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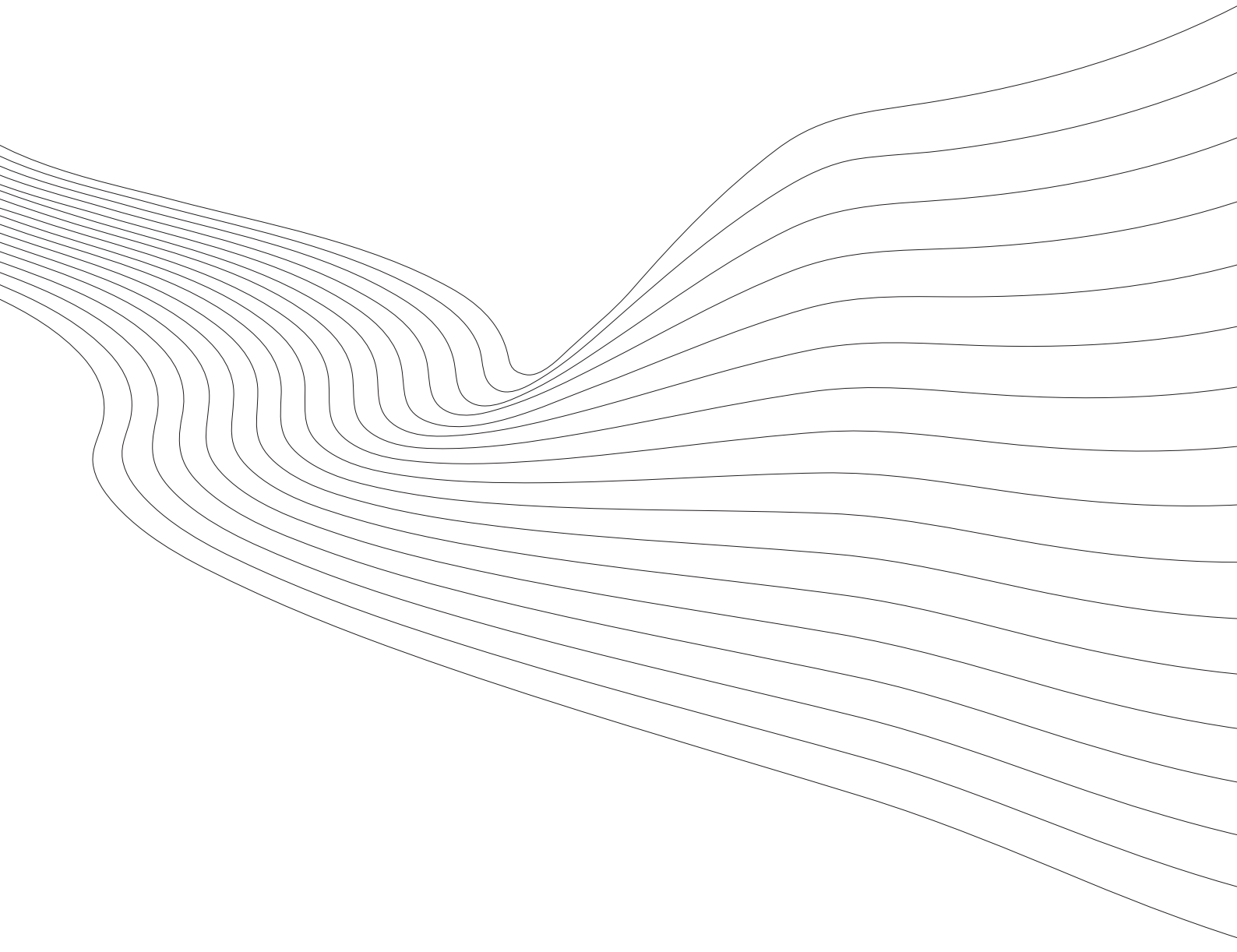
Forecasting High-Yield Bond Spreads Using the Loan Market as Leading Indicator

Dr Banu Simmons-Sueer



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FORECASTING HIGH-YIELD BOND SPREADS USING THE LOAN MARKET AS LEADING INDICATOR

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Forecasting high-yield bond spreads using the loan market as leading indicator

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Abstract

This paper attempts to find an aggregate leading indicator to predict the spreads observed for high-yield (HY) bond indices. Using a vector error correction (VEC) specification for quarterly data, we establish a long-term equilibrium relationship between the HY market spreads and its determinants, which stem from the interaction between the loan market via the banking sector and the HY market. The paper also attempts to explain the dynamic behaviour of spreads by approximating the factors behind the credit and liquidity risk components. The out-of-sample forecasting properties of the resultant econometric model are shown to be superior to naïve models.

J.E.L. Codes: G12, G15, G17

I. Introduction

Non-investment grade bonds are commonly known as 'high-yield' (HY) bonds or 'junk bonds' because of their high-risk status, as reflected in their ratings, which range from BB to C. While the yields on investment grade bonds are defined mostly by interest rate risk, i.e., the risk-free component, credit risk is a significant component of the yields on HY bonds as the probability of their default can be significant.

Credit spread, i.e., the difference in yields between a corporate bond and the corresponding (same maturity) Treasury bond, is supposed to reflect how much of a risk premium investors demand as compensation for the expected loss on a bond. Because the spread is the compensation to investors for holding credit risk, it should at least cover the cost of default. The cost of default, commonly expressed as 'expected loss', is the product of default rate and loss severity in case of default (loss given default, LGD). Loss severity is how much of a bond's par value is lost when default occurs, i.e., it is equivalent to 1-recovery rate. Rating agencies report that loss severity for HY bonds has historically been around 50% to 70%, as normally only 50% to 30% of the bond value can be recovered.

Unlike investment-grade bonds, which are issued by large, blue-chip companies that are very often publicly owned, HY bonds are usually issued by smaller companies, which are very often not stock exchange-quoted, and the cost of capital that affects companies' investment decisions is determined by the cost of financing via bond issues (spread + risk-free rate), and the cost of financing via bank loans (loan margin + risk-free rate).

Because a significant component of the yield on HY bonds is credit spread, the yields on these bonds are most sensitive to changes in general market conditions. Forecasting HY spreads therefore involves timely prediction of market conditions. The fact that bond markets react quite quickly to various economic and stock market news, the efforts to predict spread movements over a longer period, such as one-quarter ahead, face the challenge of finding suitable quarterly macroeconomic indicators, which lead bond markets. A lot of low-frequency macroeconomic data lag rather than lead financial markets, and, in fact, there is a growing body of literature proposing that HY spreads can be a useful instrument in predicting economic activity (Bernanke, et al. (1999), and Gilchrist et al. (2009)). Before completely dismissing macroeconomic indicators as useless in forecasting bond spreads, one needs to consider if meaningful aggregates can still be constructed to approximate the technical and fundamental features of the HY bond market. Fundamental features relate to factors such as company debt and stock performance, which drive credit risk at company level and technical features relate to liquidity of the HY market or to changes in the supply and demand conditions of HY bonds. Throughout this paper, we will refer to HY bonds as if they are a single representative bond as we will analyse the dynamic behaviour of a HY bond index, namely the Merrill Lynch HY bond index. Given that our analysis is based on a bond index rather than single bonds, idiosyncratic issuer risks are, to a large extent, diversified away and the index spread reflects systemic default and liquidity risks.

Despite a large amount of research on credit risk modelling, the search for a satisfactory forecasting model for credit spreads continues. The main problem with the existing structural credit risk models is that despite their thorough and elegant representation of what determines credit risk premium, a significant part of the credit spread remains unaccounted for. In contrast, the so-called 'reduced-form' models are calibrated to fit the historical spread data, but in these models, default risk is a random and unpredictable event that is divorced from

economic and fundamental conditions, which limits the usefulness of these models in spread forecasting.

The contribution of this paper can be classified as an empirical study of the dynamics of credit spreads with a focus on longer-term (one-quarter ahead) prediction of HY credit spreads. The theoretical underpinnings of our analysis are embedded in a Merton-type structural model which has first explicitly formulated the link between default probability of a company and its equity market performance. Despite this, we do not impose a strictly structural form as we want to take advantage of a flexible vector autoregressive (VAR) specification, which avoids any restrictive assumptions with regard to the underlying structure. In order to construct a useful quarterly forecasting model for spreads, we concentrate on reducing the unexplained part of observed bond spreads by introducing appropriate leading indicators for credit and liquidity risk. Our paper introduces an original approach by addressing the interaction between the HY market and the leverage loan market. We argue that the spread behaviour in the HY market is influenced by the dynamics of alternative sources of financing such as bank loans. Banks' credit tightening actions have important repercussions for companies in the HY market both in terms of signalling heightened credit risk, and also leading to demand and supply shifts in trade volumes of the HY and leverage loan markets, thereby affecting liquidity. We believe that financial innovations such as structured credit products have influenced the observed spreads in bond markets without significant changes to the underlying credit risk because bundling of various bonds in collateralized debt obligation (CDO) structures has indirectly influenced the demand for these instruments and liquidity of these markets, especially during the sub-prime crisis of 2007/2008.

We represent the behaviour of HY spreads by addressing the link between the loan market and the HY market in a framework where deviations from the long-term equilibrium of

spreads may take longer than one quarter to reach its long-term path. Our econometric model also incorporates macro-level proxies of various financial variables such as 'interest cover', which is known to drive rating changes at company level.

The paper is organised as follows: in Section II, we briefly outline the main literature on modelling credit risk and forecasting spreads. In Section III, we investigate the main features of our contribution with regard to the models outlined in Section II, and we outline our econometric specification and present our results. In Section IV, we discuss the in-sample and out-of-sample properties of our model and carry out comparative tests with respect to a naïve autoregressive forecasting model. In Section V, we present our conclusions. Appendix contains the data discussion.

II. Literature on Credit Risk

A great deal of attention in the literature has been devoted to understanding the determinants of credit spreads. Theoretical models of credit risk are categorised into two groups: Structural models and reduced-form models. Structural models were pioneered by Merton (1974), who modelled default as fundamentally an economic event in which a company's value falls below the face value of its outstanding debt. In these models, a company's equity is an option on the assets of the company, with a strike price equal to the repayment required on the debt. The company defaults when the market value of the assets is insufficient to repay the liabilities. The fundamental determinants of default in such models are the value of the company's assets, the volatility of asset value and firm leverage measured as the book value of liabilities relative to the market value of the assets. Credit spreads increase with leverage and volatility in the firm value.

Over the years, Merton's structural model has been extended by various studies. Longstaff and Schwartz (1995) defined an exogenous default boundary as the original model was not suitable for complicated capital structures, and they introduced stochastic interest rates. Leland (1994), and Leland and Toft (1996) endogenised default boundary by making default a decision of managers who maximise the value of equity and issue equity to service the company's debt coupon payments, so long as it is optimal to do so. Later on, Collin-Dufresne and Goldstein (2001), improved on the Merton model's leverage assumption by generating stationary leverage ratios under the assumption of stochastic interest rates.

Despite the improvements in structural-form models, computational difficulties with regard to the estimation of parameters such as the non-observable asset value of the company have challenged their empirical performance in prediction of the actual credit spreads. Huang and Huang (2003)) show that these models underestimate the observed credit spreads. Structural models are useful in studying the theoretical underpinnings of credit risk. However, due to the restrictive assumptions they make for the sake of analytical tractability, their usefulness for a realistic representation of market behaviour is debatable. In contrast, reduced-form models are designed to have simplicity in the calibration of credit risk to historical default rates as they argue that risk premiums should be evident in market prices and solve backwards for implied default probabilities. The reduced-form models of Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997), and Duffie and Singleton (1999), hence, treat default as an exogenous stochastic process that is divorced from any fundamental concept of firm value. In contrast to structural models where default is a predictable event in a continuous diffusion process of firm value, in reduced-form models default is an unpredictable event, where the issuer's default intensity follows a stochastic Poisson process, characterized by random jumps.

Both structural and reduced-form models concentrate on explaining the pricing of default risk. Although credit spreads are supposed to be a risk premium for holding credit risk, inspection of historical default rates shows that in reality credit spreads are much higher than the actual cost of default. Assuming a recovery rate of 40% in case of default, and given the historical speculative grade bond default frequencies (from Moody's), the actual credit risk (loss) can be calculated as the product of the (1-average recovery rate) and the one-year default probabilities[i]. As can be seen in Fig. 1, the HY spreads have been generally higher than the realised bond losses, and sometimes the risk premium for default risk has been as high as three times the actual risk of a bond defaulting. Various reasons have been suggested for this so-called 'credit puzzle', or why the default probabilities that are backed out of the observed

bond spreads are much higher (Altman (1989)). The most common explanation is that corporate bonds are relatively illiquid and illiquidity risk is much higher for non-investment grade bonds. Another non-default component of the credit risk premium is the risk of 'credit contagion' as default probabilities of bonds are highly correlated and during economic downturns, the systemic risk increase leads to investors demanding higher risk premiums. Longstaff et al. (2004) link the non-default part of the spread to liquidity factors, which they measure with money market mutual fund flows as well as the spreads between off-the run and on-the-run Treasury bonds. The former measure relates to the technical aspect of demand for bonds, whereas the latter measure of liquidity is a direct indicator of transaction costs. Elton et al. (2001) attribute the non-default part of the risk premium to state taxes and factors commonly associated with equity premium. Huang and Kong (2003) use daily trading data to explain the spread variation on investment grade and HY bonds with an Autoregressive Conditional Heteroscedasticity (ARCH) model. They find that the return on an equity market index provides valuable information in forecasting credit spread for the next trading day as the estimated coefficients of lagged Russell 2000 index returns are found to be significantly negative in credit spread equation. Demchuk and Gibson (2006) build a two-factor structural model where the past performance of the stock index has a significant impact on the firm's target leverage ratio and on credit spreads. Bhar and Handzic (2008), employing a three-factor model, claim to capture the systematic variation in credit spreads across ratings, as their extracted factor series are closely correlated with the long bond rate, the implied volatility index (VIX), and the S&P 500 level. While the role of stock market performance has been a major theme in these studies of spreads, there have been a few recent studies that also analyse the impact of business cycles on spreads together with the equity risk premium (Chen et al. (2008), and Bhamra et al. (2010)). A study by Koopman et al.(2009), using an intensity-based framework find that the economic impact of the observed macro variables for credit risk are rather low.

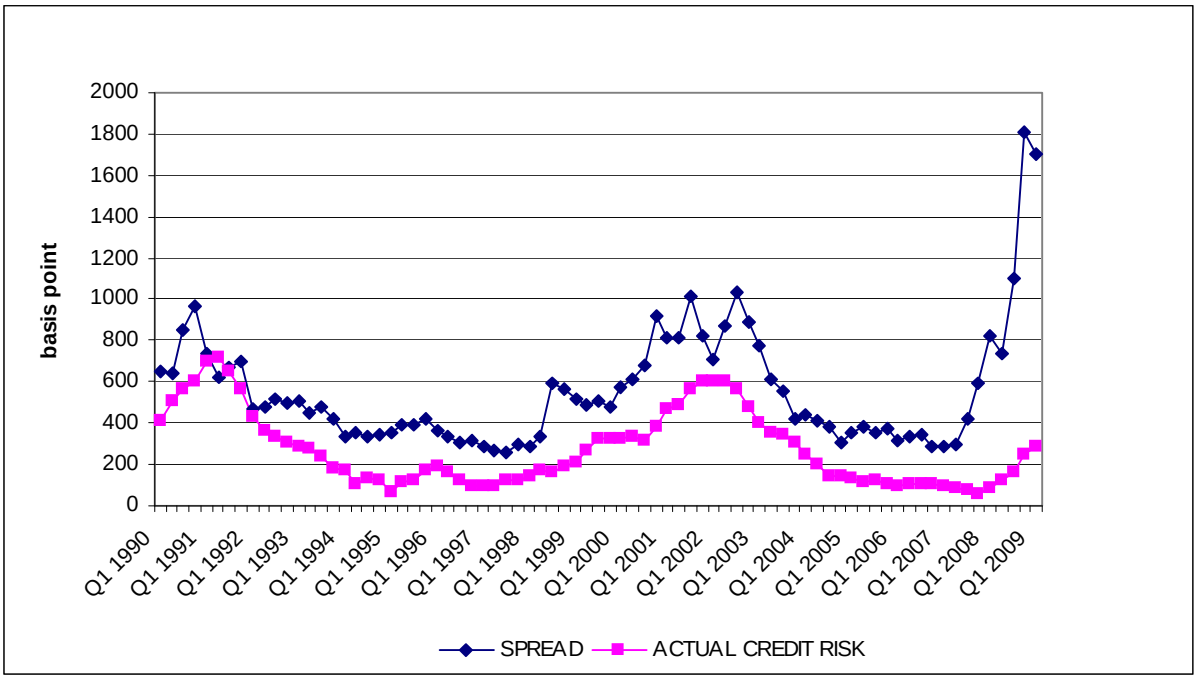

Fig.1. High-Yield spreads and actual loss rates on speculative grade bond defaults

Source: Merrill Lynch and Moody's

III. An Econometric Model of HY Spreads:

The Determinants of the spreads:

Our empirical model of HY spreads does not make a formal distinction between the default risk and the non-default risk. In this regard, our model shares common ground with reduced-form models as in the latter default and non-default or liquidity risks are also not separated. However, unlike the reduced-form models, we offer an economic explanation for the changes in observed credit spreads by introducing various macro-level indicators as explanatory variables in our model specification. Although the economic explanatory variables of our model are inspired by the fundamentals of Merton-type structural models, given the nature of our empirical model, we are able to avoid the restrictive assumptions of theoretical models where the non-default component of credit spreads (for example, liquidity) usually goes unexplained for the sake of mathematical tractability. Apart from the computational convenience, a specification without a strict structural form seems empirically plausible as default risk and non-default risks are correlated, and the market-wide systemic risk drives both default risk and influences the technical factors such as trade volumes in capital markets, i.e., liquidity. To the best of our knowledge, our empirical model makes a novel contribution by addressing for the first time the links between the HY and the leverage loan market where banks' decisions with regard to tightening lending is transmitted to the HY bond markets in terms of spread widening.

In the 1990s, with the rise of mergers, acquisitions, and leveraged buyouts (LBOs), HY issuance became a popular means of financing LBOs. In an LBO, a company acquires another company by issuing HY bonds to raise funds to pay for the acquisition and then uses the

target company's cash flow to pay the debt. The acquiring company avoids the equity dilution that can result from the issuance of new common shares, and HY debt is less costly than equity on an after-tax basis. Moreover, compared with bank loans, HY bonds generally impose fewer restrictive covenants on the issuer, and cannot be called at par and offer longer maturities than commercial banks offer.

In contrast to HY bonds, bank loans are positioned at the most senior level of a company's capital structure, i.e., in the event of default, holders of these loans have senior claims to the defaulted company's assets, and loans are often secured by some collateral assets, have relatively short maturities and contractually must be repaid at par or 100% of the amount outstanding. To finance LBOs, bank loans that are made to non-investment grade borrowers can be syndicated through participation of other banks or institutions. These leveraged loans are priced using the floating Libor plus a spread for the credit risk of the loan, and are traded in the global capital markets like any other financial instrument with an average rating very similar to that of HY bonds. Many non-investment grade companies have more than two-thirds of their debt in the form of bank loans and the remainder in HY bonds.

While typical HY bond investors are mutual funds and other traditional institutional investors, typical leveraged loan investors are structured vehicles (mostly collateralized loan obligations, or CLOs). Supply and demand conditions in the HY bond and leveraged loan markets are intertwined as companies' decisions to issue bonds instead of borrowing from banks are influenced by banks' lending practices and also by investors' demand for these bonds. Following the sub-prime crisis of 2007/2008, falling investors' appetite for CLOs and other structured instruments affected trading volumes and spreads both in the leverage loan and the HY bond markets.

Given the interaction between these markets, at the beginning of an economic downturn, as in the case of the sub-prime crisis, banks tighten their lending with rising delinquency rates and higher company leverage[ii]. Companies turn to the HY market to finance LBOs, causing a technically-induced spread widening as the increased issuance volume is not matched by equally strong demand. Restrictive actions of commercial banks are aggravated further if these banks have to keep their risky loans on their balance sheets as loan securitisations in capital markets decline. As shown in our model below, we measure the impact of such credit actions of banks by using data from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices.

Recognition that lending practices of commercial banks may have an impact on HY spreads raises the question of whether deterioration in credit quality of bank loans can have a direct impact on bond spreads. Although a bond spread is a risk premium for default probability of a bond issuer, in reality actual defaults are rare events and the observed spreads indicate that the perceived default risk of investors is often higher. Because at an aggregate index level the HY spread is supposed to reflect the 'perceived' rather than the actual default risk, including delinquency rates on commercial bank loans in our model specification has the following merit: Loan delinquency rates constitute an early warning sign for forthcoming defaults and thus, can be used as an indicator for increased credit risk by risk-neutral bond investors. Actual bond default rates as indicators of credit risk are less useful as it may take a few rating downgrades before the actual default event occurs. HY spreads widen even when bond defaults are avoided as investors demand higher spreads for credit deterioration, i.e., rating migration.

In Section II, we mentioned that there have been quite a few studies that address the interaction between credit and market risk by linking equity performance to credit spreads. In Merton-style models, this is done formally for each bond issuer via measuring the market

value of a firm's company's assets, which is not an observable variable but depends on the firm's company's equity value. In ad-hoc empirical models of credit spreads, a stock market index is very often used to incorporate the interaction between the two markets. In models that use high-frequency, monthly, weekly or daily data, it has been customary to use the VIX to approximate market risk (Collin-Dufresne et al (2001), Bhar and Handzic (2008)). However, these studies explain the contemporary relationship between credit spreads and implied volatility. Lag values of volatility indicators are not used in forecasting spreads as the impact of such information on spreads is contemporary and quickly absorbed in the current period spreads. To include in our model, we construct an equity market indicator, which has a longer impact horizon with regard to bond spreads. This indicator is called 'Tobin's Q and measures the market value of a company relative to the replacement cost of its assets. A value greater than 1 indicates that a company's assets could be purchased more cheaply than the company itself and, hence, the market is overvaluing the company, while Tobin's Q ratios less than 1 indicate market undervaluation. Although it is not the exact equivalent of Tobin's Q, at aggregate level, it has been a common practice to use the ratio of stock market value to the replacement value of structures, equipment, software, and inventory that companies own. Harney and Tower (2003) show that the Tobin's Q ratio is superior to the P/E ratio in predicting market returns. We measure Tobin's Q as US market value of corporate equity (non-farm, non-financial) to US tangible assets at historical replacement cost (non-farm, non-financial). By including a proxy like this rather than the stock market index itself, we want to introduce a forward-looking indicator of the stock market. Establishing a contemporaneous relationship between credit spreads and equity returns is less useful for predicting one-quarter-ahead spreads.

At an individual bond issuer level, two financial variables are known to be important determinants of a company's creditworthiness or rating: the leverage ratio and 'interest cover'.

The leverage ratio is defined as the debt-to-equity ratio. According to the Modigliani-Miller theorem, a company's value is independent of its capital structure. In Merton-type models, high leverage reduces a company's distance to default, and thus increases default probability. Excessive leverage heightens the default risk, especially in stressful market conditions when the required return on equity is too low to cover the cost of debt. However, the relationship between leverage and systemic risk is rather ambiguous and should be investigated empirically. Generally, a company's decision to issue debt or equity depends on market conditions. Collin-Dufresne and Goldstein (2001) criticise Merton-type models for the treatment of leverage as fixed, and introduce the concept of mean-reverting leverage. Their model attempts to capture dynamic restructuring, which means that companies decide to issue more debt if leverage falls below some target level or they reduce leverage when it is above target. Compared with the Merton-type structural models, their model generates larger credit spreads for companies with low initial leverage ratios, more in line with empirical observation. Another debt-related indicator that measures a company's debt-servicing capacity in a specific year is interest cover. Interest cover is earnings before interest and tax (EBIT) divided by interest expenses for the company's debt in the same period and generally moves in an opposite direction to leverage. We conduct some preliminary analysis below to select the debt-related indicator for inclusion in our model.

Apart from the credit risk indicators mentioned above, we include the risk-free interest rate in our model to explain spread movements. In bond pricing models, there is no consensus on the sign of the relation between the risk-free rate and credit spread. Some studies find a negative

correlation between changes in credit spreads and changes in the level of interest rates (e.g., Duffee (1998), and Das and Tufano (1996)). In contrast, Leland and Toft (1996) acknowledge the possible positive relationship between interest rates and default risk and credit spreads as the value of a company's assets normally falls as a result of increases in the risk-free rate, increasing the default probability.

Another non-default risk factor that plays a role in the supply and demand momentum of the HY bond and leverage loan markets is future inflation expectations. Even though HY bond yields are by definition high, inflation expectations are an important driver of the playing field between fixed and floating rate lending. Leverage loans are priced with a floating rate component that is immune to changes in the inflation rate as Libor increases with the inflation rate. In contrast, HY bond yields are fixed and when inflation rises, interest rates go up and bond prices fall. Although the inflation-driven fall in bond prices is due to the changes in the risk-free rate, in reality spreads of HY bonds are also affected due to the technical reason that investor demand shifts in favour of floating rate non-investment grade instruments such as leveraged loans.

Preliminary analysis:

Some of the factors that influence the dynamic behaviour of credit spreads may move together as they represent the similar fundamental features of a company. Therefore, to reduce the problem of multicollinearity in general, conducting a principal components analysis (PCA) may be useful to detect the common driving factors to reduce the number of explanatory variables to be included in the spread equation. In this empirical study of forecasting credit spreads, we employ preliminary analysis such as PCA and Granger causality tests to establish which economic data might serve as the best indicators of credit risk. Below, we present the principal components for the chosen variables computed on the basis of the ordinary

correlation matrix. When the criterion of minimum Eigen value of 1 is imposed, four principal components are identified for the variables in consideration (see Table 1). The first PC seems to be the credit cycle effect as it is positively related to spread, defaults, delinquencies and tightening of banks' lending standards, and negatively related to the equity performance indicators such as the S&P 500 and Tobin's Q and also to the debt-servicing capacity (COVERAGE). The US leading indicator (CYCLE) is only affected a little at this stage. The second PC possibly represents the policy reaction factor such as quantitative easing and interest rate cuts (SRATE), which has a quicker positive impact on stock markets, and companies react to stock market gains by reducing their target leverage. At this point, the negative impact on the leading indicator seems more prominent.

Table 1. Principal components

Principal Components Analysis
Sample (adjusted): 1990Q2 2009Q1
Minimum eigenvalue: 1

Number	Value	Cumulative Value	Cumulative Proportion
1	4.50	4.50	40.9%
2	2.54	7.04	64.0%
3	1.45	8.48	77.1%
4	1.13	9.62	87.4%

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4
SPREAD	0.35	0.39	0.00	-0.16
DELINQUENT	0.41	-0.17	0.11	0.03
LEVERAGE	0.41	-0.23	0.05	-0.22
SP500	-0.28	0.47	0.01	0.07
TC	0.29	0.41	0.21	-0.06
SRATE	-0.09	-0.22	0.57	0.25
COVERAGE	-0.34	-0.23	0.17	-0.45
TOBIN	-0.34	0.36	0.04	0.27
DEFAULT	0.36	0.07	-0.03	0.55
INFLATION	-0.08	-0.19	0.48	0.38
CYCLE	-0.08	-0.31	-0.60	0.37

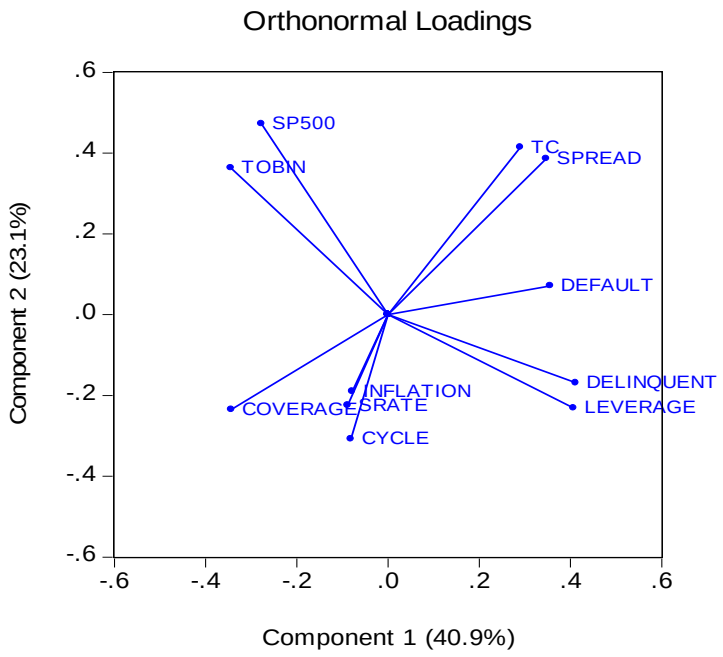

Fig. 2. Eigen vector loadings (1 and 2)

Fig. 2 shows the variable loadings plot for PC1 and PC2. The HY spread (SPREAD) and Credit tightening (TC) variables show very similar component patterns. In fact, these variables show a correlation as high as 84%. Similarity in the PCs is also evident for the leverage ratio (LEVERAGE) and delinquency rates (DELINQUENT) on bank loans. Bond defaults (DEFAULT) and interest cover (COVERAGE) seem to have opposite of the PCs as the credit cycle's impact in terms of higher bond defaults coexists with a reduction in earnings and interest cover. As expected, the US leading indicator (CYCLE) has more commonality with interest rates as monetary policy responds to the economic downturn quite quickly.

As a next step, we assess if tightening in lending standards can be a better leading indicator for spreads than the usual macroeconomic indicators such as the US leading indicator by conducting the Granger's causality test, the results of which are shown in Table 2. Although the hypothesis of spread not Granger causing credit tightening cannot be rejected at two-period lags, it is unlikely for banks to react so quickly to spread movements in the bond market. The tightening in lending standards, on the other hand, points to strong Granger causality both in the two-lag and the four-lag models, which suggests that this variable can be useful in forecasting spreads. The test conducted for two-period and four-lags confirm our suspicion that the US leading indicator is not in reality leading the dynamics of the bond market and, hence, not a very useful factor in forecasting spreads

Table 2. Granger causality tests*

Pairwise Granger Causality Tests Sample: 1995Q1 2010Q4		Lags: 2		Lags:4
Null Hypothesis:	F-Statistic	Prob.	F-Statistic	Prob.
CYCLE does not Granger Cause SPREAD	0.5402	0.5857	0.7690	0.5504
SPREAD does not Granger Cause CYCLE	7.0988	0.0018*	5.1135	0.0015*
TC does not Granger Cause SPREAD	18.7291	0.0000*	7.3088	0.0001*
SPREAD does not Granger Cause TC	6.6201	0.0026*	3.3389	0.0166

* denotes test statistic significance at the 1% level to reject the null hypothesis.

Model specification:

VAR models are ideal for studying dynamic relationships between endogenous variables when there is a priori ambiguity about the structural form of the relationships. We believe that in order to explain the dynamic behaviour of HY spreads with the aim of generating one-quarter-ahead forecasts, a flexible functional form such as VAR would be ideal. As the cornerstone of our model specification, we intend to address the relationship between the HY market and bank loans which we believe, plays a prominent role in determining the HY spreads.

In order to conduct the VAR, we first test the unit root for the variables to guarantee that the variables feeding into the VAR model are all stationary. In order to conduct the unit root tests, we select the automatic lag selection with a maximum leg length of 11 via modified Akaike information criterion (AIC), Schwartz and Hannan-Quinn (modified for small sample size). All the modified tests indicate two-period lag for HY spreads, one-period lag for delinquency rates and zero-period lag for tightening in lending standards. The conducted augmented Dickey Fuller (ADF) tests have shown that the assumption of nonstationarity cannot be rejected for any of the variables with the exception of interest cover in the sample period (1990Q1-2009Q4). Although stationarity in the long-term is a plausible assumption for variables such as HY spreads, default and delinquency rates and tightening in lending standards, in shorter time horizons in which the number of business cycles is a few, their pattern may look non-stationary as shocks to these variables seem to drift longer than one quarter to revert to their mean-reversion values[iii].

A critical element in the specification of VAR models is the determination of the lag length of the VAR[iv]. On the basis of the Schwartz Criterion test, we opt out for the 2 lag VAR specification as our sample size with 76 observations is relatively small. In fact, Hannan-Quinn criterion (HQC) also supports a 2 lag VAR structure.

As a next step, we test for a co-integrating vector between spreads, tightening in lending standards and delinquency rates. Even when the variables mentioned above are nonstationary according to ADFs, if a co-integrating vector exists between them, a linear combination of variables would be stationary, confirming a long-run relationship among them.

We test for the presence of a co-integrating vector using the Johansen maximum likelihood procedure for a finite-order VAR (Johansen (1991)) with the assumption of linear deterministic trend in data and a lag selection of two-periods[v]. For the HY spreads, delinquency rates and tightening in lending standards, we reject the null hypothesis of no-co-integrating vector at the 1% level, implying a co-integrating vector exists for these variables. This co-integrating relation can be interpreted as a long-term equilibrium path for the HY credit spreads.

We estimate a Vector Error-Correction (VEC) model, which is a restricted VAR that has co-integration relations built into the specification so that the long-run behaviour of HY spreads, delinquency rates and tightening in lending converge to their co-integrating relationships while allowing for short-run adjustment dynamics. The VEC can be represented in its general form by the following equation:

$$\Delta Y_t = \Gamma(L)\Delta Y_t + DX_t + \alpha\beta'\left[Y_t - 1\right] \qquad (1)$$

Where Y_t is a vector of endogenous variables (i.e., spreads, tightening in lending standards, and delinquency rates); Γ is a matrix of parameters for a nth-order lag process; X_t is a vector

of stationary exogenous variables; and *D* is the matrix of parameters associated with the exogenous variables. The α parameters measure the speed at which the variables in the system adjust to restore a long-run equilibrium, and the β vectors are estimates of the long-run co-integrating relationships between the variables in the model. We specify a symmetric 2-period lag structure for the first difference terms in the VEC and include various exogenous variables to take into account some of the factors that are mentioned above for having a possible influence on the spread dynamics. These variables are the lagged change in the risk-free rate (SRATE), the lagged change in Tobin's Q (TOBIN), the lagged interest cover (COVERAGE) and the lagged Inflation rate (INFLATION). While unit root tests have shown COVERAGE and INFLATION are stationary, for TOBIN, nonstationarity cannot be rejected and therefore, this variable is included in first differences to acknowledge the interaction between stock market performance and credit risk. The selection of the exogenous variables is predominated with the need that contemporaneous effects are not useful in forecasting spreads and the included factors should have a lead over spreads. We therefore, included the exogenous variables only if we found that their lagged values had a significant impact in the spread equation. Below we report the estimation results on the final specification[vi].

Estimation results:

As can be seen in Table 3, the long-run co-integration relationship between the HY spreads, delinquency rates and tightening in credit/lending standards produces a very significant error-correction coefficient, indicating that the adjustment to the long-run path is very fast and within one quarter 64% of the convergence to the long-run equilibrium is completed. Despite the fast adjustment to the long-term path, certain shocks in the past have led spreads to drift longer than a couple of quarters before the long-term equilibrium is reached. Therefore, the error-correction representation of the HY equation, which includes both the first-difference

and level terms, appears to be preferable to a specification that includes HY, delinquencies and credit tightening in levels[vii].

As mentioned in Section II, up to now, no consensus has emerged in the literature on the nature of the relationship between the risk-free rate (SRATE) and bond spreads. Our results confirm a positive relationship[viii], which is economically plausible, as rising rates reduce the value of a company by reducing its debt-servicing capacity and thus, increases the probability of default. The lagged changes in Tobin's Q represent the state of the stock market, and upward movements and speculative bubbles are mirrored in the HY market in terms of lower spreads. The fact that the coefficient on Tobin's Q is negative, the HY market seems to be oblivious to the stock market overvaluations. Interest coverage is a leading indicator for HY spreads as the ratio expresses company earnings (EBIT) in relation to its debt-servicing ability. As expected, the lagged value of this variable has a negative impact on spreads. The lagged value of inflation pushes the spreads up, presumably because the price reductions in HY corporate bonds (relatively illiquid) due to interest rate hikes are usually higher than the price reduction in Treasury bonds (liquid), leading to a spread widening. Another interpretation for the positive sign on inflation is a technical factor. The HY market is dominated by fixed rate bonds, which also constitute the Merrill Lynch HY index. In the alternative leverage loan market, loans are priced with a floating interest rate (Libor + Spread). This feature of leveraged loans makes them more desirable for investors than HY when inflation is rising as their price is not affected by changes in the risk-free rate.

Table 3. Estimation results

Sample (adjusted): 1991Q1 2009Q4			
Standard errors in ( ) & t-statistics in [ ]			
Cointegrating Equation:	CointEq1		
SPREAD(-1)	1		
DELINQUENT(-1)	-34.08		
	(10.83)		
	[-3.15]**		
TC(-1)	-5.60		
	(2.25)		
	[-2.49]**		
C	-415.78		
Error Correction:	D(SPREAD)	D(DELINQUENT)	D(TC)
CointEq1	-0.64	0.00	0.01
	(0.14)	(0.00)	(0.01)
	[-4.53]**	[1.86]	[1.13]
D(SPREAD(-1))	0.76	0.00	0.02
	(0.12)	(0.00)	(0.01)
	[6.20]**	[1.95]	[1.94]
D(SPREAD(-2))	-0.36	0.00	0.00
	(0.11)	(0.00)	(0.01)
	[-3.12]**	[-0.74]	[0.30]
D(DELINQUENT(-1))	11.42	0.38	3.75
	(113.70)	(0.11)	(9.28)
	[0.11]	[3.36]**	[0.40]
D(DELINQUENT(-2))	140.18	0.41	-13.81
	(111.85)	(0.11)	(9.13)
	[1.25]	[3.63]**	[-1.51]
D(TC(-1))	1.55	0.00	-0.22
	(1.55)	(0.00)	(0.13)
	[1.00]	[2.54]*	[-1.73]
D(TC(-2))	5.74	0.00	0.02
	(1.26)	(0.00)	(0.10)
	[4.56]**	[3.86]**	[0.22]
C	183.15	-0.14	-17.74
	(64.47)	(0.06)	(5.26)
	[2.84]**	[-2.21]*	[-3.37]**
D(SRATE(-1))	70.00	0.03	-1.62
	(27.06)	(0.027)	(2.21)
	[2.59]**	[0.97]	[-0.74]
D(TOBIN(-2))	-338.76	-0.01	-7.09
	(114.03)	(0.11)	(9.31)
	[-2.97]**	[-0.07]	[-0.76]
COVERAGE(-2)	-126.96	0.07	7.66
	(36.28)	(0.037)	(2.96)
	[-3.50]**	[2.01]*	[2.59]**
INFLATION(-1)	65.27	0.04	7.81
	(25.27)	(0.025)	(2.06)
	[2.58]**	[1.59]	[3.79]**
R-squared	0.65	0.87	0.43
Adj. R-squared	0.59	0.85	0.33
S.E. equation	99.44	0.10	8.12
F-statistic	10.89	38.62	4.37
Log likelihood	-450.88	73.61	-260.44
Akaike AIC	12.18	-1.62	7.17
Schwarz SC	12.55	-1.25	7.54

Standard errors in ( ) & t-statistics in [ ], ** and * denote significance at 1% and 5% level respectively.

IV. Forecasting Performance

In Table 4, we present the root mean squared error (RMSE) and the mean absolute percentage error (MAPE) of the actual credit spread for the entire 1991Q1-2010Q1 sample period and also for the forecast period. The in-sample properties of the forecast are good, as the bias and volatility proportions of the Theil's inequality are close to zero. The out-of-sample MAPE is a bit larger than the in-sample error, which is to be expected considering the high volatility of the spread in the forecast period. Despite this, the proportion of the Theil's inequality attributable to the covariance portion is still the highest, which is a desirable property for a forecast model.

In the light of the estimation results presented in Table 3, we proceed to generate one-step-ahead (out-of-sample) forecasts. For the purpose of forecasting, we use the HY spread equation, inserting the actual values of all the explanatory variables up to the inception point of the forecast. We argue that selecting the inception point for the 'out-of-sample' forecast is important. Given the relatively small size of our period, we think that 2007Q4 can be a good inception point for the out-of-sample forecasts. This way, it would be interesting to see how the model performs versus some alternative (naïve) models in forecasting the financial crisis of 2008. In order to generate the out-of-sample forecasts, we re-estimate the HY equation in-error-correction form as it appears in the VEC specification for the 1991Q1-2007Q4 period. The first simulated out-of-sample forecast is made for 2008Q1. Then, by adding the actual data observations for 2008Q1, we re-estimate the parameters of the equation for the 1991Q1-2008Q1 period; then, the values of the regressors at 2008Q1 are used to forecast 2008Q2. All parameters are then re-estimated, including the actual data on 2008Q3 to forecast the spread value of 2008Q3 and so on. The final simulated out-of-sample forecast was made using the parameters from the estimation for the 1991Q1-2009Q4 period to forecast 2010Q1. Throughout this exercise of running rolling regressions, we keep the model variables and the

lag structure the same, i.e., we do not attempt to search for the best-fitting lag or drop the insignificant lags to make MAPE smaller. We remain true to the HY spread specification shown in the VEC model.

Table 4. Forecasting properties in and out-of-sample

Forecast Performance Indicators:	Model 199Q1-2010Q1 Forecast in Sample 1991Q1-2010Q1	Model 1991Q1-2007Q4 Forecast out-of-sample 2008Q1-2010Q1
Root Mean Squared Error:	87.78	249.35
Mean Absolute Error[a]:	66.74	184.00
Mean Absolute Percentage Error:	13.40%	17.12%
Theil Inequality Coefficient:	7.00%	12.00%
Bias Proportion:	0.00%	32.00%
Variance Proportion:	2.40%	12.00%
Covariance Proportion:	97.60%	56.00%

[a] denotes basis points (of credit spread)

Sophisticated forecasting models very often cannot outperform naive models such as the random walk or the univariate AR models. In order to check if our model's out-of-sample forecasts outperform the naïve-model forecasts, we define a number of naïve alternative models and calculate the Theil's U test for the average of the RMSE ratio between our model and each of the naïve models for the period 2008:1 to 2010:1[ix]. If A_{t+n} denotes the actual values of a variable in period t+n, F_{t+n} the model forecast made in period t for t+n, and NF_{t+n} the naïve model forecasts, then the Theil statistic is defined as:

$$Theil'sU = \left[\sum_{t=1}^{n} (A_{t+n} - F_{t+n})^2 / \sum_{t=1}^{n} \left(A_{t+n} - NF_{t+n} \right)^2 \right]^{0.5} \quad (2)$$

The ratio of the root mean square error (RMSE) of model forecasts to the RMSE of naïve forecasts gives the Theil's U statistic[x]. We define three alternative naïve models:

Naïve Model 1: Random Walk model: $Y_t = Y_{t-1}$ (3)

Naïve Model 2: First-order autoregressive, or AR(1), model: $Y_t = c + \beta Y_{t-1} + \varepsilon_t$ (4)

Naïve Model 3: Lagged Credit Loss: $Y_t = \rho_{t-1} \times (1 - \tau)$ (5)

where ρ_{t-1} is the default rate at t-1 and τ is the long-term recovery rate (40%).

Table 5 shows the Theil's U for each of the one-step-ahead, out-of-sample forecasts. The average of the U statistic shows that the existing model has a superior out-of-sample performance to the naïve alternatives. Naïve models are especially poor in predicting the turning point in the financial crisis. The nine-period average Mean Absolute Percentage Error (MAPE) is 21% for our model.

Table 5. Theil's U test[a,b]

Alternative Models:	2008Q1	2008Q2	2008Q3	2008Q4	2009Q1	2009Q2	2009Q3	2009Q4	2010Q1	average
Naive 1: Random walk	1.006	0.088	0.651	0.740	0.003	0.380	0.691	2.464	1.631	0.790
Naive 2: AR1	0.963	0.136	0.611	0.699	0.002	0.374	0.874	3.046	0.966	0.801
Naive 3: Lagged Credit Risk	0.301	0.012	0.241	0.322	0.000	0.322	1.757	2.811	0.255	0.333

a: If U is <1, (U is >1), the forecasts from the model outperform (under perform) the naïve forecasts.
b: Diebold-Mariano tests of the model versus Naïve 1, Naïve 2, and Naïve 3 models give the p values of .05, .049, and .034 respectively.[xi] Thus, the null hypothesis of equal predictive ability can be rejected at 5% significance level for all the naïve models in favour of the chosen model.

V. Conclusions:

This paper analyses the dynamic behaviour of HY spreads and addresses the link between bank loans and HY bond markets. Using data on loan officers' survey and bank delinquency rates, we are able to define the long-term path for HY spreads in a co-integration relationship. Although the adjustment to this path is quick, it nevertheless takes longer than a quarter. The bank data on credit tightening and delinquency rates serve well as leading indicators for predicting spread movements as these factors provide a good proxy for the systemic credit risk and also for the supply and demand conditions in the HY market, which affect trading costs (i.e., liquidity risk). An important contribution of our paper is the explicit recognition of the interplay between the leverage loan and the HY markets as the former constitutes not only an alternative form of financing for the HY bond issuers but also an alternative form of investment for anyone who wants to invest in non-investment grade debt for a high return. Despite the differences in our methodology, our results seem to be consistent with the findings of Koopman et al. (2009) who argue that default intensities are driven by risk factors other than the common macro fundamentals as they find that lagged business cycle variables generate non-intuitive signs for current defaults and downgrades. Unlike the usual macroeconomic indicators, such as the US leading indicator, the information we extract from the bank-survey data provides a more useful indicator for spread movements indicating that bank react to changes in business cycle rather quickly.

In reduced-form models the observed spread is by definition a premium for risk-neutral investors for holding credit and liquidity risk together and there is no attempt to separate the two. In this respect, our model shows similarity to reduced-form models as we also do not attempt to isolate credit risk from liquidity risk. Instead, we try to account for both by

recognising the high correlation between the two, as was the case during the sub-prime crisis. Rising delinquency and default rates, and credit tightening during an economic downturn is not merely a reflection of the increased credit risk. These factors influence the technical conditions in these markets, where flight to quality and the supply-demand mismatch eventually leads to drying up of liquidity and causes even higher spreads.

Unlike the reduced-form models, which are divorced from any economic reasoning, our model incorporates some economic factors that influence credit risk as in the Merton-type structural models. Using variables such as the equity market indicator (Tobin's Q) and the leverage indicator (interest cover), our model provides a good fit to the historical spread data without imposing restrictive assumptions on company leverage, interest rates, etc. Given that our model uses the lagged value of these fundamental factors, our error-correction equation for the HY spreads provides a satisfactory instrument in generating one-period-ahead forecasts with a MAPE of less than 20% and is shown to be superior to the chosen naïve models.

Appendix A.

A1. Data:

The quarterly data we use for the HY credit spreads is obtained by aggregating the monthly Merrill Lynch option-adjusted spreads[xii] of non-investment grade corporate bond index (Merrill Lynch High Yield Master II index). The HY index is a market value-weighted average of individual credit spreads on speculative bonds within a given maturity, and credit rating. To qualify for inclusion in the index, securities must have a below investment grade rating (based on an average of Moody's, S&P, and Fitch). Each security must have greater than 1 year of remaining maturity, a fixed coupon schedule, and a minimum amount oustanding of $100 million. The index is rebalanced at the end of each month, which means bond issues that do not meet the qualifying criteria are dropped from the index and new issues that meet the qualifying criteria are included. This rebalancing procedure guarantees that the rating, maturity and amount outstanding characteristics of the index are maintained, and the changes in the spreads of the index reflects the changes in credit risk and not the changes in the composition of the index. The ML indices are quoted in the *Wall Street Journal* and are considered high-quality indicators of aggregate credit risk by the financial industry. The sample period extends from 1991Q1 to 2010Q1. To be included in an index, qualifying bonds are required to have a fixed coupon schedule and at least one year to maturity.

We calculate the leverage ratio as Debt to (Debt+Equity). We use as a debt proxy the US credit market debt for non-farm, non-financial corporate business. Equity is the current market value for non-farm, non-financial corporate sector. We construct the Tobin's Q by dividing the market value of non-farm, non-financial corporate sector by the tangible assets at historical replacement cost. These data are provided by the US Federal Reserve. For interest cover, we use corporate earnings before tax and interest payments divided by a proxy for the

cost of interest payments on annually-payable debt. Corporate profits (with inventory valuation and capital consumption adjustments) are the net current-production income of corporations. The source of these seasonally-adjusted data is US Bureau of Economic Analysis. We construct the proxy in the denominator by assuming that the credit debt of the corporate sector is on average spread over seven years and by also assuming that the interest paid on debt is as the same rate as the yield on non-investment grade bonds. Thus, we multiply the one-seventh of the debt by (1+high-yield rate) to derive a proxy for average interest payments. By dividing the corporate earnings by this proxy, we obtain an interest cover index that has a similar trend to the company level interest cover measures, i.e., our index is on average close to 1.5 and falls below unity during the downturns in the business cycle. For the variable of 'tightening in lending practices', we use the US Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices (http://www.federalreserve.gov/boarddocs/snloansurvey). We use the survey results on Net Percentage of Domestic Respondents Tightening Standards for small-size Commercial and Industrial (C&I) loans. In this survey, the respondents are given the following possibilities to answer the question (Has there been a tightening in lending standards?) in comparison with the status in the previous quarter: a) clearly higher, b) higher, c) same, d) somewhat lower, and e) much lower. If the % of respondents answering (a) or (b) exceeds the % of respondents answering (d) or (e), then, the net % balance is positive and vice versa.

The delinquency rates that are used in this paper are those of the 100 largest US banks. Delinquent loans are those that are 30 days or more past due and still accruing interest as well as those in non-accrual status. They are measured as a percentage of end-of-period loans. The delinquency data and the data on short-term interest rates (3-month Treasury bill rate), inflation, and the S&P 500 index were taken from Thomson Reuters DataStream. Default rates are taken from Moody's default rates on speculative-grade US bonds. The data from

Moody's Investors Service contains the credit histories of nearly 10,000 corporate and sovereign entities and over 80,000 individual debt securities since 1970. These default rates have been calculated without any issuer weighting.

A2. Hypothesis tests for HY spreads:

Table A.2. Unit-root tests for the HY spreads[a]

Null Hypothesis: HY spread has a unit root			
Exogenous: Constant			
Lag Length: 2 (Automatic based on Modified AIC, MAXLAG=11)			
		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.384351	0.1494
Test critical values:	1% level	-3.516676	
	5% level	-2.899115	
	10% level	-2.586866	
Elliott-Rothenberg-Stock DF-GLS test statistic		-2.313938	
Test critical values:	1% level	-2.594946	
	5% level	-1.945024	
	10% level	-1.61405	
Bandwidth: 1 (Newey-West using Bartlett kernel)			
Phillips-Perron test statistic		-2.736119	0.0725
Test critical values:	1% level	-3.514426	
	5% level	-2.898145	
	10% level	-2.586351	
Null Hypothesis: HY spread is stationary			
Exogenous: Constant			
Lag length: 2 (Spectral OLS AR based on Modified AIC, MAXLAG=11)			
		LM-Stat.	
Kwiatkowski-Phillips-Schmidt-Shin test statistic		3.040823	
Asymptotic critical values:	1% level	0.739	
	5% level	0.463	
	10% level	0.347	

a: The tests support non-stationarity of HY spreads

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Notes:

[i] The data on historical bond recovery rates from Moody's indicate that on average a long-term recovery rate of 40% is a plausible assumption.

[ii] Ivashina and Scharfstein (2010) report that after the failure of Lehman Brothers in September 2008, there was a run by short-term bank creditors, making it difficult for banks to roll over their short term debt coupled with a simultaneous run by borrowers who drew down their credit lines, leading to a spike in commercial and industrial loans reported on bank balance sheets. They argue that these stresses in liquidity led banks to cut lending.

[iii]Table A.1 shows the stationarity tests for the HY spreads. The nonstationarity of credit spreads indices has also been reported by Pedrosa and Roll (1998).

[iv]Ivanov and Kilian (2001) compare various criteria in terms of the mean-squared error of the implied impulse response estimates and come to the conclusion that for quarterly VAR models the HQC is the most accurate criterion with the exception of sample sizes smaller than 120, for which the Schwarz Information Criterion (SIC) is more accurate.

[v] Lütkepohl (1993) indicates that over-fitting (selecting a higher order lag length than the true lag length) causes an increase in the mean-square forecast errors of the VAR and that under-fitting the lag length often generates autocorrelated errors. To be on the safe side, we conduct VEC Lag Exclusion Wald Tests on the three-lag version of the model where the insignificance of the third lag cannot be rejected according to the joint Chi-square statistic at 1%. VEC Residual Portmanteau Tests for Autocorrelations cannot reject 'no autocorrelation' at 1% for the third lag. All the tests stated here but not shown in Appendix are available on request.

[vi] The selection was made on the basis of the lowest Schwartz Criterion and parameter stability in the rolling-regressions. Although in our sample period there have been a few events which caused high volatility in spreads (LTCM's default, September 11th, Lehman Brothers' default), separate dummies used for these events were found to be statistically insignificant at 5% level

[vii] We also tried such a specification where the first-difference terms of the variables in the long-term relationship are excluded. However, the out-of-sample-forecast performance is somewhat inferior to the error-correction specification (MAPE is on average 2.6% higher).

[viii] This finding is in contrast with the counter-intuitive finding of Duffee (1998) who found a negative relationship between interest rate and credit spreads.

[ix] Armstrong and Fildes (1995) have advocated using the Theil's U statistic for comparing the accuracy of various forecasting methods.

[x] A U-statistic of 1 indicates that the model forecasts match the performance of naïve forecasts. A U-statistic >1 shows that the naive forecasts outperform the model forecasts. If U is <1, the forecasts from the model outperform the naïve forecasts.

[xi] The Diebold-Mariano (DM) test (Diebold & Mariano (1995)) aims to test the null hypothesis of equality of expected forecast accuracy against the alternative of different forecasting ability across models. The null

hypothesis of the test can be written as $d_t = E\left[g(e_t^M) - g(e_t^A)\right] = 0$, where e_t^M and e_t^A are the forecast errors of the model and the alternative model respectively when performing *h* steps ahead forecasts. DM is then simply the ratio of d to its estimated standard error. DM statistic is distributed as a standard normal distribution. We use the modified version of the DM test to take into account the small-sample adjustment. (as suggested by Harvey,, Leybourne and Newbold (1997))

[xii] The option-adjusted spread calculation begins by using statistical methods to generate a large number of possible interest rate paths that can occur over the term of the bond and measures the resulting impact of the scenarios on the bond's value. By averaging the results of all the scenarios, the implied spread over the Treasury yield curve is determined.