French [1996] high-minus-low factor can explain more than 40% of credit spread changes for five out of nine Merrill Lynch credit spread series analyzed in this study. In particular, these eight variables can explain 67.68% and 60.82% of credit spread changes for the B- and BB-rated portfolios, respectively.

Overall, we find that credit spread changes for high-yield bonds are more closely related with the interest rate and equity market factors. This finding is confirmed with both monthly and weekly credit spread data and is also confirmed with credit spread data from the S&P.

Our findings are important for both pricing and managing credit risk. First, from a pricing perspective, we provide evidence that credit risk models may need to take into account the impact of macroeconomic variables on credit spreads. From a risk management perspective, small-cap equity indexes such as the Russell 2000 index may be used in hedging the equity component of corporate bond credit spreads. These considerations may call for a hedging strategy based on the interest rate, the equity market return and volatility, and macroeconomic variables.

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Table 1

Summary Statistics for Monthly Changes in the Option-Adjusted Credit Spread for Merrill Lynch Corporate Bond Indexes

This table reports the indicated summary statistics for monthly option-adjusted credit spread changes for nine Merrill Lynch corporate bond indexes. ΔCS denotes the credit spread change in basis points. Parameter ρ represents the first-order serial correlation coefficients. The average number of issues included in each index over the sample period is reported in the last row. Each credit spread series includes 67 monthly observations from January 1997 to July 2002.

ΔCS (bp)	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
Mean	-0.08	-1.13	-0.00	2.62	1.11	0.81	6.66	11.99	19.87
Std Dev.	5.07	10.46	6.57	11.47	12.09	12.21	44.82	63.29	105.91
Skewness	0.47	-1.26	-0.77	1.38	1.21	-0.25	1.82	0.59	0.56
Kurtosis	2.29	5.05	3.27	5.41	5.14	2.69	6.9	3.27	2.43
Max	16.62	23.35	15.85	48.98	53.77	37.03	195.26	229.2	384.47
90%	7.16	12.46	8.25	15.37	16.91	16.02	30.61	88.73	137.6
10%	-6.10	-12.87	-6.64	-7.89	-10.83	-12.28	-30.8	-37.58	-110.2
Min	-14.84	-47.54	-25.73	-30.77	-30.28	-41.24	-96.77	-169.76	-236.7
ρ	0.24	0.12	0.23	0.12	0.15	0.08	0.2	0.12	0.13
Issues	82	5	45	813	75	494	419	552	175

Table 2

Description of Explanatory Variables

Variable	Description	Sign
$\Delta df_{a,t}$	changes in Moody's trailing 12-month default rates of all U.S. corporate issuers	+
$\Delta df_{s,t}$	changes in Moody's trailing 12-month default rates of U.S. corporate speculative grade issuers	+
$\Delta level_t$	changes in yield of Merrill Lynch Treasury Master Index	-
$\Delta slope_t$	changes in yield of Merrill Lynch 15+ years Treasury Index minus yield of Merrill Lynch 1-3 year Treasury Index	-
$\Delta\sigma^{r}_{hv,t}$	changes in historical volatility of Merrill Lynch Treasury Master Index yields	+
$\Delta\sigma^{r}_{iv,t}$	changes in implied volatility of 30-year Treasury bond futures options traded on Chicago Board of Trade (CBOT)	+
rus_t	Russell 2000 index return	-
$\Delta\sigma^{rus}_{hv,t}$	changes in historical volatility of Russell 2000 index return	+
$\Delta\sigma^{rus}_{iv,t}$	changes in implied volatility of Russell 2000 index options	+
sp_t	S&P 500 index return	-
$\Delta\sigma^{sp}_{hv,t}$	changes in historical volatility of S&P 500 index return	+
ΔVIX_t	changes in CBOE VIX index	+
SMB_t	Fama-French small-minus-big factor returns	-
HML_t	Fama-French high-minus-low factor returns	-
$\Delta liquid_t$	changes in corporate bond mutual funds liquid asset as percentage of total net assets	+
ΔNCF_t	changes in corporate bond mutual funds net new cash flow as percentage of total net assets	-
$\Delta lead_t$	changes in Conference Board leading index	-
Δci_t	changes in Conference Board coincident index	-
Δlg_t	changes in Conference Board lagged index	+

Table 3

Relation between Changes in Credit Spreads and Changes in Realized Default Rates

For each credit spread series from Merrill Lynch, we estimate the following regression:

$$\Delta CS_t = \alpha + \beta\, \Delta df_t + \varepsilon_t,$$

where $\Delta df_t = \Delta df_{a,t}$ for investment-grade credit spread indexes and $\Delta df_t = \Delta df_{s,t}$ for high-yield indexes. Each credit spread series includes 67 monthly observations from January 1997 to July 2002. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 3 lags.

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	0.36	-0.44	0.57	3.12	2.35	1.49	8.97	16.72	27.21
	(0.46)	(0.28)	(0.66)	(1.66)	(1.21)	(0.87)	(1.13)	(1.84)	(1.72)
Δdf_t	-7.71	-12.26	-10.12	-8.7	-21.8	-12.01	-18.09	-36.95	-57.42
	(1.47)	(1.13)	(1.66)	(0.77)	(1.69)	(1.1)	(0.71)	(1.14)	(1.09)
Adj R^2	2.83%	1.05%	2.93%	-0.46%	4.58%	0.28%	-0.7%	1.53%	1.11%

Table 4

Relation between Changes in Credit Spreads and Interest Rate Variables

For each credit spread series from Merrill Lynch, we estimate the following two regression models:

$$\Delta CS_t = \alpha + \beta_1 \Delta level_t + \beta_2 \Delta slope_t + \beta_3 \Delta\sigma^r_{hv,t} + \varepsilon_t;$$
$$\Delta CS_t = \alpha + \beta_1 \Delta level_t + \beta_2 \Delta slope_t + \beta_3 \Delta\sigma^r_{iv,t} + \varepsilon_t.$$

Panel A reports the OLS estimation results using the historical interest rate volatility and the data consist of 67 monthly observations from January 1997 to July 2002; Panel B reports the OLS estimation results with the CBOT option implied interest rate volatility and the data consist of 56 monthly observations from January 1997 to August 2001. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 3 lags.

Panel A: Regressions with Historical Interest Rate Volatility

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	-0.01	-0.01	0.02	2.03	1.14	0.62	2.37	5.98	9.95
	(0.03)	(0.01)	(0.02)	(1.66)	(0.83)	(0.48)	(0.57)	(1.07)	(0.92)
$\Delta level_t$	-7.14	-0.19	-9.83	-21.92	-14.18	-22.4	-112.6	-157.3	-204.6
	(2.20)	(0.03)	(1.68)	(2.65)	(1.57)	(2.18)	(4.34)	(4.44)	(3.34)
$\Delta slope_t$	-6.37	-24.47	-6.77	-2.42	-10.05	-11.53	16.41	22.49	72.84
	(1.45)	(2.76)	(1.06)	(0.21)	(0.89)	(0.87)	(0.46)	(0.38)	(0.82)
$\Delta\sigma^r_{hv,t}$	1.24	-0.27	-0.01	3.09	0.9	3.25	11.79	20.02	31.91
	(1.35)	(0.16)	(0.00)	(1.38)	(0.39)	(1.36)	(1.38)	(1.63)	(1.52)
Adj R^2	7.16%	15.81%	4.99%	15.47%	1.29%	12.13%	32.84%	34.08%	25.21%

Panel B: Regressions with Option Implied Interest Rate Volatility

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	-0.09	-0.2	0.33	1.49	0.26	0.72	1.19	6.86	12.58
	(0.14)	(0.18)	(0.37)	(1.14)	(0.21)	(0.55)	(0.39)	(1.17)	(1.16)
$\Delta level_t$	-2.85	13.34	-0.73	-8.9	3.48	-6.69	-65.12	-116.17	-123.05
	(0.81)	(2.18)	(0.15)	(1.23)	(0.50)	(0.75)	(3.11)	(2.98)	(1.81)
$\Delta slope_t$	-9.84	-35.53	-7.6	-16.27	-27.28	-22.96	-39.12	-24.59	-4.15
	(1.83)	(4.26)	(0.99)	(1.45)	(2.86)	(1.65)	(1.43)	(0.35)	(0.04)
$\Delta\sigma^r_{iv,t}$	0.5	-1.30	0.24	0.47	0.45	0.96	3.32	8.45	19.34
	(0.60)	(1.07)	(0.21)	(0.37)	(0.28)	(0.56)	(0.68)	(0.92)	(1.40)
Adj R^2	6.5%	38.57%	-1.3%	4.26%	19.21%	7.5%	20.77%	14.3%	6.1%

Table 5

Relation between Credit Spread Changes and the Russell 2000 Index Variables

For each credit spread series from Merrill Lynch, we estimate the following regression:

$$\Delta CS_t = \alpha + \beta_1 \, rus_t + \beta_2 \, \Delta\sigma^{rus}_{hv,t} + \varepsilon_t.$$

The data consist of 67 monthly observations from January 1997 to July 2002. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 3 lags.

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	-0.06	-0.85	0.03	2.69	1.24	0.99	7.04	12.61	20.2
	(0.11)	(0.69)	(0.04)	(2.34)	(0.90)	(0.93)	(1.62)	(2.49)	(2.15)
rus_t	-0.26	-0.65	-0.32	-0.72	-0.79	-0.98	-3.25	-4.92	-6.61
	(2.43)	(2.41)	(2.26)	(3.51)	(2.95)	(3.79)	(3.77)	(3.92)	(3.26)
$\Delta\sigma^{rus}_{hv,t}$	0.17	-0.18	0.18	0.43	0.32	0.34	1.71	2.55	4.69
	(2.33)	(0.89)	(2.38)	(3.06)	(1.88)	(2.56)	(3.11)	(2.78)	(2.60)
Adj R^2	23.76%	9.27%	17.98%	33.67%	26.9%	38.25%	41.12%	47.09%	39.66%

Table 6

Regression Analysis with the Russell 2000 Index Variables and the Fama-French (1996) HML Factor

For each credit spread series from Merrill Lynch, we estimate the following regression:

$$\Delta CS_t = \alpha + \beta_1 rus_t + \beta_2 \Delta\sigma^{rus}_{hv,t} + \beta_3 HML_t + \varepsilon_t.$$

The data consist of 67 monthly observations from January 1997 to July 2002. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 3 lags.

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	-0.03	-0.83	0.09	2.77	1.28	1.08	7.46	13.23	21.36
	(0.05)	(0.68)	(0.12)	(2.39)	(0.94)	(1.04)	(1.76)	(2.56)	(2.40)
rus_t	-0.34	-0.69	-0.45	-0.89	-0.88	-1.18	-4.17	-6.31	-9.19
	(2.44)	(2.54)	(2.79)	(3.44)	(2.71)	(4.19)	(3.92)	(4.69)	(4.57)
$\Delta\sigma^{rus}_{hv,t}$	0.17	-0.17	0.18	0.43	0.33	0.35	1.73	2.57	4.72
	(2.25)	(0.88)	(2.21)	(2.98)	(1.84)	(2.46)	(3.46)	(3.01)	(2.77)
HML_t	-0.21	-0.09	-0.32	-0.43	-0.22	-0.51	-2.37	-3.55	-6.6
	(1.39)	(0.32)	(1.48)	(1.73)	(0.61)	(1.43)	(3.19)	(3.40)	(4.98)
Adj R^2	27.13%	8.06%	23.18%	36.54%	26.67%	42.14%	47.93%	54.94%	49.45%

Table 7

Relation between Credit Spread Changes and the Supply/Demand for Liquidity from Corporate Bond Mutual Funds

For each credit spread series from Merrill Lynch, we estimate the following regression:

$$\Delta CS_t = \alpha + \beta_1 \Delta liquid_t + \beta_2 \Delta NCF_t + \varepsilon_t.$$

The data consist of 61 monthly observations from July 1997 to July 2002. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 3 lags.

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	0.06	-1.12	0.03	3.01	1.42	0.96	7.5	13.56	21.82
	(0.08)	(0.79)	(0.03)	(1.81)	(0.77)	(0.55)	(1.27)	(1.85)	(1.79)
$\Delta liquid_t$	0.52	2.96	0.65	1.7	2.08	2.87	6.59	9.53	15.8
	(0.40)	(0.84)	(0.47)	(0.65)	(0.70)	(0.97)	(1.28)	(1.01)	(0.92)
ΔNCF_t	-2.4	1.2	-1.31	-4.31	-3.51	-3.82	-11.27	-21.17	-37.09
	(1.86)	(0.62)	(0.97)	(1.22)	(1.14)	(1.09)	(2.54)	(3.30)	(3.72)
Adj R^2	1.85%	-1.6%	-2.28%	0.35%	-0.71%	0.29%	4.47%	10.15%	11.31%

Table 8

Relation between Credit Spread Changes and Macroeconomic Indicators

For each credit spread series from Merrill Lynch, we estimate the following regression:

$$\Delta CS_t = \alpha + \beta_1 \Delta lead_t + \beta_2 \Delta ci_t + \beta_3 \Delta lg_t + \varepsilon_t.$$

The data consist of 67 monthly observations from January 1997 to July 2002. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 3 lags.

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	-0.72	-2.24	-1.21	3.59	0.2	0.08	7.38	16.82	26.75
	(0.77)	(1.68)	(1.02)	(1.41)	(0.09)	(0.03)	(0.82)	(1.27)	(1.21)
$\Delta lead_t$	-4.64	0.93	-7.08	-14.43	-13.36	-18.99	-65.22	-93.99	-121.3
	(2.35)	(0.29)	(2.62)	(3.46)	(2.57)	(4.88)	(3.15)	(4.10)	(3.11)
Δci_t	6.88	4.83	11.77	6.36	15.28	18.7	47.79	49.29	59.32
	(2.16)	(0.91)	(2.69)	(0.81)	(2.32)	(2.50)	(1.51)	(1.06)	(0.76)
Δlg_t	0.49	2.44	0.41	0.06	-3.43	-0.97	-6.63	-2.55	23.12
	(0.25)	(0.62)	(0.22)	(0.01)	(0.92)	(0.28)	(0.37)	(0.10)	(0.55)
Adj R^2	11.48%	-1.9%	19.34%	15.08%	10.37%	27%	20.32%	22.24%	14.48%

Table 9

Regression Analysis with Interest Rate, Equity Market, and Macroeconomic Variables

For each credit spread series from Merrill Lynch, we estimate the following regression:

$$\Delta CS_t = \alpha + \beta_1 \Delta level_t + \beta_2 \Delta slope_t + \beta_3 \Delta\sigma^{r}_{hv,t} + \beta_4 rus_t + \beta_5 \Delta\sigma^{rus}_{hv,t} + \beta_6 HML_t + \beta_7 \Delta lead_t + \beta_8 \Delta ci_t + \varepsilon_t.$$

Panel A reports the OLS estimation results using the 67 monthly observations from January 1997 to July 2002; Panel B reports the OLS estimation results with the sub-sample consisting of the 33 monthly observations from January 1997 to September 1999; Panel C reports the OLS estimation results with the sub-sample consisting of the 34 monthly observations from October 1999 to July 2002. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance estimator with 3 lags.

Panel A: 1997.1 – 2002.7 Sample Period (N = 67)

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	0.18	2.51	-0.54	4.72	2.68	2.15	3.83	14.71	16.96
	(0.27)	(1.57)	(0.53)	(2.17)	(1.94)	(1.53)	(0.86)	(1.66)	(0.92)
$\Delta level_t$	-1.69	4.86	-1.03	-9.46	0.03	-3.89	-60.57	-79.82	-83.05
	(0.72)	(0.77)	(0.33)	(1.67)	(0.01)	(0.7)	(4.38)	(3.68)	(1.84)
$\Delta slope_t$	-6.03	-30.09	-2.91	-8.15	-12.04	-10.93	25.08	15.68	79.62
	(1.49)	(2.89)	(0.63)	(0.69)	(1.31)	(1.16)	(0.83)	(0.38)	(1.05)
$\Delta\sigma^{r}_{hv,t}$	-0.00	-1.33	-1.79	0.29	-2.3	-0.42	0.79	3.6	5.53
	(0.00)	(0.81)	(1.63)	(0.2)	(1.55)	(0.26)	(0.15)	(0.44)	(0.42)
rus_t	-0.27	-0.8	-0.34	-0.74	-0.78	-0.95	-3.23	-5.15	-7.79
	(1.93)	(3.81)	(2.23)	(3.58)	(2.67)	(3.83)	(4.69)	(3.57)	(4.16)
$\Delta\sigma^{rus}_{hv,t}$	0.18	0.03	0.21	0.41	0.4	0.34	1.27	1.99	3.73
	(2.27)	(0.21)	(2.48)	(2.63)	(2.45)	(2.6)	(2.55)	(2.71)	(2.46)
HML_t	-0.16	-0.18	-0.23	-0.37	-0.17	-0.38	-1.74	-2.88	-5.79
	(1.10)	(0.84)	(1.17)	(1.4)	(0.5)	(1.21)	(3.03)	(2.45)	(3.33)
$\Delta lead_t$	-2.42	-0.1	-5.22	-6.4	-7.98	-11.98	-20.83	-31.58	-37.64
	(1.77)	(0.04)	(2.16)	(2.15)	(2.33)	(4.36)	(2.4)	(2.62)	(1.34)
Δci_t	1.85	-9.33	7.71	-4.71	1.83	5.54	18.96	0.21	19.73
	(0.71)	(1.49)	(2)	(0.69)	(0.36)	(1.12)	(0.9)	(0.01)	(0.31)
Adj R^2	28.96%	28.89%	32.94%	41.58%	29.47%	51.4%	60.82%	67.68%	55.54%

Panel B: 1997.1 – 1999.9 Sample Period (N = 33)

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	3.07	6.99	3.84	-1.45	-2.79	-1.11	-5.08	-8.84	-29.41
	(1.71)	(1.54)	(1.59)	(0.50)	(0.65)	(0.34)	(1.13)	(0.8)	(1.35)
$\Delta level_t$	-1.45	7.49	1.66	-1.32	7.48	3.69	-45.89	-64.98	-68.61
	(0.46)	(0.92)	(0.39)	(0.27)	(1.24)	(0.67)	(2.75)	(2.03)	(1.13)
$\Delta slope_t$	3.86	-39.46	17.25	10.98	-4.16	18.79	39.71	86.70	195.03
	(0.68)	(1.67)	(2.22)	(1.12)	(0.40)	(1.90)	(1.75)	(1.76)	(1.95)
$\Delta\sigma^{r}_{hv,t}$	2.63	4.49	1.35	1.41	-3.33	-0.97	-0.87	3.36	2.24
	(1.93)	(0.98)	(0.62)	(0.60)	(1.02)	(0.32)	(0.19)	(0.40)	(0.16)
rus_t	-0.15	-0.83	-0.27	-0.10	0.06	-0.22	-0.75	-1.43	-4.07
	(1.01)	(1.60)	(1.68)	(0.37)	(0.16)	(0.76)	(1.26)	(1.16)	(2.03)
$\Delta\sigma^{rus}_{hv,t}$	-0.1	-0.50	-0.01	0.11	0.31	0.29	1.05	2.57	3.52
	(0.70)	(1.87)	(0.04)	(0.48)	(0.72)	(0.77)	(2.15)	(2.7)	(2.36)
HML_t	-0.03	0.36	0.67	-0.01	0.44	0.55	0.31	-0.32	-4.75
	(0.13)	(1.02)	(2.45)	(0.05)	(1.64)	(1.98)	(0.46)	(0.23)	(2.24)
$\Delta lead_t$	-3.07	0.37	-1.18	-4.32	-4.55	-3.69	-8.29	-28.85	-56.97
	(1.44)	(0.05)	(0.36)	(1.29)	(0.72)	(0.75)	(0.87)	(1.47)	(1.6)
Δci_t	-5.83	-24.89	-6.53	10.69	11.22	8.27	27.52	63.81	159.46
	(1.10)	(1.41)	(0.97)	(1.14)	(0.77)	(0.87)	(1.77)	(1.70)	(2.1)
Adj R^2	2.98%	32.04%	33.38%	0.5%	-2.21%	33.14%	63.23%	64.14%	56.16%

Panel C: 1999.10 – 2002.7 Sample Period (N = 34)

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	0.34	2.49	0.20	6.20	4.26	4.33	-7.48	27.7	36.12
	(0.42)	(1.20)	(0.20)	(2.31)	(2.55)	(3.00)	(1.08)	(2.91)	(1.53)
$\Delta level_t$	-0.41	4.19	-3.87	-10.50	4.41	-2.04	-35.86	-6.96	0.81
	(0.08)	(0.28)	(0.65)	(0.74)	(0.28)	(0.18)	(0.97)	(0.15)	(0.01)
$\Delta slope_t$	-7.96	-24.01	-10.09	-14.48	-11.17	-20.35	33.99	2.13	49.26
	(1.64)	(2.97)	(2.83)	(0.94)	(0.84)	(2.32)	(0.75)	(0.05)	(0.51)
$\Delta\sigma^{r}_{hv,t}$	-0.47	-3.20	-2.75	0.52	-2.57	-1.01	-0.99	-7.35	-6.64
	(0.53)	(2.11)	(2.32)	(0.21)	(1.28)	(0.44)	(0.10)	(0.59)	(0.28)
rus_t	-0.48	-0.84	-0.46	-1.09	-1.30	-1.40	-5.04	-8.55	-11.42
	(2.69)	(2.66)	(0.21)	(3.42)	(3.00)	(5.69)	(6.47)	(9.32)	(3.84)
$\Delta\sigma^{rus}_{hv,t}$	0.25	0.20	0.21	0.58	0.48	0.36	1.45	1.95	4.03
	(2.74)	(1.42)	(2.37)	(2.79)	(3.04)	(2.80)	(2.04)	(2.13)	(1.81)
HML_t	-0.24	-0.32	-0.44	-0.55	-0.47	-0.71	-2.82	-5.29	-8.18
	(1.58)	(1.22)	(2.12)	(2.16)	(1.44)	(2.67)	(4.86)	(4.70)	(3.28)
$\Delta lead_t$	-1.17	0.11	-4.93	-5.76	-7.25	-13.15	-21.05	-38.12	-40.36
	(0.62)	(0.02)	(1.95)	(1.00)	(1.32)	(3.58)	(2.09)	(3.07)	(0.81)
Δci_t	-0.35	-7.37	-0.04	-9.15	3.20	-2.15	20.08	-46.08	-34.85
	(0.07)	(1.09)	(0.01)	(0.96)	(0.32)	(0.31)	(0.40)	(1.04)	(0.36)
Adj R^2	45.18%	34.15%	50.22%	52.35%	39.63%	64.11%	63.58%	75.45%	52.38%

Table 10

Regression Analysis Using Weekly Credit Spread Changes

For each credit spread series from Merrill Lynch, we estimate the following regression:

$$\Delta CS_t = \alpha+\beta_1\Delta level_t+\beta_2\Delta slope_t+\beta_3\Delta\sigma^{r}_{hv,t}+\beta_4 rus_t+\beta_5\Delta\sigma^{rus}_{hv,t}+\varepsilon_t.$$

The table reports the OLS estimation results using the 295 weekly observations from January 1997 to July 2002. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 5 lags.

	AA-AAA 1-10 Yr	AA-AAA 10-15 Yr	AA-AAA 15+ Yr	BBB-A 1-10 Yr	BBB-A 10-15 Yr	BBB-A 15+ Yr	BB	B	C
α	0.12	0.21	0.16	0.44	0.57	0.36	0.90	0.7	1.68
	(0.74)	(0.73)	(0.74)	(1.53)	(1.66)	(1.19)	(1.13)	(0.49)	(0.52)
$\Delta level_t$	-0.76	7.30	-1.74	-7.52	-4.56	-7.77	-55.03	-113.57	-165.21
	(0.47)	(1.96)	(0.74)	(3.27)	(1.36)	(2.80)	(6.79)	(8.96)	(4.99)
$\Delta slope_t$	0.29	-8.80	-0.61	1.29	-5.97	-1.91	5.77	26.03	59.31
	(0.09)	(1.95)	(0.19)	(0.26)	(1.33)	(0.40)	(0.33)	(1.20)	(1.85)
$\Delta\sigma^{r}_{hv,t}$	0.68	0.27	0.72	1.26	0.56	1.22	2.33	5.89	-1.74
	(1.40)	(0.23)	(1.07)	(1.84)	(0.68)	(1.37)	(0.80)	(1.94)	(0.26)
rus_t	-0.17	-0.51	-0.21	-0.3	-0.46	-0.39	-1.10	-1.81	-0.31
	(1.42)	(2.78)	(1.43)	(1.95)	(2.54)	(2.00)	(3.13)	(3.29)	(0.30)
$\Delta\sigma^{rus}_{hv,t}$	0.17	0.20	0.12	0.35	0.38	0.42	0.97	2.27	5.11
	(2.37)	(1.33)	(1.38)	(2.81)	(2.20)	(3.21)	(3.20)	(4.41)	(3.19)
Adj R^2	7.1%	6.37%	4.47%	15.92%	9.85%	17.19%	28.91%	42.19%	23.22%

Table 11

Regression Analysis Using the S&P Credit Spread Data

For each credit spread series from the S&P, we estimate:

$$\Delta CS_t = \alpha+\beta_1\Delta level_t+\beta_2\Delta slope_t+\beta_3\Delta\sigma^{r}_{hv,t}+\beta_4 rus_t+\beta_5\Delta\sigma^{rus}_{hv,t}+\varepsilon_t; \quad (1)$$
$$\Delta CS_t = \alpha+\beta_1\Delta level_t+\beta_2\Delta slope_t+\beta_3\Delta\sigma^{r}_{hv,t}+\beta_4 rus_t+\beta_5\Delta\sigma^{rus}_{hv,t}+\beta_6\, HML_t+\beta_7\Delta lead_t+\beta_8\Delta ci_t+\varepsilon_t, \quad (2)$$

where weekly and monthly changes in the spread are used respectively in regression models (1) and (2). The sample period is from December 31 of 1998 through July 31 of 2002. Panel A reports the OLS estimation results using the 186 weekly observations; Panel B reports the OLS estimation results using the 43 monthly observations. In parentheses are the absolute values of t-statistics, based on the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 4 lags for the weekly series and with 3 lags for the monthly series.

Panel A: Using Weekly Credit Spread Changes for the S&P Indexes (N=186)

	Investment-grade	High-yield
α	0.37	2.95
	(1.03)	(1.92)
$\Delta level_t$	-16.27	-149.32
	(4.00)	(10.05)
$\Delta slope_t$	0.33	-16.28
	(0.05)	(0.82)
$\Delta\sigma^{r}_{hv,t}$	0.84	3.08
	(0.96)	(0.96)
rus_t	-0.49	-1.55
	(2.97)	(2.98)
$\Delta\sigma^{rus}_{hv,t}$	0.26	2.91
	(1.74)	(4.00)
Adj R^2	29.25%	60.45%

Panel B: Using Monthly Credit Spread Changes for the S&P Indexes (N=43)

	Investment-grade	High-yield
α	4.46	20.94
	(3.20)	(1.94)
$\Delta level_t$	-16.55	-94.38
	(1.56)	(2.22)
$\Delta slope_t$	-15.2	6.82
	(1.59)	(0.16)
$\Delta\sigma^{r}_{hv,t}$	0.41	-4.53
	(0.16)	(0.37)
rus_t	-1.18	-6.3
	(5.48)	(6.70)
$\Delta\sigma^{rus}_{hv,t}$	0.2	2.44
	(1.46)	(2.85)
HML_t	-0.5	-3.83
	(2.12)	(3.88)
$\Delta lead_t$	-12.62	-46.3
	(3.32)	(2.49)
Δci_t	-0.29	-6.49
	(0.05)	(0.15)
Adj R^2	63.37%	72.95%