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Macro Factors in the Term Structure of Credit Spreads

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Abstract

We estimate arbitrage-free term structure models of US Treasury yields and spreads on BBB and B-rated corporate bonds in a doubly-stochastic intensity-based framework. A novel feature of our analysis is the inclusion of macroeconomic variables – indicators of real activity, inflation and financial conditions – as well as latent factors, as drivers of term structure dynamics. Our results point to three key roles played by macro factors in the term structure of spreads: they have a significant impact on the level, and particularly the slope, of the curves; they are largely responsible for variation in the prices of systematic risk; and speculative grade spreads exhibit greater sensitivity to macro shocks than high grade spreads.

In addition to estimating risk-neutral default intensities, we provide estimates of physical default intensities using data on Moody's KMV EDFs™ as a forward-looking proxy for default risk. We find that the real and financial activity indicators, along with filtered estimates of the latent factors from our term structure model, explain a large portion of the variation in EDFs™ across time. Furthermore, measures of the price of default event risk implied by estimates of physical and risk-neutral intensities indicate that compensation for default event risk is countercyclical, varies widely across the cycle, and is higher on average and more variable for higher-rated bonds.

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1 Introduction

We provide new evidence on the impact of macroeconomic conditions on corporate bond spreads. There are compelling reasons to expect that spreads are influenced by the macroeconomy. Theoretical models of default risk, as well as general equilibrium models with financial frictions and nominal rigidities, predict systematic relationships between spreads, output and/or inflation (e.g. Bernanke, Gertler and Gilchrist (1999)). Estimates of unconditional correlations indicate a close empirical link between credit spreads, the state of financing conditions faced by borrowers and the business cycle. For example, the monthly correlation between five-year US BBB-rated industrial spreads and real output is -0.52. Indeed, several past studies have examined the empirical relationship between default risk and macroeconomic conditions. Jonsson and Fridson (1996), Chava and Jarrow (2004) and Duffie, Saita and Wang (2005), amongst others, have shown there is a countercyclical relationship between default risk and economic activity. In a study of default loss rates, Altman, Brady, Resti and Sironi (2003) estimate negative correlations between default rates, loss given default and the business cycle. Cantor and Mann (2003) document the procyclicality of credit quality changes using a long history of Moody's credit ratings data.[1] But apart from a few studies, the relationship between corporate bond spreads and macroeconomic variables has been left largely unexamined. Previous work has mainly focused on explaining changes in spreads using regression analysis (e.g. Collin-Dufresne, Goldstein and Martin (2001), Morris, Neal and Rolph (2001)).

In this paper, by contrast, we analyse spreads in a multi-factor term structure model subject to restrictions imposed by the absence of arbitrage opportunities. Default risk is modelled using a doubly-stochastic intensity-based framework (Lando (1998), Duffie and Singleton (1999)), where risk-neutral instantaneous default loss rates ("instantaneous spreads") are assumed to be affine functions of the state variables. One innovation of our approach is that the state vector is comprised of both observable macroeconomic variables – indicators of real activity, inflation and financial activity – and unobserved latent factors. Most of the existing empirical work on reduced-form term structure models has been based on latent factors only (e.g. Duffee (1999), Driessen (2005)).

[1] For a more complete review of how macroeconomic factors have been incorporated into credit risk models, see Allen and Saunders (2003).

Thus, our paper seeks to extend these earlier studies by drawing additional insights from the inclusion of observable variables as factors. Ideally, we would like to specify a completely observable state space to model yields and spreads, but our findings point to a crucial role played by latent factors in improving the fit of our model to market data. This result may be due to an overly restrictive state space (we include three macro factors), or it may reflect a well-known finding by Collin-Dufresne, Goldstein and Martin (2001) that, in addition to macroeconomic variables, there appears to be a common "unknown" factor in corporate bond returns. Moreover, since we do not explicitly account for liquidity or tax effects on corporate bond prices, such as in Driessen (2005), latent factors in our model may implicitly pick up these other influences on spreads.

In one regard, our work builds on recent studies of affine term structure models of default-free yields with macroeconomic factors (e.g. Ang and Piazzesi (2003), Dewachter and Lyrio (2003), Hordhal, Tristani and Vestin (2003)).[2] In these models, real activity and consumer price inflation are amongst the drivers of government bond yields due to their influence on the risk-free rate and the discount factors agents use to price assets. Motivated by firm-value (Merton-type) models of default risk and the ratings methodologies of rating agencies (e.g. Standard & Poor's (2003)), our model of defaultable bond pricing also includes a measure of financial activity along with real output and inflation as observable state variables. Despite the poor performance of specific formulations of firm-value models in explaining spreads (Huang and Huang (2003), Eom, Helwege and Huang (2004)), regression estimates presented below suggest that key drivers of default risk in these models have substantial explanatory power for spreads. Our particular indicator of financial conditions combines information on leverage, interest coverage, cash flow and asset volatility.

Yang (2003) also examines the role of output and inflation in the term structure of spreads, although there are several important differences in the scope, methodology and results of our respective studies. For example, we allow the risk-free rate to depend upon macroeconomic variables (in contrast to Yang), we examine the relationship between financial activity variables and spreads, and our data covers a longer time

[2] Affine models have been the workhorse in the empirical term structure literature on default-free debt. It is impossible to cite all of the relevant contributions here. See Dai and Singleton (2001) and Piazzesi (2003) for a broad overview of these types of models.

span. By comparison, Bakshi, Madan and Zhang (2004) add several firm-specific risk factors, including leverage and volatility, to latent factor models, but do not examine the potential role of output or inflation as factors. They find that including leverage as an observable state variable helps to significantly reduce model pricing errors for high-yield, but not investment grade, bonds.[3]

We concentrate our analysis on spread dynamics at the sector-rating level, specifically, BBB and B-rated industrial firms.[4] Our chosen sector-rating classes are amongst those with the largest number of outstanding issues in the investment grade and high-yield markets, respectively. Of particular interest in this paper are potential differences in the sensitivities of investment grade and high-yield spreads to macroeconomic conditions. Economic theory suggests that lower-rated firms likely face tighter financing constraints, especially in cyclical downturns, and that they generally suffer greater adverse effects from financial market imperfections. Consequently, we expect speculative grade spreads to be more sensitive, all else equal, to aggregate economic activity (see, e.g., Gertler and Lown (1999)). By estimating a model on both BBB and B-rated bonds, we can examine whether spreads on lower-rated debt respond differently to the macroeconomy.

Our study begins by presenting regression estimates of Treasury yields and corporate spreads on macroeconomic variables. In general, we find that both yields and spreads are strongly related to real economic activity and financial conditions, and less so to inflation. Moreover, as anticipated, spreads on lower-rated debt are affected more by macroeconomic variables than those on investment grade bonds. The regression results are a good indicator of what we find in our affine term structure model; after all, our model predicts that yields and spreads are affine functions of the state variables. However, as noted elsewhere (Duffee (2002), Piazzesi (2003)), there are many insights to be gained from a no-arbitrage term structure model that cannot be inferred from

[3]In other contemporaneous work, Wu and Zhang (2005) examine the role of output, inflation and market volatility in term structure models applied to bond data on individual firms.

[4]One advantage of using aggregate index data, in contrast to firm-level data (Duffee (1999), Driessen (2005)), is that noise from idiosyncratic firm-level shocks is eliminated, thereby allowing more efficient estimation of the role of macroeconomic variables in the term structure. One disadvantage is that we are unable to assess the relative importance of firm-level versus aggregate shocks in the pricing of individual bonds.

simple regressions.

One of our main objectives is to assess the separate impact of the macroeconomy on risk-free rates, expected losses from default and the prices of systematic risk. This leads us to new insights about bond risk premia and the relationship between risk-free rates and spreads. First, recent macro-finance models of the term structure have shown that Treasury bond risk premia are driven by macroeconomic variables (see references above). Since default risk tends to rise in recessions when investors' incomes are relatively low, we would also expect business cycle risk to be priced in spreads. In fact, we find that movements in risk premia on corporate bonds can be largely attributed to our observable macro factors, especially output and inflation risk. Second, an advantage of our approach is that we can shed further light on the source of the negative unconditional correlation between risk-free rates and spreads documented in previous studies (e.g. Duffee (1999)). Our results indicate that real activity is primarily responsible for the negative correlation between these variables: the risk-free rate rises in response to an increase in output, whereas spreads, especially at short-medium maturities, decline.

Our paper also contributes to the literature linking physical default probabilities to macroeconomic variables. As noted above, several studies on default prediction point to a large negative correlation between default probabilities and the business cycle. While the use of spreads data in our term structure model only enables us to uncover *risk-neutral* instantaneous loss rates (see Jarrow, Lando and Yu (2005) for further discussion of this issue), by using an additional source of data on default risk we can also estimate *physical* instantaneous loss rates. In our case, this is accomplished by fitting one-year default probabilities implied by a doubly-stochastic intensity model to Expected Default Frequencies (EDFs$^{\mathrm{TM}}$) from Moody's KMV, which are assumed to be proxies for real world default probabilities. By assuming that physical default intensities are driven by the same factors determining spreads, we are able to explain a large portion of the time series variation in EDFs$^{\mathrm{TM}}$ on both BBB and B-rated industrial bonds. The real and financial activity indicators, in particular, have significant marginal predictive power for future default risk.

Estimates of physical and risk-neutral default intensities obtained using data on EDFs$^{\mathrm{TM}}$ and spreads, respectively, provide new evidence on the size and evolution of the price of default *event* risk. If investors can conditionally diversify credit portfolios – that is, investors can eliminate their exposure to individual defaults – then the default event itself will not be priced (Jarrow, Lando and Yu (2005)). Recent evidence indicates this not to be true and that the market price of default event risk has been large and highly volatile over time (Driessen (2005), Berndt, Douglas, Duffie, Ferguson and Schranz (2005), Amato and Remolona (2005)). For instance, using data on credit default swaps, Berndt, Douglas, Duffie, Ferguson and Schranz (2005) find that the average price of default event risk is approximately between one and two, which means that risk-neutral default probabilities are more than twice the size of physical default probabilities even in the absence of systematic risk. To our knowledge, we are the first to estimate the market price of default event risk across the business cycle and, in particular, to assess how it is related to observable measures of macroeconomic activity. We find that the price of default event risk is countercyclical, varies significantly across the cycle, and is higher and more variable for higher rated debt.

Finally, our results also shed new light on the role of macroeconomic variables in the term structure of Treasury yields. For instance, our data sample covers a period when inflation was relatively low and stable, and therefore our results provide a test of the stability of estimates obtained elsewhere over a longer sample period that includes the high and variable inflation of the 1970s and early 1980s (e.g. Ang and Piazzesi (2003)). In contrast to their results, we find that shocks to real activity have a much stronger initial effect on the entire yield curve compared to inflation shocks. In addition, we show that our financial conditions indicator affects the entire Treasury curve, including the risk-free rate.

2 Data

2.1 Treasury Yields

We use data on zero-coupon constant maturity US Treasury yields to estimate the benchmark default-free curve in our model and to construct the spreads data. Data at various maturities is taken from interpolated yield curves available in the BIS DBS database, which have been constructed based on closing market bid yields on actively traded Treasury securities obtained by the Federal Reserve Bank of New York. The sources of all data series used in this paper are summarised in Table 1. In estimation, we use maturities of one, three, 12, 36, 60 and 120 month(s) (denoted 1M, 3M, 12M, 36M, 60M and 120M, respectively). A monthly time series of yields is assembled by taking month-end observations. Our sample period is dictated by the availability of data on corporate bond yields, and runs from 1992:05 to 2004:04, giving 144 observations in total.

Table 2 reports summary statistics on US Treasury yields, and the top panel of Figure 1 shows plots of these yields at 1M, 60M and 120M maturities. The unconditional means point to an upward-sloping yield curve on average — from 3.71% at 1M to 5.72% at 120M. The term structure of the unconditional volatilities is hump-shaped, increasing from 1M to 12M, and then decreasing at longer maturities. Yield levels are highly persistent, with first-order serial correlations equal to or greater than 0.95. There is some evidence that yields are platykurtic and have negative skewness, but the departures from normality are not strong.

Pairwise correlations in Treasury yields at all maturities are high, with contemporaneous correlations for adjacent maturities often in excess of 0.95. Table 3 shows the percentage of variation in yields explained by the six ordered principal components, on a marginal and cumulative basis. Most of the variability is accounted for by the first two components (over 99%). This suggests that a small number of common factors determine movements across the whole yield curve, consistent with many previous studies (see Litterman and Scheinkman (1991)).

2.2 Corporate Bond Yields

Corporate spreads are constructed using data on corporate bond yields extracted from Bloomberg's Fair Market Value yield curves. These curves are constructed on a daily basis for various sectors and rating classes from a sample of Bloomberg Generic bond prices at market closing. Bonds with embedded options are adjusted to create option-adjusted yields. We utilise data on the curves for BBB and B-rated industrial firms.[5] As with Treasury yields, we create monthly time series using month-end observations. Corporate spreads are calculated as the differences between the industrial yields and Treasury yields. In estimation, we utilise maturities of 12M, 36M, 60M, 84M and 120M.

Table 2 reports summary statistics on corporate spreads and Figure 1 plots time

[5] Credit ratings are based on the Bloomberg composite rating, which is a blend of ratings of the major agencies.

series of these variables. As with Treasuries, the unconditional means of BBB and B-rated spreads are increasing in maturity. By contrast, higher moments display some differences. The term structure of unconditional volatility is upward sloping for BBB-rated spreads, while it slopes downward for B-rated spreads. BBB-rated spreads appear to be platykurtic, whereas B-rated spreads exhibit excess kurtosis. Spreads in both rating classes are positively skewed, especially at long maturities. In summary, there is some evidence of non-normality in the distribution of spreads, but as with Treasury yields, the departures from the Gaussian assumption are not dramatic.

Corporate spreads are also highly correlated across maturities. Table 3 shows that the first principal component accounts for almost 93% of the variation in the five BBB-rated spreads included in our study, and over 99% of the variation is captured by the first three components together; the corresponding values for B-rated spreads are even larger.

One reason we concentrate our analysis on the BBB and B-rated industrial sectors is that these are amongst the broadest and deepest rating-sector categories in the US corporate bond market. Figure 2 shows a breakdown by industry of the number of bonds used to create the BBB-rated industrial curve on 24 August 2004. The industries with the greatest representation are transportation, food, forest products, and oil and gas.

2.3 Macroeconomic Factors

To construct the real activity, inflation and financial conditions factors, we adopt the methodology of Ang and Piazzesi (2003); details are given in Appendix A. Each of these variables is computed as a common factor – specifically, the first principal component – from a set of observable macroeconomic time series. The main purpose of utilising common factors in our model, instead of the observable variables directly, is to reduce the dimensionality of the state space. Table 1 summarises the data series used. The series corresponding to real activity and inflation are the same as in Ang and Piazzesi (2003), though our respective sample periods differ. For real activity, these are the index of Help Wanted Advertising in Newspapers (HELP), unemployment rate (UE), the growth rate of employment (EMPLOY) and the growth rate of industrial production (IP). The inflation measures are the growth rates of the Consumer Price Index (CPI), Producer Price Index of finished goods (PPI) and a broad-based Commodity Prices

Index (PCOM). All growth rates are measured as the 12-month difference in logs of the index.

The financial activity factor is based on variables that represent leverage, interest coverage, cash flow and assets volatility. These quantities play a key role in firm-value models of credit risk and the ratings methodologies of the major ratings agencies. In fact, in several well-known Merton-type models, "distance-to-default" – which is essentially a volatility-adjusted measure of leverage – is a sufficient statistic for default risk. Even though our financial activity indicator does not explicitly depend upon an aggregate distance-to-default measure, it does incorporate information on both aggregate leverage and volatility. Leverage is measured as DEBT/PRO, where DEBT is Credit Market Debt and PRO is Profit After Tax; interest coverage is set equal to INT/GDP, where INT is Net Interest Payments and GDP is real Gross Domestic Product; a proxy for the ability of firms to generate cash flow is PRO/SALES, where SALES is Final Sales of Domestic Product; and the volatility of assets is proxied by call implied volatility on the S&P 500 (IMPVOL) obtained from Bloomberg.[6] Data on DEBT, PRO, INT, and GDP refer to non-financial corporate business and are in real terms.

Plots of the macro factors are shown in Figure 3. They are normalised to have mean zero and a standard deviation of one. As would be expected, the factors display relatively little high frequency volatility; instead, most of the movement is at business cycle frequencies. For example, the real activity factor increases for several years on the heels of the 1991 recession, and later falls significantly at the onset of the recession in 2001. The financial variable reflects the deleveraging undertaken by firms at the start of the recovery in the early 1990s, and the subsequent rebuilding up of leverage in the latter stages of the 90s boom, only to fall sharply again with the winding down of the recent recession.

[6] Bloomberg's data on call implied volatility begins in 1994. IMPVOL is extended back to 1992 using the VIX index. Values of the VIX index and implied volatility are almost identical in the month following the start of the latter, so there is no apparent break in the longer series.

3 Regression Analysis

The model we construct in the next section implies that Treasury yields and corporate spreads are affine functions of the state variables. Thus, a natural starting point is to investigate the relationship between yields, spreads and macroeconomic variables using linear regression analysis. Unrestricted regression equations do not impose the necessary cross-equation restrictions implied by the absence of arbitrage in the bond pricing model. Nonetheless, the partial correlations uncovered in regression estimates should indicate the nature of the relationships we should expect to find in estimation of the no-arbitrage model.

Unconditional linear correlations of selected variables are reported in Table 4. Both real activity and inflation are positively correlated with Treasury yields at all maturities, with much higher correlations for real activity (0.7-0.9) than inflation (about 0.2) in our sample period. While the correlation of real activity and spreads is large and negative, it is almost nil for inflation and spreads. The financial activity factor has a high and negative correlation with Treasuries, and a positive, and higher in absolute value, correlation with spreads.

Table 5 reports regression estimates of yields and spreads on the macro factors. In addition to reporting results for various maturities, the table also gives estimates of equations for, in the terminology of Litterman and Scheinkman (1991), the "level", "slope" and "curvature" of the term structures.[7]

Looking first at the Treasury yield estimates, three points are worth emphasising. First, the results for the 1M yield confirm the finding in many other studies of a strong link between the short rate and standard macro variables (e.g. Amato and Laubach (1999)). The estimated coefficients on real activity and inflation are positive, although the latter is not significant. A new result is the finding of a positive and significant relationship between the 1M yield and the financial activity variable. If we interpret this equation as a proxy for the monetary policy reaction function, then these estimates suggest that the Federal Reserve has tightened monetary policy in response to

[7] For the Treasury curve, in terms of yields at given maturities, the level is defined as (1M+36M+120M)/3; the slope as (120M-1M); and the curvature as (1M+120M)-2x36M. For the corporate curves, the 12M and 60M spreads replace the 1M and 36M spreads, respectively, in the above formulae.

developments in the financial sector beyond what they imply for output and inflation. Second, the large adjusted-R^2 statistics in the multiple regressions provide the basis for including macro variables in the yield curve model. Interestingly, both real activity and financial conditions, as opposed to inflation, seem to be more important for higher-maturity Treasury yields as well, in contrast to the larger role played by inflation in Ang and Piazzesi's (2003) analysis of yield curve dynamics (see below). Third, macro variables capture a significant portion of the variation in the level and slope of the Treasury curve. An increase in the financial activity indicator, for example, leads to a flattening of the yield curve.

Now consider the regressions for BBB and B-rated spreads. First, the fit of the regressions are similar to or better than they are for Treasury yields in many cases. Thus, this is compelling evidence for including macro factors in a corporate spreads model. Second, financial conditions have the strongest impact on spreads. Spreads widen with an increase in financial activity, with the size of the impact increasing in maturity. By contrast, real activity tends to have a larger (negative) impact on spreads at short maturities. Third, as in the case of Treasury yields, macro variables capture a large portion of the variation in the level and slope of the spreads curves; for instance, over half of the variation in the slope of the term structure of B-rated spreads can be explained by our three economic indicators.

4 Term Structure Model

In this section we describe our model of the joint dynamics of Treasury yields, BBB-rated and B-rated corporate spreads. We specify processes for the risk-free rate, the risk-neutral instantaneous spreads on bonds of both rating classes and the prices of systematic risk to be affine functions of the state variables.

The state vector X_t consists of a set of six risk factors, the three macro factors and three latent factors:

$$X_t \equiv \begin{bmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \\ X_{f,t} \\ X_{y,t} \\ X_{\pi,t} \end{bmatrix}$$

We assume that X_t evolves according to a multivariate Gaussian diffusion process under the physical measure P:

$$dX_t = -KX_t dt + \Sigma dW_t \tag{1}$$

where W_t is a vector of independent Brownian motions.[8] We have imposed the long-run means of all factors to be zero. This is done without any loss in generality, as the means cannot be separately identified from the constants in the equations for the risk-free rate and instantaneous spreads given below. Similarly, we have normalised the unconditional variances of the factors to equal one, as these are not separately identified from the factor loadings on these variables in the equations for the risk-free rate and instantaneous spreads. Restrictions are placed on the elements of Σ such that the innovations to the latent factors are mutually independent and independent of the innovations to the macro factors. Finally, the matrix governing mean-reversion is specified as:

$$K = \begin{pmatrix} k_{11} & 0 & 0 & 0 & 0 & 0 \\ k_{21} & k_{22} & 0 & 0 & 0 & 0 \\ k_{31} & k_{32} & k_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & k_{ff} & k_{fy} & k_{f\pi} \\ 0 & 0 & 0 & k_{yf} & k_{yy} & k_{y\pi} \\ 0 & 0 & 0 & k_{\pi f} & k_{\pi y} & k_{\pi\pi} \end{pmatrix} \tag{2}$$

The zero-restrictions in the off-diagonal blocks of (2) are imposed to reduce the dimensionality of the parameter space.

The instantaneous risk-free rate r_t is determined according to:

$$r_t = \delta_0 + \delta_1 X_{1,t} + \delta_2 X_{2,t} + \delta_3 X_{3,t} + \delta_f X_{f,t} + \delta_y X_{y,t} + \delta_\pi X_{\pi,t} \tag{3}$$

This specification is similar to that used in recent studies on the role of macroeconomic factors in the term structure (Wu (2000), Ang and Piazzesi (2003), Rudebusch and Wu (2003), Hordahl, Tristani and Vestin (2003)), and encompasses standard latent factor models with Gaussian factors (e.g. Vasicek (1977)). Equation (3) also takes the form of a monetary policy reaction function or Taylor-type rule, although there are two main differences between (3) and standard monetary policy rules. First, composite indicators of real economic activity and inflation are used instead of observable variables such as real GDP and CPI inflation. Since the Federal Reserve is generally regarded

[8] In the terminology of Duffee (2002), our model is part of the essentially affine ($EA_0(6)$) class of term structure models.

as responding to forecasts of inflation (rather than current inflation), one advantage of using the composite indicator $X_{\pi,t}$ in (3) is that it appears to provide more accurate forecasts of future consumer price inflation than predictions based on the current value of consumer price inflation itself (see appendix A). Second, a term representing financial conditions is rarely included in models of the risk-free short rate, yet the results in the previous section pointed to a strong negative correlation between Treasury yields and $X_{f,t}$, suggesting that its inclusion in (3) may help our understanding of short-rate dynamics and their implications for the yield curve.[9]

Default is modelled in a doubly-stochastic intensity-based framework. Specifically, the default time τ_j on a bond with rating $j = \{BBB, B\}$ arrives according to a Poisson process with associated physical default intensity $h^P_{j,t}$. For pricing purposes, we are interested in the *risk-neutral* intensity $h^Q_{j,t}$. The difference between $h^P_{j,t}$ and $h^Q_{j,t}$ depends upon the price of default event risk, which is analysed in a later section. Even though recent work by Duffie, Saita and Wang (2005) rejects the doubly-stochastic model using firm-level data, it still may be a reasonable assumption for modelling spreads at the sector-wide level, as interdependence amongst firms tends to be strongest within sector.

The pricing of defaultable securities depends upon the treatment of recovery in the event of default. We follow Duffie and Singleton (1999) and assume that recovery is determined as a fixed fraction of the market value of the bond just prior to default (known as "Recovery of Market Value" (RMV))[10]. This assumption allows us to work in terms of the risk-neutral instantaneous default loss rate, or *instantaneous spread*, defined as $s^Q_{j,t} \equiv h^Q_{j,t} \cdot L^Q_{j,t}$ for bonds with rating j, where $L^Q_{j,t}$ is the risk-neutral rate of loss given default. As with the risk-free rate, we assume that $s^Q_{j,t}$ is an affine function of the state:

$$s^Q_{j,t} = \gamma^j_0 + \gamma^j_1 X_{1,t} + \gamma^j_2 X_{2,t} + \gamma^j_3 X_{3,t} + \gamma^j_f X_{f,t} + \gamma^j_y X_{y,t} + \gamma^j_\pi X_{\pi,t} \tag{4}$$

[9] The risk-free rate is a highly persistent process, even after conditioning on persistent macroeconomic variables, as in (3). This can be handled by explicitly including lagged interest rates or, as we have done, persistent latent factors in the short rate equation. See Ang, Dong and Piazzesi (2005) for a discussion on the observational equivalence of models with latent factors and lagged observable variables in short rate equations.

[10] Two other common recovery assumptions in the literature are "Recovery of Face Value" and "Recovery of Treasury". See Bakshi, Madan and Zhang (2001) and Duffie and Singleton (2003) for empirical analysis and a discussion of the relative attributes of these alternatives.

for $j = \{BBB, B\}$. The loadings on the factors in (4) are allowed to differ across rating categories. The inclusion of macro factors in (4) extends intensity-based models that contain only latent factors, such as Duffee (1999) who allowed three latent factors to drive the risk-neutral intensity, two of which were the determinants of the risk-free rate. The specifications (3) and (4) are sufficiently general to allow all three latent factors to affect Treasury yields and spreads. Whether such generality is necessary, given the inclusion of macro variables in these equations, as well as our findings above that only a few factors are necessary to capture most of the variation in yields and spreads, will be borne out by our estimates.

Note that equations (1), (3) and (4) imply that r_t and $s^Q_{j,t}$ could become negative, depending upon the configuration of realised values for the Gaussian state variables. Of course, it is desirable to have processes for interest rates and spreads that are always positive. In the results reported below, it turns out that r_t, $s^Q_{BBB,t}$ and $s^Q_{B,t}$ remain positive throughout the sample.

Finally, we assume that the prices of bonds are arbitrage-free, which implies the existence of a stochastic discount factor and an associated equivalent martingale measure Q.[11] In line with the affine term structure literature, we assume that the market prices of systematic risk Λ_t are affine in the factors:

$$\Lambda_t = \lambda_0 + \lambda_1 X_t \tag{5}$$

where

$$\lambda_0 = \begin{pmatrix} \lambda_{0,1} \\ \lambda_{0,2} \\ \lambda_{0,3} \\ \lambda_{0,f} \\ \lambda_{0,y} \\ \lambda_{0,\pi} \end{pmatrix} \text{ and } \lambda_1 = \begin{pmatrix} \lambda_{1,(1,1)} & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda_{1,(2,2)} & 0 & 0 & 0 & 0 \\ 0 & 0 & \lambda_{1,(3,3)} & 0 & 0 & 0 \\ 0 & 0 & 0 & \lambda_{1,(f,f)} & \lambda_{1,(f,y)} & \lambda_{1,(f,\pi)} \\ 0 & 0 & 0 & \lambda_{1,(y,f)} & \lambda_{1,(y,y)} & \lambda_{1,(y,\pi)} \\ 0 & 0 & 0 & \lambda_{1,(\pi,f)} & \lambda_{1,(\pi,y)} & \lambda_{1,(\pi,\pi)} \end{pmatrix}$$

The structure of λ_1 is chosen to allow for rich interactions amongst the macro factors in the pricing of macroeconomic risk, while at the same time achieving a manageable dimensionality of the parameter space.[12]

[11] In the current context where markets are incomplete, it is not guaranteed that this measure would be unique.

[12] In estimation of alternative parameterisations of the model, we have found that imposing more zero restrictions in λ_0 or λ_1 leads to a much poorer fit of the data.

Under our assumptions, the price of a zero-coupon Treasury bond with N periods left to maturity at time t is:

$$P_t(N) = E_t^Q \left[\exp \left(- \int_{u=t}^{t+N} r_u du \right) \right] \tag{6}$$

where $E_t^Q(\cdot) \equiv E^Q(\cdot|I_t)$ is the expectation under Q conditional on the information set at time t. The price of a zero-coupon defaultable bond with rating j is given by:

$$V_{j,t}(N) = E_t^Q \left[\exp \left(- \int_{u=t}^{t+N} \left(r_u + s_{j,u}^Q \right) du \right) \right] \tag{7}$$

Using results in Duffie and Kan (1996), the expectations in (6) and (7) can be solved to give the following expressions:

$$P_t(\tau) = \exp \left(A_T(N) + B_T(N)^\top X_t \right) \tag{8}$$

and

$$V_{j,t}(\tau) = \exp \left(\tilde{A}_j(N) + \tilde{B}_j(N)^\top X_t \right) \tag{9}$$

where $A(\tau)$ and $B(\tau)$ are obtained as solutions to a set of ordinary differential equations (see Appendix B). Yields on zero-coupon Treasury and corporate bonds are therefore given by:

$$y_{T,t}(N) = -\frac{\ln P_t(N)}{N} = -\frac{1}{N} \left(A_T(N) + B_T(N)^\top X_t \right) \tag{10}$$

and

$$y_{j,t}(N) = -\frac{\ln V_{j,t}(N)}{N} = -\frac{1}{N} \left(\tilde{A}_j(N) + \tilde{B}_j(N)^\top X_t \right) \tag{11}$$

which implies that the corporate bond spread at maturity N is:

$$\begin{aligned} S_{j,t}(N) &\equiv y_{j,t}(N) - y_{T,t}(N) \\ &= -\frac{1}{N} \left(\left[\tilde{A}_j(N) - A_T(N) \right] + \left[\tilde{B}_j(N) - B_T(N) \right]^\top X_t \right) \\ &\equiv -\frac{1}{N} \left(A_j(N) + B_j(N)^\top X_t \right) \end{aligned} \tag{12}$$

5 Estimation Results

5.1 Estimation Procedure

One of the novel features of our approach is that we conduct joint estimation of the model for Treasury yields and spreads in both rating categories. The typical approach taken in the literature has been to impose orthogonality conditions in the model that permits estimation on a firm-by-firm basis or by rating-sector category. In addition, the parameters related to the Treasury portion of these models are usually estimated in a first step before estimating the corporate term structure. In our setting, each of the latent factors can affect the valuation of all securities, and we also allow for rich interactions in the joint evolution of the latent factors and in the prices of systematic risk. By estimating the model jointly across all bonds, we hope to obtain more efficient estimates. Furthermore, we test our assumption that a common set of latent factors, in addition to macroeconomic variables, are needed to explain prices across Treasury and corporate bond markets.

The macro factors are assumed to be exogenous with respect to yields and spreads, so we can estimate the model in two steps. First, since a discretized version of the process for X_t in (1) is a vector autoregression (VAR) of order one, we estimate these parameters by OLS. In addition, we estimate the coefficients on the macro factors in the equations for the instantaneous risk-free rate and instantaneous spreads by OLS. We use the 1M Treasury yield to proxy for the risk-free rate.[13] Similarly, we utilise the lowest maturity spread available (3M) to estimate the coefficients on the macro factors in (4) for both BBB and B-rated bonds.

In the second step we estimate the remaining parameters using maximum likelihood estimation. This sequential procedure is similar to the method used by Ang and Piazzesi (2003) for estimating a Treasury curve model with macro factors. We assume that all yields and spreads are observed with measurement error, and so the likelihood function and estimates of the latent factors are constructed using the Kalman filter (see, e.g., Duan and Simonato (1995) and Lund (1997)). Appendix B gives further details on the estimation procedure.

5.2 Parameter Estimates

Table 6 reports estimates of the parameters. The parameters are grouped into those governing the persistence and cross-dynamics of the factors; the loadings in the risk-

[13]If we use the Federal Funds Rate as the regressand, coefficient estimates and the R^2 statistic are similar to those obtained for the 1M Treasury yield. This suggests that the equation for the 1M Treasury yield resembles the Federal Reserve's reaction function.

free rate and instantaneous spreads; and the market prices of systematic risk. Consider these in turn.

First, OLS estimates of the VAR coefficients, expressed in the table in continuous time as elements of K, indicate a high degree of persistence in the macro factors. Similarly, each of the latent factors exhibits a high degree of autocorrelation, with the latent factor labelled Latent 3 ($X_{3,t}$) being the least persistent.

Second, as already noted in the discussion of the regression results of the 1M yield shown in Table 5, an increase in each of the macro factors raises the risk-free rate. Since the standard deviations of all factors are normalised to one, the magnitudes of the coefficients are directly comparable. Thus, real activity has the largest impact on the risk-free rate. Real activity also has the biggest effect on the instantaneous spread for B-rated bonds ($\gamma_y^B = -0.00052$), whereas the financial factor has the largest impact in the case of BBB-rated bonds ($\gamma_f^{BBB} = 0.00011$). An increase in real activity lowers instantaneous spreads, while increases in the other two macro factors raise instantaneous spreads. Estimates of the loadings on the latent factors in the risk-free rate are positive, whereas the signs are mixed on these terms in the equations for instantaneous spreads. Below we give an interpretation of these factors. For now, note that all of the latent factors have statistically significant coefficients in r_t, $s^Q_{BBB,t}$ and $s^Q_{B,t}$.

Third, the estimates of λ_0 suggest that all of the risk factors contribute to average systematic risk premia. There is substantial time variation in systematic risk premia, which in our model is driven solely by variation in the prices of risk as determined by λ_1 (factor conditional variances are constants). All of the estimated elements of λ_1 are statistically significant. The values of the lower three diagonal elements in λ_1 – the "own loadings" on each of the macro factors – are negative. In the case of the financial activity factor, for example, the negative value of $\lambda_{1,(ff)}$ implies that positive innovations to this factor lead to an increase in risk premia and a widening of corporate spreads, with the impact increasing in maturity. The off-diagonal terms in the lower-right block of λ_1 indicate that there are important interactions amongst the macro factors in the pricing of macroeconomic risk.

Estimated time series of the prices of systematic risk are plotted in Figure 4. Overall, the prices of risk on observable macroeconomic variables exhibit much greater time variation than those associated with latent factors. One of the most important episodes in terms of real output risk was when its market price became strongly negative prior to the recession in 2001. This episode illustrates the interdependence among the macro factors in the pricing of risk. Even though the downturn in output had not yet transpired, the price of output risk had nonetheless been changing by early 2000 due to rising inflation and leverage. The increase in inflation also had a marginally negative impact on the price of inflation risk, although the (still) elevated level of real output meant that the total price of inflation risk remained positive prior to the recession (the value of $\lambda_{1,(\pi y)}$ is large and positive).

One drawback of our study is that our estimates of systematic risk premia may be distorted by liquidity and tax effects. Several papers point to the presence of significant liquidity premia in corporate bond spreads (Delianedis and Geske (2001), Janosi, Jarrow and Yildirim (2001), Driessen (2005), Longstaff, Mithal and Neis (2005)), although estimates vary widely. Liquidity effects are arguably less severe in our corporate yield data as a result of the procedure used by Bloomberg to construct the credit curves. Nonetheless, to the extent that one or more of the latent factors incorporate liquidity risk, our estimates suggest that time variation in liquidity premia is dominated by variation in premia arising from macroeconomic risk.[14] Regarding the implications of taxes, Elton, Gruber, Agarwal and Mann (2001) and Driessen (2005) argue that spreads should include compensation for the differential treatment of taxes on interest income from corporate bonds relative to US Treasuries. While spreads probably reflect taxes to some extent, marginal tax rates on corporate bond income vary widely across jurisdictions, and, therefore, the impact of taxes on spreads will depend upon where the marginal investor resides.

5.3 Loadings on Macro Factors

The factor loadings, denoted by $-B_i(N)/N$, give the initial impact of an innovation to a factor on Treasury yields and corporate spreads at maturity N. Figure 5 displays these loadings for maturities $N = 1, ..., 120$. Examining Treasuries first (left-hand panel), a shock to real activity generates the largest impact on yields at short maturities, while financial activity has a bigger effect at maturities beyond 60 months. While the effect of real activity monotonically declines towards zero as maturity increases, the

[14] It is also possible that liquidity premia in the corporate bond market is driven, in part, by our macro factors.

sign on financial activity switches sign at about the two-year maturity. This implies that a positive innovation to the financial factor has an inversion effect on the yield curve, with short-term rates rising and long-term rates falling. The large impact of financial activity on Treasury yields is a new finding that has not been documented in previous term structure studies. Inflation, by contrast, has a relatively muted effect on Treasury yields, with its impact increasing slightly with maturity. This result differs sharply from estimates obtained in many previous studies, including Ang and Piazzesi (2003).[15] They estimate that shocks to inflation, versus those to real activity, had a much stronger initial effect on the yield curve. One key difference is that our model is estimated over a sample period of relatively low and stable inflation, whereas Ang and Piazzesi's data sample covered the 1970s and early 1980s, a period when both inflation and Treasury yields were high and highly volatile.

The centre and right-hand panels in Figure 5 report the factor loadings in BBB and B-rated spreads, respectively. Positive shocks to the financial activity indicator have a positive impact on spreads that is largely increasing in size with maturity. This is consistent with standard structural models of default, in which an increase in leverage or volatility, for example, raises the probability of default and, hence, spreads. An increase in real activity reduces BBB-rated spreads at short maturities, but the sign of the loadings changes for maturities greater than about 60 months. In any case, the loadings on real activity are much smaller in magnitude compared to financial activity. By contrast, a rise in real activity lowers B-rated spreads at most of the maturities considered. A rise in inflation leads to a widening of short-maturity B-rated spreads, though it has a negligible impact on BBB-rated spreads. The relatively stronger impact of real activity and inflation on high-yield versus investment grade debt is consistent with theories that attribute a greater impact to cyclical fluctuations on lower-rated debt, possibly due to sharper financial frictions faced by these firms.

Previous literature has documented a negative unconditional correlation between proxies for the risk-free rate and corporate spreads. In empirical work on corporate term structure models with latent factors, Duffee (1999) found that the two latent factors determining the risk-free rate in his model had negative loadings, on average, in the risk-neutral intensities of the 169 firms in his sample. In our sample, the unconditional correlations between the one-month Treasury yield and 60-month spreads are -0.36

[15] Our findings on inflation are closer to the results in the VAR(12) model in Ang and Piazzesi (2003).

and -0.45 for BBB and B-rated bonds, respectively. One advantage of our modelling approach is that we can determine the contribution of macroeconomic variables to these correlations from the loadings plotted in Figure 5. Recall that all three macro factors have a positive impact on the risk-free rate in our model. Furthermore, it is evident that real activity is the only macro factor that has a strong negative impact on 60-month B-rated spreads. Thus, the differential response of risk-free rates and spreads to real activity is one source of the observed negative correlation between these variables. For BBB-rated spreads, by contrast, it seems that innovations to Latent 1, which could be interpreted as monetary policy shocks, are the primary source of this negative unconditional correlation, whereas the contribution of macro factors is minor.

5.4 Latent Factors

Turning to the latent factors, it can be seen in Figure 5 that a positive shock to Latent 1 or Latent 2 raises Treasury yields at all maturities, with the size of the effect decreasing (increasing) with the former (latter). Latent 3 has little impact on the Treasury curve. An increase in Latent 1 leads to a narrowing of BBB-rated spreads at all maturities. By contrast, positive shocks to Latent 2 or Latent 3 lead to a widening of spreads, with the impact of Latent 2 declining monotonically across the BBB curve and the opposite for Latent 3. The loadings on the latent factors are relatively large (in absolute value) compared to real activity and inflation, and similar in size to those on financial activity. For B-rated bonds, an increase in Latent 3 also leads to a widening of spreads, whereas the impact of the other latent factors differs from BBB-rated bonds, specifically, an increase in Latent 2 lowers the term structure of B-rated spreads and Latent 1 has only a minor impact across the curve.

We would like to relate the latent factors to the shapes of the term structures. Figure 6 plots filtered estimates of the latent factors with the levels, slopes and curvatures of the Treasury and corporate curves (as defined in the regression analysis above). Table 7 reports estimates from univariate regressions of the filtered latent factors on the curve variables. As foreshadowed by the factor loadings in Figure 5, Latent 1 is closely related to the level of the Treasury curve. One interpretation of this result is that Latent 1 is capturing interest rate smoothing by the Federal Reserve. Since our specification of the risk-free rate explicitly omits *lagged* risk-free rate terms, this latent factor picks up much of the persistence in the three-month Treasury bill rate (see Table 2). There is also a strong relationship between Latent 1 and the level and curvature of the BBB-rated curve, suggesting a link between the smoothing behaviour of the Fed and movements in the term structure of investment grade spreads. In contrast, the link between Latent 1 and the B-rated curve is much weaker.

The regression results also indicate that Latent 3 explains a larger portion of the variation in the level of the credit curves than does Latent 2. Yet while Latent 2 also appears to be related to the level of the BBB-rated curve, there is no relationship between Latent 2 and the level of the B-rated curve. Finally, note that the latent factors capture relatively little of the variation in the *slopes* of the term structures of spreads. This is where the macro factors have a relatively bigger impact on the shapes of the curves (see Table 5, as discussed above).

5.5 Variance Decompositions

Evidence on the proportion of the variance in conditional forecast errors due to each of the factor innovations is given in Table 8. The table reports variance decompositions of Treasury yields and spreads at 3M, 12M and 60M maturities and forecast horizons of 3, 12 and 60 months.

Both macro and latent factors contribute significantly to the conditional variability of Treasury yields. At a 3-month horizon, one-third of the variation in the 3M Treasury yield is due to real activity and two-thirds to Latent 1 and Latent 2. For higher maturities, the latent factors account for a greater percentage of the variation. As the forecast horizon increases, the financial activity factor accounts for a greater fraction of the variation in Treasury yields, for example, 38% of the 12M Treasury at a 60-month horizon. Inflation accounts for virtually none of the conditional variances of Treasury yields at the horizons considered. By contrast, Ang and Piazzesi (2003) found that inflation accounts for about 60-70% of the variation in 12M yields.

Most of the conditional variances of spreads is driven by the financial activity and latent factors. Innovations to Latent 2 are responsible for most of the variation in BBB-rated spreads, particularly for shorter maturities. Latent 1 becomes more relevant at a 60M maturity. For B-rated spreads, Latent 3 is the main driver of conditional variances. As anticipated from Figure 5, the financial factor also contributes to the conditional variances of spreads, particularly at longer horizons.

The dominance of the latent factors in driving variation in spreads of both rating categories recalls one of the main conclusions in the study by Collin-Dufresne, Goldstein and Martin (2003); namely, that an unknown "corporate bond market factor" seems to be the principal source of fluctuations in spreads. Our results point to one dominant factor per rating category, which suggests that independent local demand and supply factors may be operating in different segments of the corporate bond markets. A topic for future research is to assess whether a richer state space of observable macroeconomic variables would attach less weight to latent factors in the conditional variances of spreads.

6 Decomposing Instantaneous Spreads

If investors can conditionally diversify default and recovery risk, then the physical and risk-neutral instantaneous default loss rates will be identical; otherwise, the default event itself will be priced by the market. Even if default event risk can be (approximately) hedged, there still may exist principal-agent frictions that would lead to this risk being priced in equilibrium.[16] Using data on spreads at several maturities, as we did in our term structure model, we can only identify the risk-neutral instantaneous spread and the prices of systematic risk, but not the price of default event risk. In this section we illustrate one approach for decomposing instantaneous spreads into their various components utilising additional information on physical default probabilities.

As can be seen by recalling the expression $s^Q_{j,t} = h^Q_{j,t} \cdot L^Q_{j,t}$, risk-neutral instantaneous spreads embody information on the risk-neutral intensity and risk-neutral loss given default. Moreover, the risk-neutral intensity $h^Q_{j,t}$ can be split into the physical intensity $h^P_{j,t}$ and the market price of default event risk $\Gamma_{j,t}$:[17]

$$h^Q_{j,t} = h^P_{j,t} \cdot [1 + \Gamma_{j,t}] \tag{13}$$

The prices of default event risk, which may be bond-specific, differ from the prices of systematic risk, though they could be determined by the same underlying risk factors.

[16] See Berndt, Douglas, Duffie, Ferguson and Schranz (2005) for further discussion.

[17] Further discussion, including a derivation of this relationship, is provided in Piazzesi (2003).

Our approach is to derive estimates of the market price of default event risk from estimates of physical and risk-neutral intensities.

6.1 Risk-Neutral Intensities

To obtain estimates of risk-neutral intensities from our estimates of instantaneous spreads, we make an assumption about the risk-neutral rate of loss given default, $L^Q_{j,t}$. We follow common practice in industry and the academic literature by assuming that $L^Q_{j,t}$ is constant over time and equal to the historical loss rate on defaulted debt. The average recovery rate on US senior unsecured corporate bonds is about 40% based on data from Moody's. By setting $L^Q_{j,t} = 0.6$, we can construct time series estimates of $h^Q_{BBB,t}$ and $h^Q_{B,t}$, which are plotted in Figure 7 (dashed lines). The risk-neutral intensities vary widely across the sample period, suggesting that a constant intensity assumption would likely fit the data quite poorly. (More formally, we can reject the null hypothesis of constant intensities based on the estimates presented in Table 6.) It is also evident that risk-neutral intensities of different ratings generally move together and reach their highs and lows at similar times.[18]

Two drawbacks in our approach to estimating $h^Q_{j,t}$ are that risk-neutral rates of loss given default may differ from real-world loss rates and they may vary systematically over time. In regard to the former, unfortunately, as noted by Pan and Singleton (2005) and Berndt, Douglas, Duffie, Ferguson and Schranz (2005), there is as yet little compelling evidence on how risk-adjusted expected recovery rates differ from real-world recovery rates. In regard to the latter, recent evidence on the time series properties of recovery rates suggests that they are negatively correlated with default rates (e.g. Altman, Resti, Brady and Sironi (2003)). If so, this would mean that our estimates of $h^Q_{j,t}$ in Figure 7 are too high when default rates are highest (e.g. just prior to and during the recession in 2001) and too low at other times.

[18] The minimum and maximum values of $h^Q_{BBB,t}$ are 171 basis points (November 1997) and 324 basis points (December 2001), respectively; for $h^Q_{B,t}$, these values are 387 basis points (February 1998) and 1091 basis points (October 2001).

6.2 Estimation of Physical Intensities Using EDFs$^{\text{TM}}$

Obtaining estimates of physical intensities requires using an additional source of data on real-world default risk. We utilise data on physical default probabilities provided by Moody's KMV. Moody's KMV produces time series of one-year and five-year conditional default probabilities known as Expected Default Frequencies (EDFs$^{\text{TM}}$), which are available at the firm level for publicly traded companies in the United States and elsewhere. Our use of EDFs$^{\text{TM}}$ as a proxy for default probabilities is predicated on the assumption that they (approximately) represent the market's view of default risk. By construction, EDFs$^{\text{TM}}$ are normalised to equal, on average, historical default rates of firms in a similar rating-sector category. Relative to ratings, however, EDFs$^{\text{TM}}$ vary much more through time in an attempt to capture short-term changes in default risk. See Kealhofer (2003) for further discussion of EDFs$^{\text{TM}}$ and the methodology employed by Moody's KMV.

Our data consists of monthly time series of aggregated one-year EDFs$^{\text{TM}}$ on firms rated BBB and B by Standard and Poor's over the sample period 1993:10-2004:04. These are shown as the solid lines in Figure 8. For both BBB and B-rated bonds, EDFs$^{\text{TM}}$ were low and stable until late 1998 and then began to rise prior to the recession. Whereas the EDFs$^{\text{TM}}$ suggest that one-year default probabilities on BBB-rated bonds began to fall from late-2001 onwards, they indicate that conditional default probabilities on B-rated bonds rose sharply once again thereafter, following the collapse of Worldcom.

Preliminary evidence on the relationship of EDFs$^{\text{TM}}$ to our factors is given in Table 9. For both ratings, column 1 shows that the macro factors alone explain a significant portion of the variation in EDFs$^{\text{TM}}$. Most of the coefficients are significant, although, somewhat unexpectedly, those on real activity have positive signs. The coefficients on real activity change sign in univariate regressions (not reported), which implies the existence of complex conditional relationships between default probabilities, economic activity and financial conditions. Column 2 shows that the latent factors from the term structure model have significant marginal explanatory power for EDFs$^{\text{TM}}$. The six factors together explain 95% of the variation in aggregate EDFs$^{\text{TM}}$ for BBB-rated industrials. Columns 3 and 4 add total monthly corporate bond issuance and the within-month default rate (based on data from Moody's). Conditioning on the six term structure model factors, neither of these variables are statistically significant.

We assume that the physical default intensity is a function of the observable macro factors and filtered estimates of the latent factors from the term structure model. Preliminary results based on an affine functional form produced negative values of the physical intensity in one or more months in our sample.[19] To avoid this undesirable feature, we specify a proportional-hazard model for physical intensities:

$$h_{j,t}^{P} = \exp\left(\omega_0 + \omega_f X_{f,t} + \omega_y X_{y,t} + \omega_\pi X_{\pi,t} + \omega_1 X_{1,t|t} + \omega_2 X_{2,t|t} + \omega_3 X_{3,t|t}\right) \tag{14}$$

where $X_{j,t|t}$ is the filtered estimate of $X_{j,t}$ from the term structure model (as shown in Figure 6). One aspect of the way Moody's KMV constructs EDFs$^{\text{TM}}$ is worth highlighting in the context of set of state variables in (14). EDFs$^{\text{TM}}$ are based on a non-parametric mapping of distance-to-default to historical default rates of issuers within the same rating-sector category. Since, in effect, our objective here is to model EDFs$^{\text{TM}}$, (14) can be seen as one way of approximating the Moody's KMV methodology, and where our indicator of financial activity, in particular, is used as a source of information on distance-to-default.

Our approach to estimating physical default intensities is closely related to two other recent studies, although there are several important differences in implementation. Berndt, Douglas, Duffie, Ferguson and Schranz (2005) estimate a latent factor Black-Karasinski model of physical intensities using firm-level data on EDFs$^{\text{TM}}$ across three sectors. Duffie, Saita and Wang (2005) estimate proportional-hazard models using a panel data set based on actual survival/default histories of firms. Apart from the feature that we estimate (14) by rating category instead of by firm, the marginal contribution of this part of our study is to model physical intensities as functions of observable macroeconomic variables and the other (latent) factors found to be important for driving corporate spreads curves.

In a doubly-stochastic intensity-based model, the m-period ahead conditional physical default probability is given by:

$$P\left(\tau_j < t+m|t\right) = 1 - E_t^P\left[\exp\left(-\int_{s=t}^{t+m} h_{j,s}^P ds\right)\right] \tag{15}$$

We use maximum likelihood estimation to estimate the parameters $\{\omega_i\}$ in (14) by assuming that EDFs$^{\text{TM}}$ are noisy observations of the model-based one-year default

[19] As noted above, this problem was not encountered in estimation of the term structure model. Spreads were generally much higher than EDFs throughout most of our sample.

probabilities given in (15):

$$EDF(t+12|t) = P(\tau_j < t+12|t) + e_t \tag{16}$$

where e_t is distributed i.i.d. $N(0, \sigma_e^2)$. Since $h_{j,t}^P$ is a nonlinear function of the factors, the solution of $P(\tau_j < t+m|t)$ is not known in closed form. We compute the likelihood function numerically by solving (15) using Monte Carlo simulation.

Parameter estimates are given in Table 10. For both rating categories, all of the coefficients are statistically significant except for real output in the intensity for B-rated spreads. The signs of the coefficients reflect the results in Table 9. The values of ω_f imply that a one-standard-deviation increase in the financial activity indicator raises one-year real-world default probabilities by 12 bps and 109 bps in BBB and B-rated bonds, respectively. The estimates also indicate that a positive shock to Latent 1, which was shown to raise the level of the Treasury curve, acts to reduce physical default intensities, whereas a positive shock to Latent 3 leads to an increase in physical default intensities and spreads.

Our model appears to capture much of the variation in EDFs$^{\text{TM}}$, as indicated in Figure 8, which plots model-based one-year default probabilities with EDFs$^{\text{TM}}$. It is evident from the graph that the estimated residuals $\hat{e}_t$ exhibit some serial correlation. However, our model has the ability to match most of the sharp moves in EDFs$^{\text{TM}}$ in the latter half of the sample, while capturing the relatively sanguine period in the mid-1990s. This is one virtue of using a proportional-hazard model in comparison to an affine specification for physical intensities.[20]

Looking back at Figure 7, the estimated sample paths of the physical intensities (dashed lines) are plotted with the risk-neutral intensities. The physical intensity for BBB-rated bonds peaks in November 2000, just prior to the recession, whereas the physical intensity for B-rated bonds, reaching a high in November 2002, appears to have been significantly influenced by changes in perceptions of default risk in lower-rated firms following the accounting scandals at Enron and Worldcom. The physical intensities are evidently much more volatile in the latter half of the sample.[21] They are also more volatile than the risk-neutral intensity of the same rating. This and other

[20] An even better alternative would seem to be a regime-switching model, a subject for future research.

[21] The full-sample standard deviations of $h_{BBB,t}^P$ and $h_{B,t}^P$ are 29 basis points and 368 basis points, respectively.

features of the relationship between physical and risk-neutral intensities are examined in the next section.

6.3 Market Prices of Default Event Risk

Given our estimates of physical and risk-neutral intensities, we construct estimates of the market price of default event risk from the relationship $\Gamma_{j,t} = h^Q_{j,t}/h^P_{j,t} - 1$ (see (13)). In Figure 9 we plot monthly time series estimates of $\Gamma_{BBB,t}$ and $\Gamma_{B,t}$. It is evident that the price of default event risk on BBB-rated bonds is higher on average and more volatile than that for B-rated bonds. The average values of $\Gamma_{BBB,t}$ and $\Gamma_{B,t}$ are estimated to be 8.5 and 1.5, respectively, and their in-sample standard deviations are 4.9 and 1.2. These values are somewhat larger than found elsewhere in the literature (Driessen (2005), Berndt, Douglas, Duffie, Ferguson and Schranz (2005), Amato and Remolona (2005)), and is further evidence that investors require more compensation per unit of default event risk for bonds of higher credit quality.

However, as with our estimates of systematic risk premia, measured prices of default event risk may implicitly incorporate the effects of taxes and liquidity. For example, Driessen (2005) estimates that a liquidity premium and taxes account for 13 basis points and 33 basis points, respectively, of the expected excess return in a 10-year BBB-rated corporate bond. This compares to a default event risk premium of 31 basis points. Moreover, previous studies indicate that the sizes of liquidity premia are roughly equal across rating categories, which might explain, at least partly, higher measured values of the price of default event risk in higher-rated bonds (i.e. liquidity premia represent a larger fraction of investment grade spreads).

What drives variation in the price of default event risk? By construction, the price of default event risk is a nonlinear function of the factors in our model. To gauge sensitivities to these factors, in Table 11 we report estimates of regressions on levels of the factors and squares of the factors. For both rating categories, the estimates under column 1 show that the levels of the macro factors alone account for 75% and 65% of the variation in $\Gamma_{BBB,t}$ and $\Gamma_{B,t}$, respectively. Adding the latent factors to the regressions helps explain almost all of the variation in the prices of default event risk (column 2). Consequently, adding in squares of the factors adds little in terms of improving the fit of the regressions (and the coefficients on the linear terms remain statistically significant).

An examination of the regression coefficients reveals several insights. First, the price of default event risk is countercyclical: a one-standard deviation increase in real economic activity leads to a decline of 0.67 in $\Gamma_{BBB,t}$ (based on results in column 2). Real activity has a smaller, but still negative impact on the price of default event risk on B-rated bonds. Second, the price of default event risk falls with a marginal increase in the financial activity factor. Third, there appears to be a strong link between the prices of default event risk and the filtered latent factors from the term structure model. In particular, compensation for default event risk rises with Latent 1 and falls with Latent 3. Recall from above that positive innovations to these factors lead to a narrowing and widening of spreads, respectively. Thus, even though spreads widen with an increase in Latent 3, the associated increase in real-world default probabilities tends to be larger in percentage terms.

Berndt, Douglas, Duffie, Ferguson and Schranz (2005) discuss several possible reasons for obtaining large and variable measured prices of default event risk. These include mismeasurement of real-world default probabilities (or, for that matter, risk-neutral default probabilities) or erroneous assumptions about risk-neutral loss given default (in particular, that it may be time-varying), both of which imply that estimates of default event risk premia are flawed. A third and more fundamental explanation concerns the impact of changes in the relative demand and supply for risk bearing in credit markets. We have little to add on mismeasurement. If loss given default is countercyclical, then by assuming it is constant means we are likely overestimating both the level and degree of variation in the prices of default event risk. However, experimental results in Berndt, Douglas, Duffie, Ferguson and Schranz (2005) suggest that the upward bias is probably a small fraction of the default event risk premium. Although, as they noted, there is little conclusive evidence on the properties of *risk-neutral* loss given default, which is the relevant quantity for pricing purposes.

An alternative possibility is that our measures of default event risk premia really reflect uncertainty premia. Compensation for uncertainty aversion may vary over time, for example, as investors become more or less confident about the reliability of public information on corporate balance sheets. To assess this hypothesis, consider the autumn of 2002, when the measured prices of default event risk rose sharply. We have already noted that this is the period following the accounting scandals at Enron and Worldcom. Even though credit fundamentals seemed to be on firmer ground at that time, amidst corporate deleveraging and improved growth prospects (and as captured by our measures of real-world default probabilities), if investors are uncertainty averse, they may have required a premium to hold corporate bonds in the wake of the accounting scandals. However, uncertainty aversion would seem to have difficulty in explaining the large drop in the price of default event risk in BBB-rated bonds in September-October 1998. After several sanguine years for corporate bond investors, corporates started to amass debt, Russia defaulted, and the events surrounding LTCM shook financial markets. If anything, one would have expected uncertainty premia to be rising, not falling, during this period.

Turning to more fundamental explanations, if the amount of risk-bearing capital available in the corporate bond market is roughly fixed over short intervals of time, then an increase in risk (e.g. volatility) could also lead to an increase in the price of risk. However, our finding of a negative marginal relationship between the prices of default event risk and the financial activity factor would seem to contradict this: implied volatility has a positive loading in this factor (see Appendix A). In fact, our regression results may be revealing reverse causation if firms increase leverage when the price of default event risk, and hence borrowing costs, are relatively low.

To further investigate the risk-taking capacity hypothesis, we add the trailing three-month moving average of corporate bond issuance and total number of defaults to regressions of the prices of default event risk on the macro factors. Following Berndt, Douglas, Duffie, Ferguson and Schranz (2005), these variables are meant to be proxies for the relative amount of risk capital available in the corporate bond market. However, as reported in columns 4 and 5 in Table 11, we find that neither of these variables is statistically significant conditional on the presence of the macro factors in the regression.

6.4 Survival Probabilities

In this paper we have considered two types of risk in corporate bonds that may be priced by the market: systematic risk in the state variables that determine risk-free rates and instantaneous spreads, and default event risk. To get a sense of the relative importance of these two types of risk premia in spreads, in Figure 10 we plot model-based five-year survival probabilities constructed under three different probability measures.

The solid lines (PP) in the figure show real-world survival probabilities, which are calculated using the physical intensity and the process for the factors under the physical measure: $E_t^P\left[\exp\left(-\int_{s=t}^{t+60} h_{j,s}^P ds\right)\right]$. The dashed lines (PQ) are survival probabilities calculated using the risk-neutral intensity but under the physical measure: $E_t^P\left[\exp\left(-\int_{s=t}^{t+60} h_{j,s}^Q ds\right)\right]$. Compared to real-world probabilities, this second measure involves an adjustment (typically downwards) to survival probabilities that takes account of investors' aversion to default event risk. Finally, the dash-dotted lines (QQ) are survival probabilities calculated using the risk-neutral intensity under the risk-neutral measure: $E_t^Q\left[\exp\left(-\int_{s=t}^{t+60} h_{j,s}^Q ds\right)\right]$. This measure, which is the most relevant one for pricing corporate bonds, adjusts probabilities for both default event risk and systematic risk.

It is evident from the figure that, even at the relatively long horizon of five-years, most of the difference between real-world probabilities and those used in pricing (PP vs. QQ) can be attributed to risk adjustments for default event risk. The proportion of the risk adjustment in QQ-probabilities attributed to systematic risk appears to increase when default risk rises, for example, during the recession in 2001 and, in the case of high-yield bonds, in the autumn of 2002. Nonetheless, it is always smaller in magnitude than the adjustment due to default event risk aversion.

A Construction of Macro Factors

We follow Ang and Piazzesi (2003) in constructing the macro factors for output and inflation, as well as the financial factor analysed in section 4. The approach taken is to utilise information on several related variables in order to construct a single indicator variable each of real activity ($X_{y,t}$), inflation ($X_{\pi,t}$) and financial conditions ($X_{f,t}$), and thereby reduce the dimensionality of the state space. This is done using principal components analysis.

The sets of observable variables used to estimate the macro and financial factors are described in section 3. Group together the variables by type, as follows:

$$X_t^y = \left[\begin{array}{cccc} HELP_t & UE_t & EMPLOY_t & IP_t \end{array}\right]$$

$$X_t^\pi = \left[\begin{array}{ccc} CPI_t & PPI_t & PCOM_t \end{array}\right]$$

$$X_t^f = \left[\begin{array}{cccc} \frac{DEBT_t}{PROF_t} & \frac{INT_t}{GDP_t} & \frac{PRO_t}{SALES_t} & IMPVOL_t \end{array}\right]$$

Table A.1 reports summary statistics on these variables.

All of the individual series in X_t^y and X_t^π are published at a monthly frequency. By contrast, only $IMPVOL_t$ is available (at least) on a monthly basis among the components in X_t^f. To construct the monthly financial conditions indicator, we first transform the quarterly series in X_t^f into monthly series. This is done using the approach in Litterman (1983). First, we impose the constraint that the average of within-quarter monthly values equals the observed quarterly value. Second, the monthly values $y_{t,i}^m$ are assumed to be linearly related to a set of P observable monthly variables $x_{t,i}^{m,p}$:

$$y_{t,i}^m = \beta_1 x_{t,i}^{m,1} + \beta_2 x_{t,i}^{m,2} + \ldots + \beta_p x_{t,i}^{m,p} + u_{t,i}^m$$

where

$$u_{t,i}^m = u_{t,i-1}^m + \epsilon_{t,i}^m$$

and

$$\epsilon_{t,i}^m = \alpha \epsilon_{t,i-1}^m + e_{t,i}^m$$

where $e_{t,i}^m$ is a white noise process with mean 0 and variance σ^2. The random walk assumption for the monthly error term $u_{t,i}^m$ defines a filter that removes all serial correlation in the quarterly residuals when the model is correct; when this is not true, then our specification of the dynamics of $\epsilon_{t,i}^{m}$ provide more accurate results. In our case, we use just one instrument $x_{t,i}^{m,1}$, the observed monthly values of $IMPVOL_t$.

We define $X_{i,t}$ $(i = y, \pi, f)$ to be the first principal component of X_t^i, namely, $X_{i,t} = \Omega_1^{\intercal} X_t^i$, where Ω_1 is the eigenvector corresponding to the largest eigenvalue Λ_1 of $var\left(X_t^i\right) = \Omega\Lambda\Omega^{\intercal}$. Table A.2 shows the loadings of the observable variables on the ordered principal components for each factor. Over 67% of the variance of the real activity variables is explained by the first principal component, 62% for inflation and 69% for financial conditions. The loadings on the first principal component have the expected sign in all cases. To aid intuition, we multiply the factors by -1 so that, for example, an increase in industrial production leads to an increase in $X_{y,t}$. Table A.3 reports the correlations between the factors and the underlying observable variables.

B Estimation using the Kalman Filter

Affine models can be naturally cast as state-space systems, where the observation equation links observable yields and factors to the state vector and the transition equation describes the dynamics of the state. The Kalman filter has been used to estimate affine term-structure models in many studies; early examples are Duan and Simonato (1995) and Lund (1997). In this appendix, we layout the state-space form of our model and provide further details on our estimation technique.

As stated in (10) and (12), zero-coupon Treasury yields and corporate spreads are a linear function of the state:

$$y_{T,t}\left(N\right) = -\frac{1}{N}\left(A_T\left(N\right) + B_T\left(N\right)^{\top} X_t\right) \tag{17}$$

$$S_{j,t}\left(N\right) = -\frac{1}{N}\left(A_j\left(N\right) + B_j\left(N\right)^{\top} X_t\right) \tag{18}$$

As shown in Duffie and Kan (1996), the functions $A_T\left(N\right)$ and $B_T\left(N\right)$ in (17) and (18) can be obtained as solutions to the following set of ordinary differential equations (ODEs):

$$\begin{aligned}
\frac{dA\left(N\right)}{dN} &= -\left(\tilde{K}\tilde{\Theta}\right)^{\intercal} B\left(N\right) + \frac{1}{2}\sum_{i=1}^{N}\left[\Sigma^{\intercal} B\left(N\right)\right]_i^2 - \delta_0, \\
\frac{dB\left(N\right)}{dN} &= -\tilde{K}^{\intercal} B\left(N\right) - \delta
\end{aligned}$$

where

$$\delta = \begin{pmatrix} \delta_T & \delta_f & \delta_y & \delta_\pi \end{pmatrix}^\intercal$$
$$\tilde{K} = K - \Sigma\lambda_1$$
$$\tilde{K}\tilde{\Theta} = -\Sigma\lambda_0$$

Similar expressions obtain for the loadings in spreads.

In estimation, we utilise time series data of length T_N for zero-coupon Treasury bond yields at maturities 1M, 3M, 12M, 36M, 60M and 120M and corporate bond spreads at maturities 12M, 36M, 60M, 84M and 120M. We assume that each of the yields and spreads is observed with measurement error. Let Y_t denote the vector of observable variables:

$$Y_t \equiv \begin{pmatrix} Y_{T,t}^\intercal & Y_{BBB,t}^\intercal & Y_{B,t}^\intercal & X_{f,t} & X_{y,t} & X_{\pi,t} \end{pmatrix}^\intercal$$

where

$$Y_{T,t} \equiv \begin{pmatrix} y_{T,t}(1M) & \cdots & y_{T,t}(120M) \end{pmatrix}^\intercal$$
$$Y_{j,t} \equiv \begin{pmatrix} S_{j,t}(12M) & \cdots & S_{j,t}(120M) \end{pmatrix}^\intercal$$

Similarly, let ε_t denote the vector of measurement errors:

$$\varepsilon_t \equiv \begin{pmatrix} \varepsilon_{T,t}^\intercal & \varepsilon_{BBB,t}^\intercal & \varepsilon_{B,t}^\intercal & 0 & 0 & 0 \end{pmatrix}^\intercal$$

The measurement equations of the state-space system can thus be written as:

$$Y_t = d + ZX_t + \varepsilon_t \tag{19}$$

where d and Z are defined implicitly in (17) and (18). ε_t is assumed to be normally distributed with mean 0 and diagonal variance-covariance matrix H:[22]

$$\varepsilon_t \sim N(0, H)$$

A discretised version of the state dynamics in (1) is:

$$X_t = \Phi X_{t-h} + \eta_t \tag{20}$$

[22] Since H has been assumed to be diagonal, there is no serial correlation and cross correlation in the measurement errors. Elements on the diagonal are allowed to differ, so that the variance of measurement error depends on maturity.

where $\Phi = \exp(-Kh)$ and

$$\eta_t \sim N(0, I)$$

We utilise data at a monthly frequency, and so $h = 1/12$. Equations (19) and (20) form our state-space model.

In our baseline model, we use the method of maximum likelihood to estimate the parameters in step two of our estimation procedure conditional on OLS estimates of a subset of parameters obtained in step 1. More specifically, let Ψ_1 and Ψ_2 denote the vectors of parameters estimated in steps 1 and 2, respectively. In step two we maximize the conditional log-likelihood function:

$$\ln L(Y_t, \Psi_2) = \sum_{t=1}^{T_N} f\left(Y_t; \Psi_2, \hat{\Psi}_1\right)$$

where $\hat{\Psi}_1$ denotes the OLS estimate of Ψ_1. The log-likelihood is constructed using the Kalman filter. The Kalman filter recursions are initialized with the stationary mean and variance of the unobserved state variables. Standard errors are obtained numerically by evaluating the inverse Hessian matrix at the maximum likelihood estimates and under the assumption that parameters estimated in step 1 are estimated without error.

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Table 1

Data Description

Variable	Data Series	Frequency, Unit
Real Activity		
HELP	Index of Help Wanted Advertising in Newspapers	Monthly, sa, Index 1987=100
UE	Unemployment rate	Monthly, sa, Per cent
EMPLOY	Employment, civilian	Monthly, sa, Persons Thousands
IP	Industrial Production Index	Monthly, sa, Index 1997=100
Inflation		
CPI	Consumer Price Index, All Urban Consumers: All Items	Monthly, sa, Index 1982-84=100
PPI	Producer Price Index, Finished Goods	Monthly, sa, Index 1982=100
PCOM	Market Commodity Prices Index	Monthly, sa, Index 1996=100
Financial Activity		
SALES	Final Sales of Domestic Product	Quarterly, sa, US $ Billion
DEBT	Credit Market Debt for NFCB	Quarterly, sa, US $ Billion
PRO	Profit After Tax for NFCB	Quarterly, sa, US $ Billion
INT	Net Interest Payments for NFCB	Quarterly, sa, US $ Billion
GDP	GDP for NFCB	Quarterly, sa, US $ Billion
IMPVOL	Implied Volatility on S&P 500 (extended back using VIX index)	Monthly
Yields		
Treasury	Zero-Coupon Bond Yields, Constant Maturity U.S. Treasury	Monthly, annualized
Industrial BBB	Fair Market Curve Index, Sector: Industrial, Rating: BBB	Monthly, annualized
Industrial B	Fair Market Curve Index, Sector: Industrial, Rating: B	Monthly, annualized

Notes: "sa" denotes seasonally adjusted; "NFCB" denotes Non-Financial Corporate Business.

Table 2
Summary Statistics on Treasury Yields and Corporate Spreads

Maturity (Months)	Mean	SD	Skew	Kurt	Min	Max	Autocorrelation Lag 1	Lag 2	Lag 3	Lag 4
Treasury Yields										
1	3.71	1.54	-0.51	2.00	0.80	6.06	0.96	0.93	0.90	0.87
3	3.98	1.66	-0.59	2.00	0.90	6.38	0.98	0.96	0.93	0.89
12	4.30	1.69	-0.58	2.07	1.09	7.20	0.98	0.95	0.92	0.88
36	4.93	1.49	-0.64	2.51	1.58	7.80	0.97	0.93	0.88	0.84
60	5.30	1.26	-0.55	2.62	2.30	7.83	0.96	0.90	0.86	0.81
120	5.72	1.03	-0.21	2.42	3.37	7.91	0.95	0.89	0.84	0.78
BBB-rated Spreads										
12	1.05	0.36	0.15	1.69	0.49	1.80	0.95	0.89	0.84	0.80
36	1.06	0.44	0.24	1.81	0.38	1.96	0.97	0.94	0.91	0.88
60	1.11	0.45	0.21	1.66	0.45	1.97	0.97	0.94	0.91	0.88
84	1.17	0.46	0.42	1.85	0.56	2.13	0.97	0.94	0.92	0.89
120	1.24	0.47	0.51	1.96	0.61	2.31	0.98	0.95	0.92	0.89
B-rated Spreads										
12	3.86	1.43	0.57	3.52	1.45	7.99	0.96	0.91	0.86	0.81
36	3.94	1.38	0.76	3.39	1.73	7.99	0.96	0.91	0.86	0.81
60	4.08	1.21	0.88	3.27	2.31	7.53	0.94	0.88	0.83	0.77
84	4.11	1.12	1.04	3.30	2.64	7.33	0.93	0.86	0.81	0.74
120	4.21	1.06	0.93	3.03	2.75	7.12	0.93	0.85	0.79	0.72

Notes: This table reports summary statistics for US Treasury yields (Panel A), BBB-rated industrial spreads (Panel B) and B-rated industrial spreads (Panel C). A spread is calculated as the difference between an industrial yield and the Treasury yield with the same maturities. Data are at a monthly frequency, using month-end observations, over the period 1992:05-2004:04 (144 observations).

Table 3
Principal Components of Yields and Spreads

Maturity	Principal Components Loadings					
(Months)	1st	2nd	3rd	4th	5th	6th
Treasury Yields						
1	-0.42	-0.45	0.67	-0.38	0.13	0.00
3	-0.47	-0.39	-0.10	0.66	-0.43	0.04
12	-0.49	-0.10	-0.53	-0.05	0.66	-0.18
36	-0.43	0.28	-0.27	-0.45	-0.36	0.58
60	-0.34	0.46	0.09	-0.13	-0.33	-0.73
120	-0.25	0.59	0.42	0.45	0.36	0.29
Variance (marg)	92.11	7.19	0.50	0.16	0.05	0.01
Variance (cum)	92.11	99.29	99.79	99.95	99.99	100
BBB-rated Spreads						
12	-0.32	0.83	-0.41	-0.20	-0.01	
36	-0.46	0.21	0.60	0.34	0.53	
60	-0.47	-0.07	-0.01	0.53	-0.70	
84	-0.48	-0.21	0.33	-0.75	-0.22	
120	-0.48	-0.47	-0.61	0.05	0.42	
Variance (marg)	92.61	5.71	1.11	0.35	0.21	
Variance (cum)	92.61	98.32	99.43	99.79	100	
B-rated Spreads						
12	-0.51	0.59	0.61	-0.14	0.09	
36	-0.50	0.27	-0.52	0.44	-0.46	
60	-0.44	-0.13	-0.36	0.00	0.81	
84	-0.41	-0.34	-0.13	-0.77	-0.34	
120	-0.36	-0.67	0.46	0.45	-0.10	
Variance (marg)	94.31	4.72	0.76	0.15	0.06	
Variance (cum)	94.31	99.03	99.79	99.94	100	

Notes: This table contains the principal components loadings for US Treasury yields, and BBB-rated and B-rated industrial spreads. The rows labeled *Variance (marg)* (*Variance (cum)*) display the marginal (cumulative) variance explained by each of the principal components. The numbers in these rows are the percentage variation in variables explained by the first k principal components computed as $100 \times \frac{\sum_{i=1}^{k} \Lambda_i}{tr(\Lambda)}$. Sample period is 1992:05 - 2004:04.

Table 4
Correlations of Macro Factors with Yields and Spreads

Variables	Real	Infl	Fin	$1M^T$	$12M^T$	$60M^T$	$12M^{BBB}$	$60M^{BBB}$	$12M^B$	$60M^B$
Real	1	0.14	-0.63	0.83	0.88	0.72	-0.53	-0.50	-0.69	-0.64
Infl	0	1	-0.11	0.18	0.17	0.20	-0.04	-0.03	0.16	0.07
Fin	0	0	1	-0.45	-0.55	-0.58	0.72	0.90	0.68	0.76
$1M^T$	0	0	0	1	0.95	0.79	-0.41	-0.36	-0.53	-0.45
$12M^T$	0	0	0	0	1	0.91	-0.43	-0.46	-0.60	-0.56
$60M^T$	0	0	0	0	0	1	-0.32	-0.55	-0.55	-0.62
$12M^{BBB}$	0	0	0	0	0	0	1	0.81	0.74	0.66
$60M^{BBB}$	0	0	0	0	0	0	0	1	0.74	0.81
$12M^B$	0	0	0	0	0	0	0	0	1	0.93
$60M^B$	0	0	0	0	0	0	0	0	0	1

Notes: This table reports unconditional linear correlations over the sample period 1992:05 - 2004:04.

Table 5
Regressions of Yields and Spreads on Macro Factors

Maturity (Months)	Real Activity Estim.	Real Activity (Std. Err.)	Inflation Estim.	Inflation (Std. Err.)	Financial Estim.	Financial (Std. Err.)	Adj. R^2
Treasury Yields							
1	0.0139	(0.0009)	0.0010	(0.0007)	0.0020	(0.0009)	0.69
60	0.0074	(0.0009)	0.0012	(0.0007)	-0.0025	(0.0009)	0.55
120	0.0033	(0.0008)	0.0016	(0.0006)	-0.0039	(0.0008)	0.44
Level	0.0094	(0.0008)	0.0011	(0.0006)	-0.0011	(0.0008)	0.66
Slope	-0.0106	(0.0009)	0.0006	(0.0007)	-0.0060	(0.0009)	0.47
Curvature	-0.0047	(0.0007)	0.0010	(0.0006)	-0.0013	(0.0002)	0.28
BBB-rated Spreads							
12	-0.0004	(0.0003)	0.0002	(0.0002)	0.0023	(0.0003)	0.52
60	0.0005	(0.0002)	0.0003	(0.0002)	0.0043	(0.0002)	0.81
120	0.0012	(0.0002)	0.0003	(0.0002)	0.0050	(0.0002)	0.83
Level	0.0004	(0.0002)	0.0003	(0.0001)	0.0039	(0.0002)	0.81
Slope	0.0017	(0.0003)	0.0002	(0.0002)	0.0026	(0.0003)	0.35
Curvature	-0.0001	(0.0002)	-0.0000	(0.0002)	-0.0013	(0.0002)	0.28
B-rated Spreads							
12	-0.0066	(0.0009)	0.0038	(0.0007)	0.0059	(0.0009)	0.63
60	-0.0034	(0.0008)	0.0022	(0.0006)	0.0072	(0.0008)	0.64
120	0.0004	(0.0007)	0.0003	(0.0006)	0.0087	(0.0007)	0.62
Level	-0.0032	(0.0008)	0.0021	(0.0006)	0.0073	(0.0008)	0.65
Slope	0.0070	(0.0006)	-0.0035	(0.0005)	0.0028	(0.0006)	0.53
Curvature	0.0007	(0.0005)	-0.0002	(0.0004)	0.0001	(0.0005)	0.00

Table 6
Estimates of Term Structure Model Parameters

	Index i:						
	0	1	2	3	f	y	π
δ_ix100	0.310 (0.006)	0.049 (0.000)	0.042 (0.000)	0.000 (0.000)	0.017 (0.008)	0.116 (0.008)	0.008 (0.006)
γ_i^{BBB}x100	0.108 (0.002)	-0.015 (0.000)	0.016 (0.000)	0.007 (0.000)	0.011 (0.002)	-0.005 (0.002)	0.002 (0.002)
γ_i^{B}x100	0.337 (0.006)	-0.009 (0.000)	-0.029 (0.000)	0.064 (0.000)	0.041 (0.008)	-0.052 (0.008)	0.032 (0.006)
k_{1i}	–	0.321 (0.031)	0	0	0	0	0
k_{2i}	–	0.082 (0.006)	0.5238 (0.075)	0	0	0	0
k_{3i}	–	-0.043 (0.004)	0.0062 (0.004)	1.797 (0.087)	0	0	0
k_{fi}	–	0	0	0	0.405 (0.033)	0.924 (0.017)	0.161 (0.034)
k_{yi}	–	0	0	0	-0.233 (0.034)	0.712 (0.018)	-0.234 (0.034)
$k_{\pi i}$	–	0	0	0	-0.260 (0.026)	0.229 (0.014)	0.662 (0.027)
$\lambda_{0,i}$	–	-0.060 (0.004)	-0.057 (0.003)	-0.035 (0.002)	-0.006 (0.003)	-0.010 (0.012)	-0.034 (0.010)
$\lambda_{1,(1i)}$	–	-0.033 (0.002)	0	0	0	0	0
$\lambda_{1,(2i)}$	–	0	-0.043 (0.002)	0	0	0	0
$\lambda_{1,(3i)}$	–	0	0	-0.073 (0.002)	0	0	0
$\lambda_{1,(fi)}$	–	0	0	0	-0.121 (0.006)	0.039 (0.012)	0.111 (0.007)
$\lambda_{1,(yi)}$	–	0	0	0	-0.426 (0.013)	-0.205 (0.016)	-0.146 (0.010)
$\lambda_{1,(\pi i)}$	–	0	0	0	0.081 (0.021)	0.255 (0.034)	-0.052 (0.022)
Log-likelihood = 1279; AIC = -25510; BIC = -25385; Number of parameters = 42							

Notes: Asymptotic standard errors are reported in parentheses.

Table 7
Regressions of Latent Factors on Curve Dynamics

	Dependent Variable:					
	Latent 1		Latent 2		Latent 3	
	Estim. (Std. Err.)	R^2	Estim. (Std. Err.)	R^2	Estim. (Std. Err.)	R^2
Treasury Level	0.81 (0.05)	0.66	0.39 (0.08)	0.16	-0.06 (0.08)	0.00
Treasury Slope	-0.04 (0.08)	0.00	0.07 (0.08)	0.00	-0.16 (0.08)	0.03
Treasury Curvature	-0.66 (0.06)	0.44	-0.43 (0.08)	0.18	0.22 (0.08)	0.05
BBB Spreads Level	-0.63 (0.07)	0.40	0.43 (0.08)	0.18	0.58 (0.07)	0.34
BBB Spreads Slope	-0.43 (0.08)	0.18	-0.07 (0.08)	0.00	0.24 (0.08)	0.06
BBB Spreads Curvature	0.72 (0.06)	0.52	0.22 (0.08)	0.05	-0.24 (0.08)	0.06
B Spreads Level	-0.48 (0.07)	0.23	0.16 (0.08)	0.02	0.81 (0.05)	0.66
B Spreads Slope	0.23 (0.08)	0.05	0.04 (0.08)	0.00	-0.27 (0.08)	0.07
B Spreads Curvature	0.28 (0.08)	0.08	0.53 (0.07)	0.28	-0.02 (0.08)	0.00

Table 8
Variance Decompositions of Treasury Yields and Corporate Spreads

Maturity	Horizon	Financial	Real Activity	Inflation	Latent 1	Latent 2	Latent 3
Treasury Yields							
	3	0.01	0.33	0.00	0.37	0.29	0.00
3	12	0.19	0.23	0.02	0.32	0.24	0.00
	60	0.40	0.11	0.11	0.23	0.15	0.00
	3	0.02	0.25	0.00	0.39	0.34	0.00
12	12	0.19	0.18	0.01	0.34	0.28	0.00
	60	0.38	0.09	0.10	0.25	0.18	0.00
	3	0.10	0.02	0.01	0.37	0.50	0.01
60	12	0.20	0.02	0.00	0.34	0.44	0.00
	60	0.28	0.01	0.04	0.30	0.37	0.00
BBB-rated Spreads							
	3	0.08	0.02	0.01	0.05	0.66	0.19
3	12	0.13	0.01	0.03	0.06	0.66	0.11
	60	0.13	0.01	0.06	0.12	0.61	0.07
	3	0.08	0.01	0.00	0.07	0.61	0.23
12	12	0.14	0.01	0.02	0.08	0.63	0.13
	60	0.13	0.01	0.04	0.14	0.59	0.08
	3	0.11	0.01	0.01	0.16	0.28	0.44
60	12	0.16	0.01	0.01	0.19	0.35	0.29
	60	0.14	0.01	0.01	0.28	0.36	0.19
B-rated Spreads							
	3	0.04	0.01	0.13	0.08	0.23	0.51
3	12	0.18	0.01	0.19	0.07	0.21	0.34
	60	0.27	0.01	0.25	0.05	0.18	0.23
	3	0.04	0.01	0.08	0.07	0.25	0.54
12	12	0.19	0.01	0.13	0.07	0.24	0.36
	60	0.30	0.01	0.20	0.05	0.20	0.24
	3	0.11	0.00	0.00	0.05	0.29	0.55
60	12	0.27	0.00	0.02	0.04	0.29	0.38
	60	0.37	0.01	0.06	0.03	0.26	0.27

Notes: In this table we report the percentage of the conditional variances of Treasury yields (top panel), BBB-rated industrial spreads (middle panel) and B-rated industrial spreads (bottom panel) explained by each of the factors at various forecast horizons.

Table 9
Regressions of EDFs™ on Macro Factors

	Dependent Variable:							
	BBB-rated Industrials EDF™				B-rated Industrials EDF™			
	1	2	3	4	1	2	3	4
Fin	2.11	1.20	1.18	1.23	18.82	11.13	10.89	10.68
	(0.10)	(0.09)	(0.10)	(0.10)	(1.44)	(1.52)	(1.56)	(1.67)
Real	0.82	0.65	0.65	0.66	1.35	2.61	2.55	2.56
	(0.10)	(0.06)	(0.06)	(0.06)	(1.45)	(0.94)	(0.94)	(0.94)
Infl	0.56	0.34	0.35	0.35	2.71	-1.33	-1.24	-1.38
	(0.08)	(0.04)	(0.05)	(0.05)	(1.11)	(0.72)	(0.74)	(0.73)
Latent 1		-0.50	-0.48	-0.50		-6.20	-5.95	-6.14
		(0.08)	(0.08)	(0.08)		(1.23)	(1.27)	(1.23)
Latent 2		0.63	0.62	0.64		0.09	0.02	-0.06
		(0.06)	(0.06)	(0.07)		(1.04)	(1.05)	(1.07)
Latent 3		0.63	0.64	0.63		11.10	11.21	11.09
		(0.05)	(0.05)	(0.05)		(0.78)	(0.79)	(0.78)
Bond iss			0.00				0.00	
			(0.00)				(0.00)	
Def rate				-0.02				0.40
				(0.04)				(0.60)
R^2	0.82	0.95	0.95	0.95	0.69	0.89	0.89	0.89

Table 10
Estimates of Physical Intensity Parameters

	BBB-rated Spreads	B-rated Spreads
ω_0	-5.93 (0.02)	-3.49 (0.03)
ω_f	0.35 (0.04)	0.26 (0.04)
ω_y	0.13 (0.03)	0.00 (0.03)
ω_π	0.09 (0.02)	-0.05 (0.02)
ω_1	-0.27 (0.03)	-0.31 (0.03)
ω_2	0.30 (0.03)	0.09 (0.03)
ω_3	0.27 (0.03)	0.44 (0.03)
σ_e	0.056 (0.006)	0.685 (0.045)

Table 11
Regressions of Price of Default Event Risk on Macro Factors

	Dep. Var.: Γ_t^{BBB}					Dep. Var.: Γ_t^{B}				
	1	2	3	4	5	1	2	3	4	5
Fin	-4.87	-1.05	-2.14	-5.52	-4.25	-1.13	-0.25	-0.45	-1.22	-1.02
	(0.29)	(0.19)	(0.27)	(0.35)	(0.52)	(0.09)	(0.05)	(0.07)	(0.10)	(0.15)
Real	-1.14	-0.67	-1.10	-1.28	-1.01	-0.26	-0.28	-0.35	-0.28	-0.24
	(0.30)	(0.12)	(0.12)	(0.27)	(0.29)	(0.09)	(0.03)	(0.03)	(0.08)	(0.08)
Infl	-1.11	-0.33	-0.05	-1.05	-1.12	0.02	0.30	0.33	0.00	0.00
	(0.23)	(0.09)	(0.09)	(0.22)	(0.21)	(0.07)	(0.03)	(0.03)	(0.06)	(0.06)
Latent 1		2.92	2.48				0.74	0.67		
		(0.15)	(0.20)				(0.04)	(0.05)		
Latent 2		-2.43	-2.05				-0.32	-0.17		
		(0.13)	(0.12)				(0.04)	(0.03)		
Latent 3		-1.93	-2.06				-0.71	-0.79		
		(0.10)	(0.09)				(0.03)	(0.02)		
Fin^2			0.25					0.05		
			(0.09)					(0.02)		
Real^2			-0.13					-0.01		
			(0.12)					(0.03)		
Infl^2			0.11					0.02		
			(0.08)					(0.02)		
$(\text{Latent 1})^2$			-0.47					0.00		
			(0.09)					(0.02)		
$(\text{Latent 2})^2$			0.09					-0.01		
			(0.08)					(0.02)		
$(\text{Latent 3})^2$			0.44					0.16		
			(0.06)					(0.02)		
Issuance				0.05					0.00	
				(0.03)					(0.01)	
Defaults					-0.23					-0.04
					(0.13)					(0.04)
R^2	0.75	0.97	0.98	0.81	0.80	0.65	0.96	0.98	0.73	0.73

Table A.1
Summary Statistics on Macro Variables

Variable	Mean	SD	Skew	Kurt	Min	Max	Autocorrelation			
							Lag 1	Lag 2	Lag 3	Lag 4
Real Activity										
HELP	70.92	17.86	-0.66	2.05	35	93	0.98	0.96	0.94	0.92
UE	5.56	1.06	0.22	2.10	3.8	7.80	0.99	0.98	0.96	0.95
EMPLOY	1.17	1.04	-0.59	2.71	-1.52	3.19	0.93	0.87	0.81	0.74
IP	2.91	3.18	-0.82	3.04	-5.55	8.05	0.96	0.92	0.88	0.82
Inflation										
CPI	2.57	0.71	0.22	3.48	1.06	4.91	0.91	0.80	0.73	0.64
PCOM	0.73	11.24	0.55	2.70	-18.65	29.22	0.94	0.86	0.78	0.69
PPI	1.41	1.71	-0.38	2.46	-2.79	4.70	0.93	0.85	0.79	0.69
Financial										
DEBT/PRO	15.16	5.16	1.78	8.73	9.49	38.41	0.82	0.70	0.64	0.58
INT/GDP	0.03	0.01	1.06	3.59	0.03	0.047	0.88	0.74	0.58	0.43
PRO/SALES	0.03	0.01	-0.01	2.19	0.01	0.042	0.93	0.86	0.80	0.73
IMPVOL	17.84	5.12	0.59	2.90	9.83	31.50	0.73	0.60	0.55	0.50

Notes: This table reports summary statistics for the varibles used in the construction of the macro factors. Panel A reports the variables that capture real activity: the index of Help Wanted Advertising in Newspapers (HELP), unemployment (UE), the growth rate of employment (EMPLOY) and the growth rate of industrial production (IP). Panel B reports various inflation measures which are based on the Consumer Price Index (CPI), the Producer Price Index of finished goods (PPI), and Market Commodity Prices Index (PCOM). Panel C reports the data used in the construction of the financial activity factors are Final Sales of Domestic Product (SALES), Credit Market Debt (DEBT), Profit After Tax (PRO), Net Interest Payments (INT), GDP, and implied volatility on the SP500 (IMPVOL). Data on DEBT, PRO, INT, and GDP refer to Non Financial Corporate Business. Data on IMPVOL are obtained joining the Bloomberg historical call implied volatily observed on the SP500 index for the period 1994-2004 with the VIX index for the early sample 1992-1994. All growth rates (including inflation) are measured as the difference in logs of the index at time t and t -12, t in months. The variables EMPLOY, IP, CPI, PPI, and PCOM are measured by annual grow rates, where IP is the annual industrial production growth rate and CPI is the annual inflation rate. We collected data on SALES, PRO, INT, and GDP from the Bureau of Economic Analysis; data on DEBT are form the Flow of Funds (Liabilities). Data for UE, EMPLOY, CPI, and PPI are from U.S. Department of Labor, Bureau of Labor Statistics; while IP and HELP are from the Board of Governors of the Federal Reserve System.

Table A.2
Principal Components of Macro Factors

	Principal Components			
Variables	1st	2nd	3rd	4th
Real Activity				
HELP	-0.54	0.01	-0.78	-0.32
UE	0.34	0.90	-0.15	-0.21
EMPLOY	-0.55	0.19	0.60	-0.55
IP	-0.54	0.39	0.07	0.74
Variance (marg)	67.56	20.41	8.42	3.60
Variance (cum)	67.56	87.97	96.40	100
Inflation				
CPI	-0.59	0.54	-0.60	
PCOM	-0.43	-0.84	-0.33	
PPI	-0.68	0.058	0.73	
Variance (marg)	62.60	29.89	7.50	
Variance (cum)	62.60	92.50	100	
Financial				
DEBT/PRO	-0.56	0.11	-0.54	-0.63
INT/GDP	-0.52	0.20	0.81	-0.20
PRO/SALES	0.56	-0.25	0.24	-0.75
IMPVOL	-0.32	-0.94	0.05	0.08
Variance (marg)	69.39	19.98	8.46	2.17
Variance (cum)	69.39	89.37	97.83	100

Notes: This table reports the eigenvectors corresponding to the eigenvalues of the covariance matrices of the three groups of varibles used to construct the Real Activity factor (Panel A), the Inflation factor (Panel B), an the Financial factor (Panel C). The rows labeled *Variance (marg)* (*Variance (cum)*) display the marginal (cumulative) variance explained by each of the principal components. The numbers in these rows are the percentage variation in variables explained by the first k principal components computed as $100 \times \frac{\sum_{i=1}^{k} \Lambda_i}{tr(\Lambda)}$.

Table A.3
Correlations of Macro Factors with Macro Variables

	HELP	UE	EMPLOY	IP
Real Activity	0.88	-0.57	0.90	0.90
	CPI	PCOM	PPI	
Inflation	0.81	0.58	0.94	
	DEBT/PRO	INT/GDP	PRO/SALES	IMPVOL
Financial	0.93	0.86	-0.94	0.54

Notes: This table reports the correlations between the macro factors and the variables used to extract the first principal components.

Figure 1
Treasury Yields and Corporate Spreads

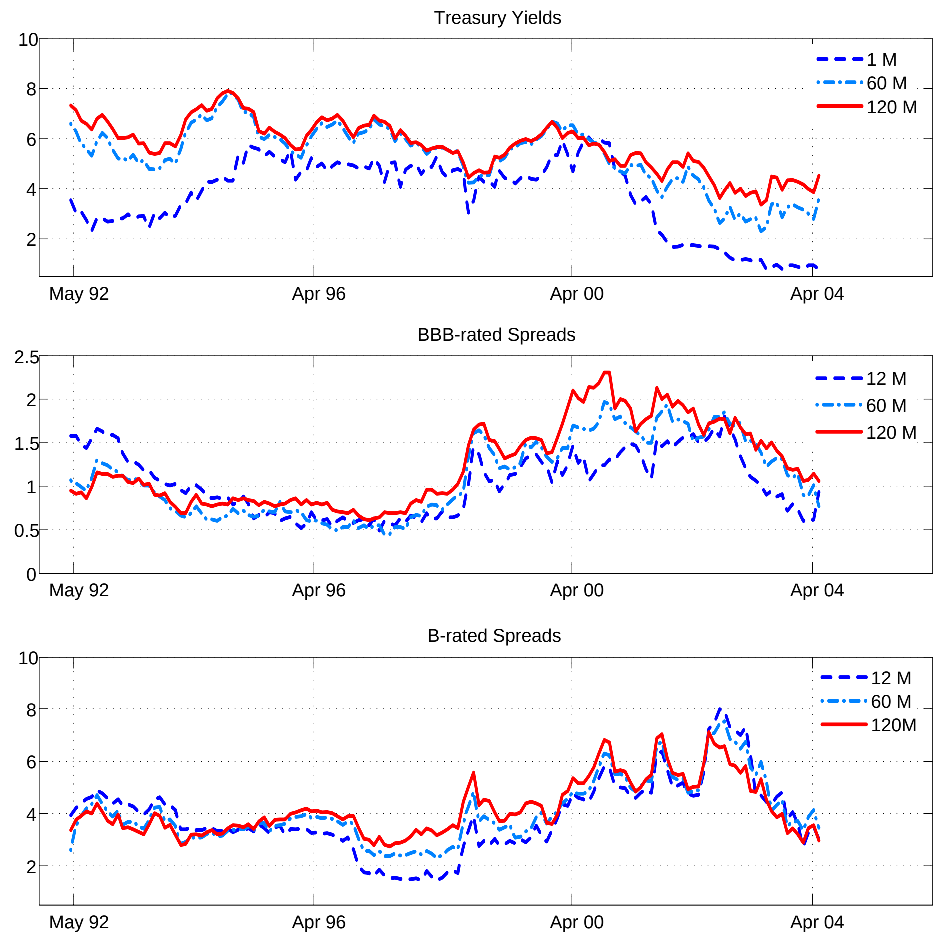
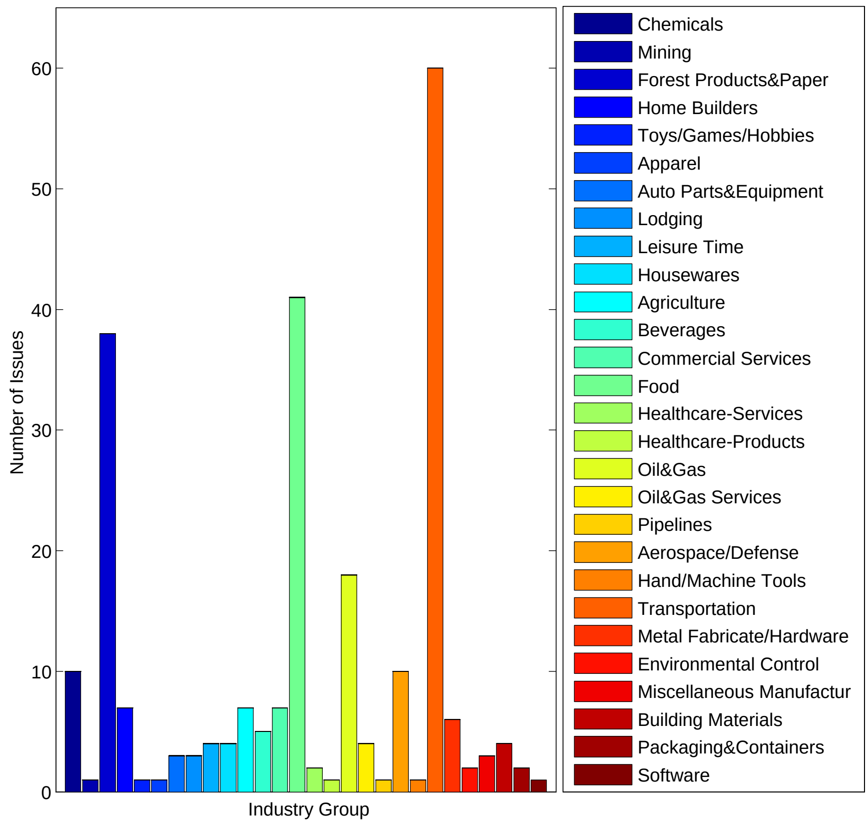


Figure 2
Industry Composition of BBB-rated Industrial Yield Curve



Notes: This graph reports the composition of the basket of bonds used to construct Bloomberg's BBB-rated industrial bond yield index on 24 August 2004.

Figure 3
Macroeconomic Factors

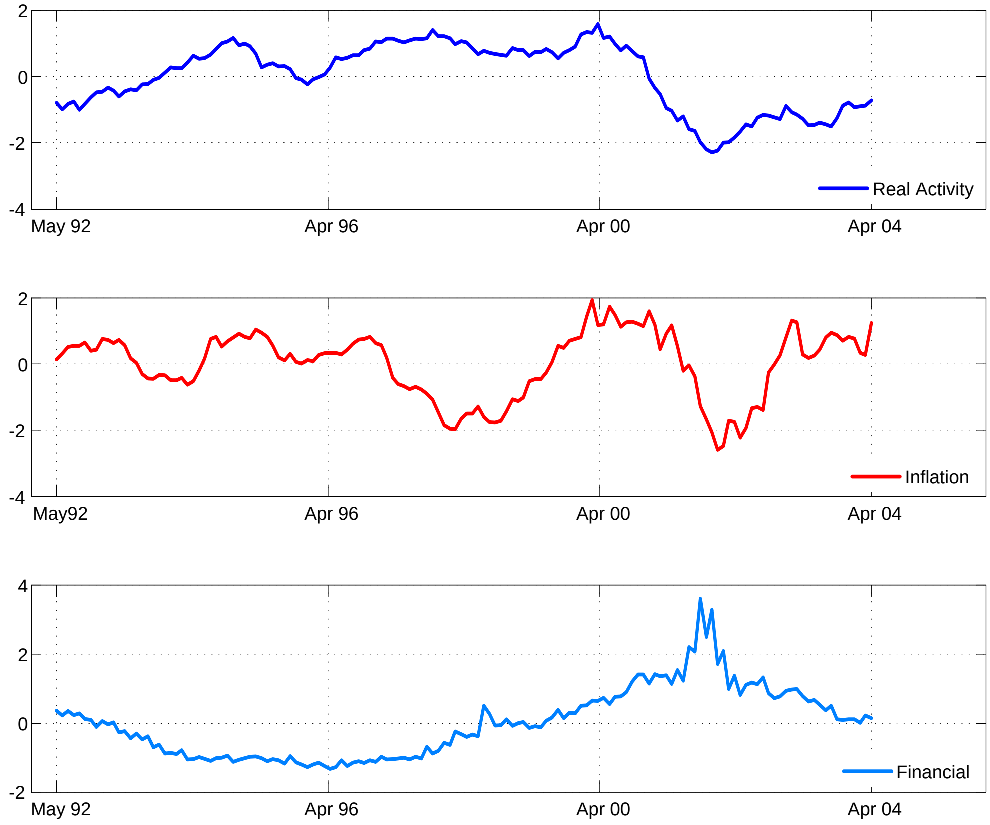


Figure 4
Market Prices of Systematic Risk

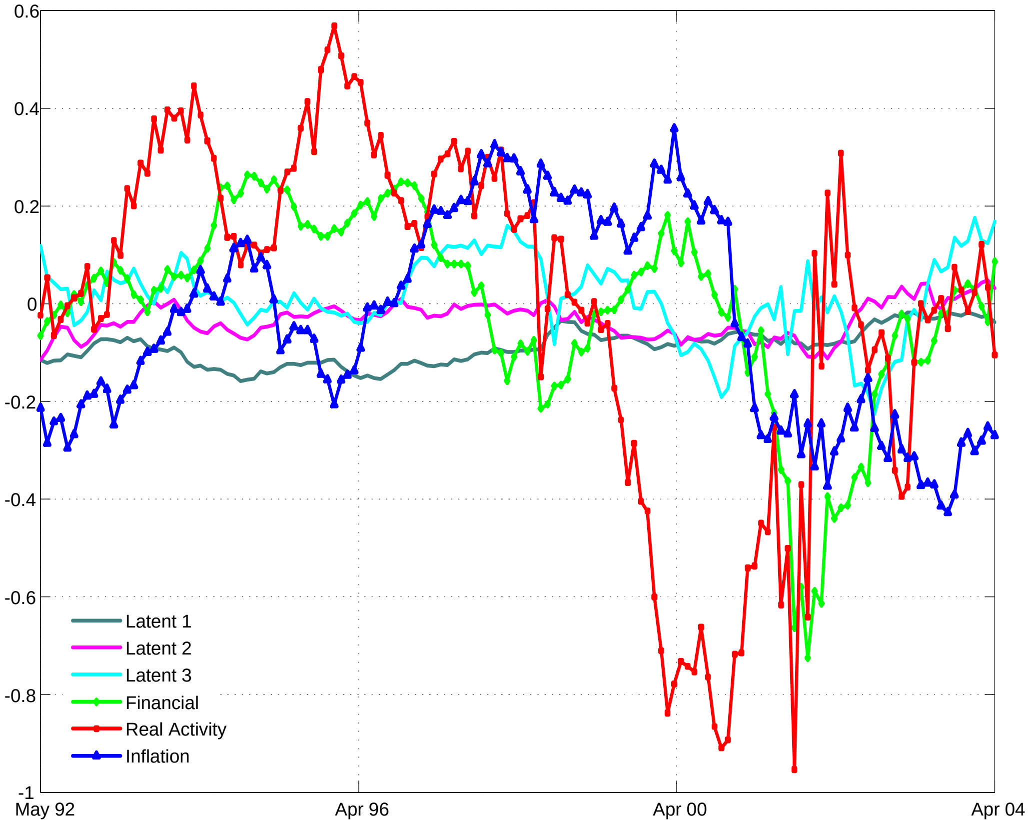
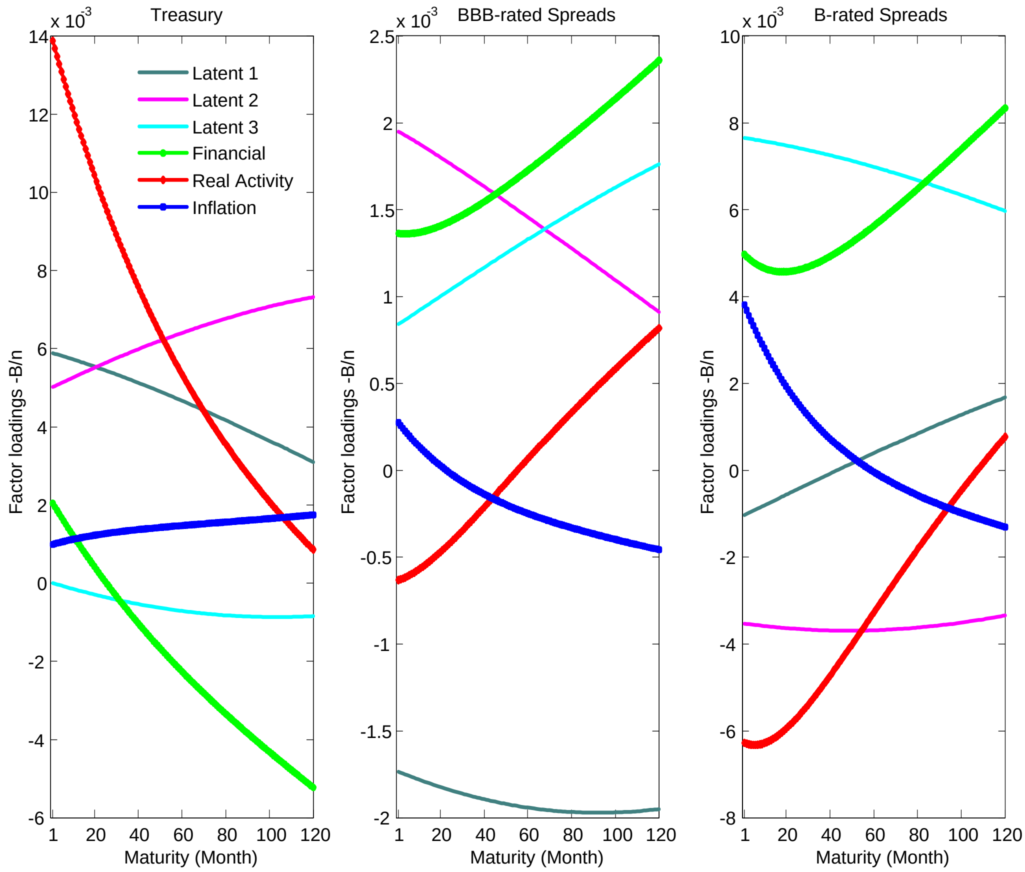


Figure 5
Factor Loadings



Notes: This figure displays the estimates of the factor loadings -B(N)/N in the affine expressions for bond yields and spreads.

Figure 6
Latent Factors

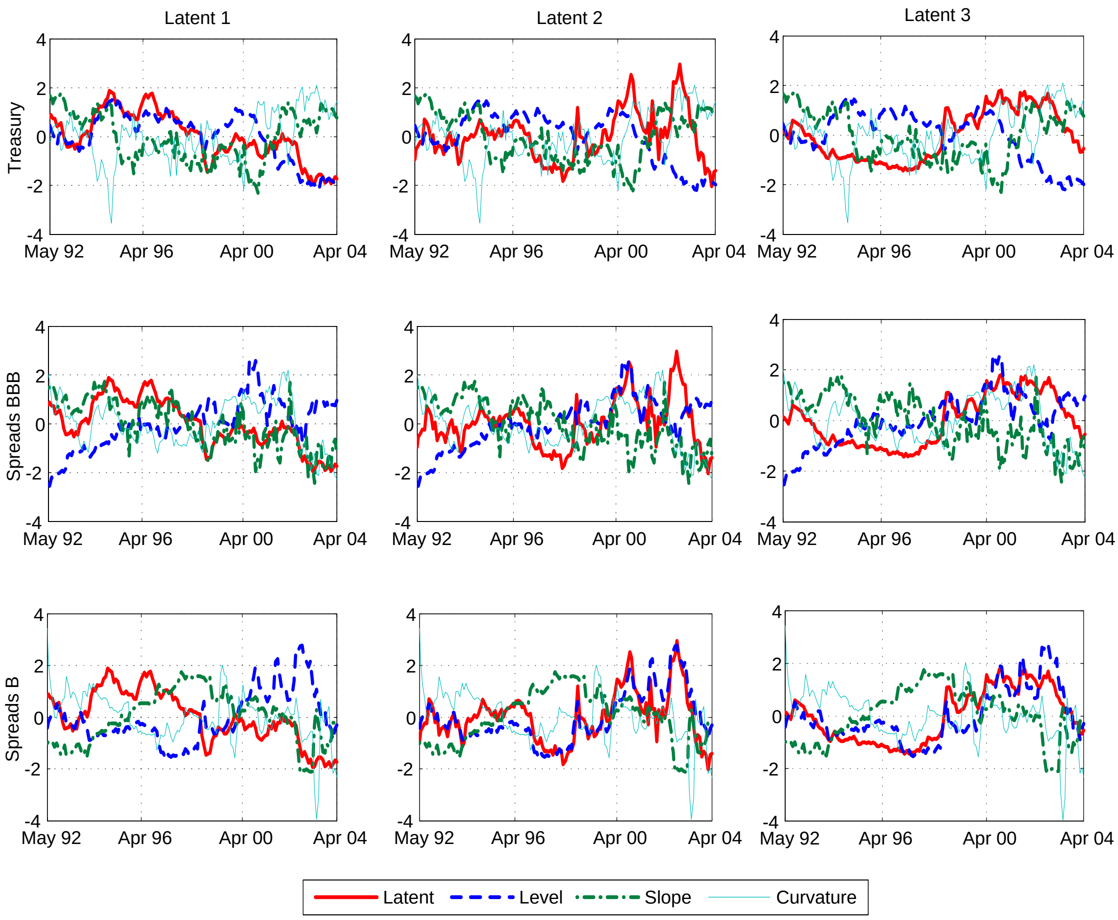


Figure 7
Risk-Neutral and Physical Default Intensities

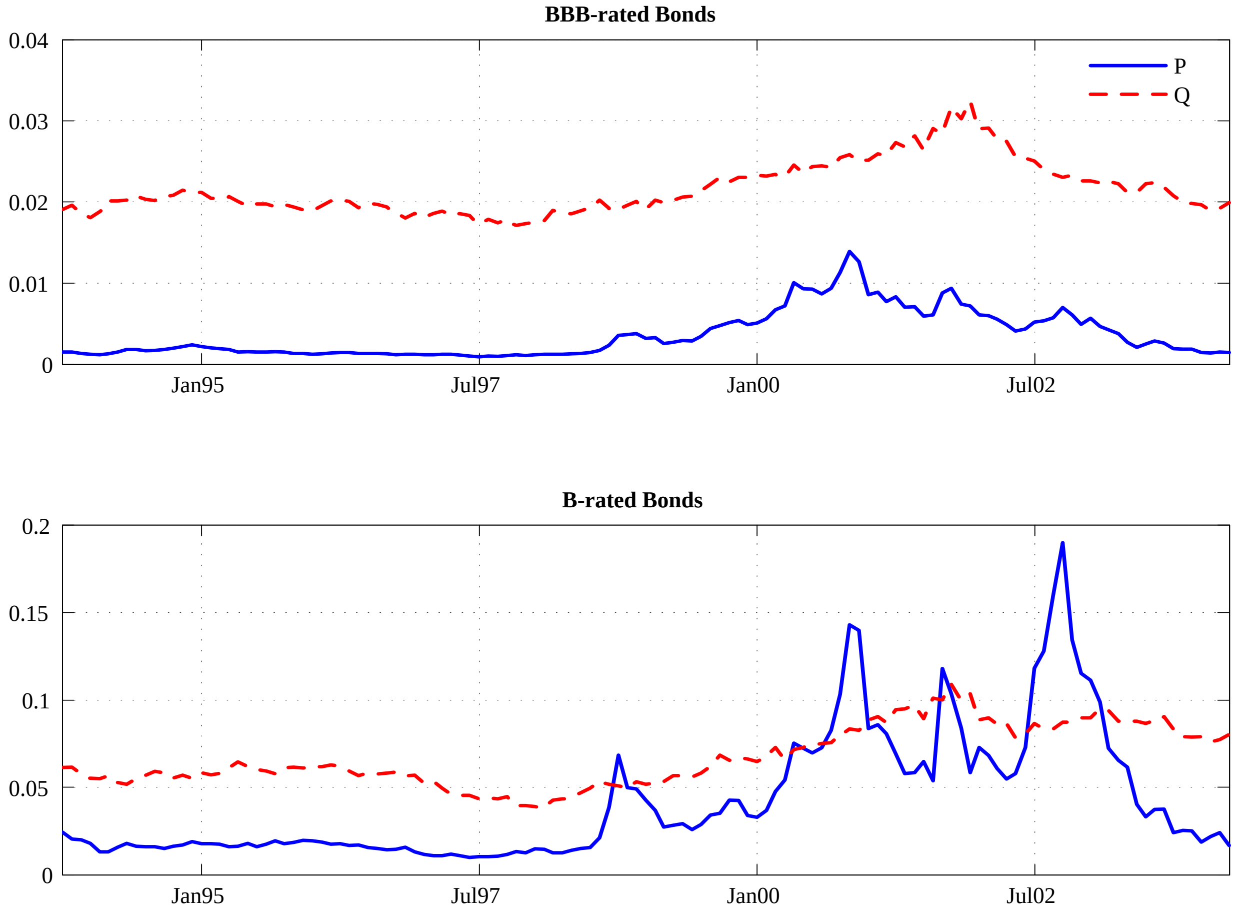


Figure 8
EDFs™ and Model-Based Physical Default Probabilities:
One-Year Horizon

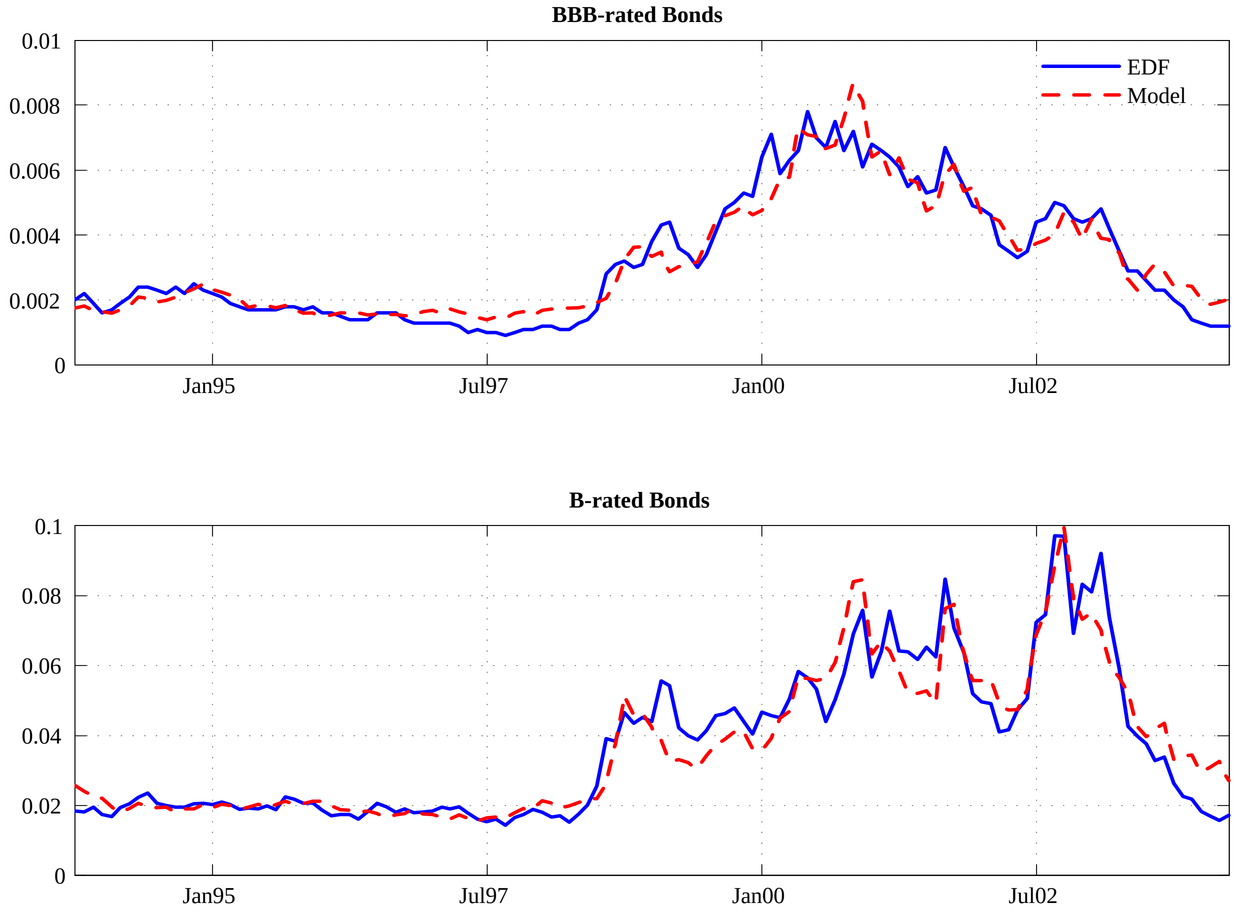


Figure 9
Market Prices of Default Event Risk

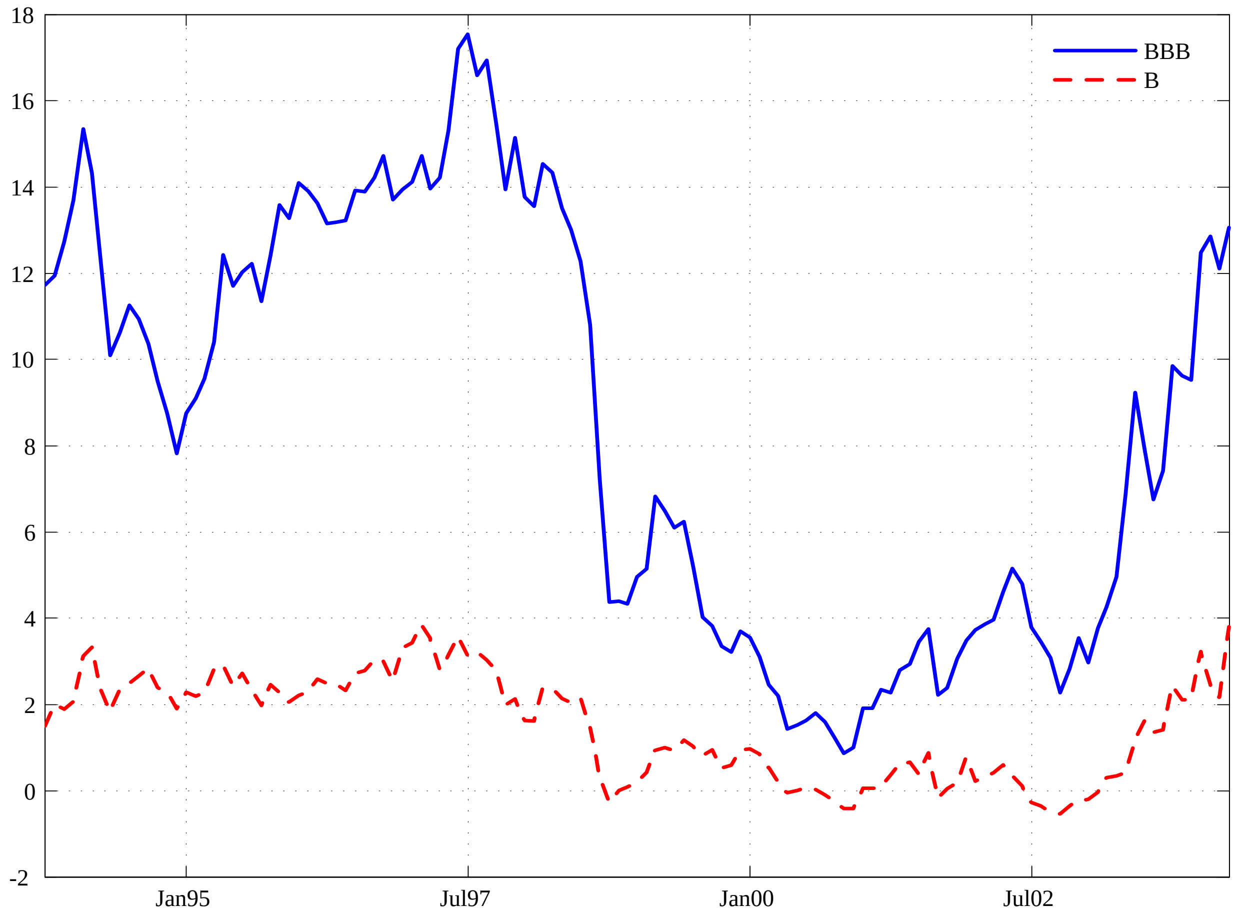


Figure 10
Model-Based Risk-Neutral and Physical Survival Probabilities:
Five-Year Horizon