Credit Spreads and Real Activity*

Preliminary. Comments are welcome.

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Abstract

This paper explores the transmission of credit conditions into the real economy. Specifically, I examine the forecasting power of the term structure of credit spreads for future GDP growth. I find that the whole term structure of credit spreads has predictive power, even though the term structure of Treasury yields has none. Using a parsimonious macro-finance term structure model that captures the joint dynamics of GDP, inflation, Treasury yields and credit spreads, I decompose the spreads and identify what drives the relationship between credit spreads and the real economy. I show that there is a pure credit component orthogonal to macroeconomic information that accounts for a large part of the forecasting power of credit spreads. The macro factors themselves also contribute to the predictive power, especially for long maturity spreads. Taken together, credit and macro factors capture virtually all predictability inherent in the actual spreads, while additional factors affecting Treasury yields and credit spreads are irrelevant. The credit factor is highly correlated with the index of tighter loan standards, thus lending support to the existence of a transmission channel from borrowing conditions to the economy.

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1 Introduction

In this paper, I explore the transmission of credit conditions into the real economy. Indeed, disturbances in the financial sector, if allowed to develop fully, could have severe negative consequences for real activity.[1] An implication of this link between credit markets and the economy is that credit spreads—i.e., the difference between corporate and Treasury yields—should forecast real activity. Establishing the presence of this link though is difficult because credit spreads in turn reflect current and lagged macroeconomic information that can potentially capture predictable components in future real activity. I use a no-arbitrage term structure model that captures the joint dynamics of GDP, inflation, Treasury yields and credit spreads to identify what drives the relationship between credit spreads and the real economy. I show that there is a component of credit spreads orthogonal to macroeconomic information that indeed forecasts future real activity, lending support to the presence of a transmission channel from borrowing conditions to the economy.

Exploring the relationship between credit spreads and future real activity can be motivated by the "financial accelerator" theory developed by Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1996, 1999). A key concept in this framework is the "external finance premium," the difference between the cost of external funds and the opportunity cost of internal funds due to financial market frictions. A rise in this premium makes outside borrowing more costly, reduces the borrower's spending and production, and consequently hampers aggregate activity. The external finance premium can fluctuate for many reasons. Changes in the premium could reflect real productivity shocks, monetary policy shocks, or even problems in the financial sector affecting borrowers' balance sheets. For forecasting future output however, it is immaterial where a shock to the external finance premium originates. The external finance premium is not directly observable. Credit spreads are a useful proxy although they need not be driven by the exact same factors as the external finance premium itself.

As a first step in my analysis, I use an OLS regression approach and examine the predictive power of credit spreads for the whole term structure and rating categories ranging from AAA to B

[1] In light of the recent turmoil in the financial markets, the relationship between financial instability and economic outlook has received a lot of attention. Federal Reserve Chairman Ben Bernanke and other Federal Reserve officials have repeatedly affirmed that the Federal Reserve Board is aware of the implications and dangers of disturbances in the financial sector for the broader economy. See, for example, Bernanke (2007a, 2007b) and Mishkin (2007a, 2007b).

by regressing future GDP growth on the spreads and control variables. I find that credit spreads across the whole spectrum of rating classes and across the whole term structure have predictive content above and beyond that contained in the term structure of Treasury yields and the history of GDP growth and inflation.

However, not every factor that affects credit spreads needs to be related to future GDP growth. Credit spreads could be related to GDP either through expectations of future rates, term premia, or one factor that is related to both.[2] The OLS approach is not suited for establishing the differences between the various potential drivers of the spreads. Understanding the difference between determinants of credit spreads and the drivers of the predictability helps learning about the transmission mechanism from borrowing conditions to real output.

A natural framework that does allow identifying and disentangling the sources of predictive power is a macro-finance term structure model.[3] Using the model we can decompose credit spreads (and Treasury yields) along two main dimensions. On the one hand, the spreads can be separated into a component given by expectations about the future short rate and the term premium. On the other hand, the spreads can be explicitly characterized as a function of the state variables in the model. Therefore, as a second step in my analysis, I estimate a parsimonious, yet flexible model with two observable (inflation and GDP growth) and three latent factors to capture the dynamics of the observed macro variables, Treasury yields and corporate bond spread curves.

Having estimated the model and explicitly separated out the various components of the credit spreads, I rerun the predictive regressions implemented in the first part of the paper using model implied spreads and individual components as regressors. The purpose is to investigate where the forecasting power inherent in the spreads originates from, which allows better GDP forecasts and more efficient use of the available information.[4] Namely, I am able to quantify the contributions of

[2] Credit spread term premia are defined as the difference between the credit spreads calculated under the risk neutral measure and the credit spreads calculated assuming zero prices of risk.

[3] This kind of model was first introduced by Ang and Piazzesi (2003). I use the term "macro-finance term structure model" to highlight the observable macro factors. Other authors simply use "no-arbitrage term structure model."

[4] Using only Treasury yields, Ang, Piazzesi, and Wei (2006) demonstrate that a macro-finance term structure model leads to more efficient and accurate forecasts compared to those obtained by the standard approach using unrestricted OLS regressions. The term structure forecasts also outperform a number of alternative predictors. Methodologically, my paper is, to the best of my knowledge, the first to examine the predictive content of the term structure of credit

expectations vs. term premia, and the relative importance of various factors in the model.

I find that one common "credit" factor is responsible for the incremental predictive power of credit spreads above the information contained in the history of inflation and GDP growth. Moreover, credit spreads across the whole term structure and for all rating classes react strongly to movements in this factor, whereas Treasury yields are largely unaffected. Finally, the credit factor is strongly correlated with the index of tighter loan standards from the Federal Reserve's quarterly "Senior Loan Officer Opinion Survey" and as such can be interpreted as a proxy for credit conditions.

Decomposing the spreads into an expectations and a term premia piece I find that both are relevant for predicting GDP growth. However, there is some variation across rating classes; the relative importance of the expectations piece is higher for lower grade credits. Unfortunately, knowing the relative importance of expectations and term premia does not provide a final answer to the question where the predictive power of the credit spreads comes from.

Separating spreads into contributions from the various factors yields more insights. I find that the most important contributor to the forecastability is the credit factor, explaining between 50% and 100% of the forecasting power. Macro factors are important for shorter forecast horizons, whereas the additional two factors in the model—while affecting Treasury yields and credit spreads—are largely irrelevant for forecasting purposes. Taken together, the macro factors and the credit factor capture virtually all predictive power inherent in the actual spreads.

The credit factor is constructed to be independent of current and past innovations in inflation and GDP growth. The strong predictive power of the credit factor provides evidence for the existence of a transmission channel from credit conditions to real activity. This finding is also consistent with the financial accelerator theory since the relationship between the external finance premium and future real activity does not depend on the origin of the shocks. The question where the shocks to the credit factor originate should be investigated in a structural model, which is beyond the scope of this paper. In the setup of this paper, disturbances in the financial sector could be purely exogenous or they could be driven by additional macro factors not captured in the empirical model.

The paper is organized as follows. Section 2 reviews the relevant literature in regards to the theoretical underpinnings why Treasury yields or credit spreads should be useful predictors of real activity. Section 3 establishes the predictive power of the term structure of credit spreads in a

spreads in a no-arbitrage framework.

simple regression framework. The macro-finance term structure model is introduced in Section 4 and the estimation methodology is discussed in Section 5. Section 6 presents the estimation results and identifies the sources of the predictive power and Section 7 concludes. The Appendix contains a detailed description of the data used in the paper, additional regression results and robustness checks, and technical details.

2 The External Finance Premium and Real Activity

Relating fixed income asset prices to future real activity involves thinking about which quantities should be in the center of focus: the level of interest rates such as the short rate or the difference between yields with different levels of risk such as credit spreads. This section describes the theoretical work that connects these ingredients with future output and provides the motivation for the empirical setup of the paper.

2.1 The Financial Accelerator Mechanism

A central measure in the relationship between fixed income asset prices and real output is the external finance premium, which is defined as the difference between the cost to a borrower of raising funds externally and the opportunity cost of internal funds. Due to frictions in financial markets, the external finance premium is generally positive. Moreover, the premium should depend inversely on the strength of the borrower's financial position, measured in terms of factors such as net worth, liquidity, and current and future expected cash flows.

A higher external finance premium—or, equivalently, a deterioration in the cash flow and balance sheet positions of a borrower—makes borrowing more costly and reduces investment and hence overall aggregate activity, thus creating a channel through which otherwise short lived economic or monetary policy shocks may have long-lasting effects. This framework is known as financial accelerator and was developed by Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1996, 1999).

Although the financial accelerator effect originally refers to the increase in persistence and amplitude of business cycles, the concept generally applies to any shock that affects borrower balance sheets or cash flows. In particular, the framework is also useful in understanding the monetary policy transmission process. Bernanke and Gertler (1995) argue that monetary policy works not only through the traditional cost-of-capital channel but also through effects similar to the financial accelerator that make monetary policy more potent. They distinguish between two separate credit channels. The balance sheet channel, builds on the premise that changes in interest rates affect net worth and thus the external finance premium. As a result, the first order effects of monetary policy actions through the cost-of-capital channel are intensified by the financial accelerator. The bank-lending channel, works in a more subtle way as it is concerned with how monetary policy can affect the supply of loans by banks. If bank balance sheets deteriorate or the external finance premium rises, the supply of loans shrinks, which eventually adversely affects economic growth.

The financial accelerator and the credit channel frameworks highlight how credit market conditions can propagate and amplify cyclical movements in the real economy or strengthen the influence of monetary policy, respectively. In addition, Bernanke and Gertler (1990) show that disturbances in the financial sector also have the potential to initiate cycles, which underlines the generality of the idea that regardless of its origin, a rise in the external finance premium or a deterioration of borrowers' balance sheets eventually results in slower growth.

2.2 Proxies for the External Finance Premium and Forecasting Real Activity

The external finance premium is not directly observable. Moreover, the short review in Section 2.1 indicates that the external finance premium can be affected by a variety of shocks. Empirically, risk-free interest rates and credit spreads may react differently to those shocks. For example, an increase in the external finance premium due to expectations of higher default rates should mainly be reflected in widening credit spreads, not rising risk-free rates. On the other hand, a higher external finance premium due to a positive monetary policy shock is reflected in a higher short-term interest, and not in credit spreads.[5]

Because fluctuations in the external finance premium can be reflected in either risk-free interest

[5] A priori, it is not obvious, how the short rate and credit spreads are linked. Morris, Neal, and Rolph (2000) provide empirical evidence that the relationship between Treasury yields and credit spreads depends on the time horizon. In the short run, Treasuries and credit spreads are negatively correlated because a rise in Treasury yields produces a proportionally smaller rise in corporate bond yields, whereas in the long run, the correlation is positive.

rates, credit spreads or both, it is sensible to investigate the empirical link between real activity and all of them. So far, the existing empirical literature concerned with predicting GDP growth using asset prices has focused on the term spread and, to a lesser extent, on the short rate.[6] Historically, the term spread has been a widely used and reliable predictor of economic activity, but its forecasting power has been declining since the mid-1980s.[7] However, this does not mean that the relationship between interest rates and real activity has disappeared but simply, that it is no longer detectable in the data. In fact, if the Federal Reserve reacts systematically and decisively to expected fluctuations in either inflation or real output under a stabilizing monetary policy, it works to eliminate them altogether. Boivin and Giannoni (2006) find that monetary policy has been more stabilizing since the early-1980s, which explains the lack of predictive power of the term spread during that period.[8]

Empirical evidence on the performance of credit spreads as predictors of GDP on the other hand is very scarce. The few existing studies consistently find that credit spreads are useful predictors of real activity. At the same time, it is an open debate which particular credit spread is the best proxy for the external finance premium. Gertler and Lown (2000) and Mody and Taylor (2004) argue that the right measure is a long-term high yield spread and they show that it outperforms other leading indicators—including the term spread—since the data has become available in the mid-1980s.[9] Chan-Lau and Ivaschenko (2001, 2002) on the other hand argue for the use of investment grade credit spreads and they also find some predictive power to back up their claim. However, the existing literature fails to explore the information content of the whole term structure and across different rating classes. It remains unclear, whether all credit spreads have the same predictive power and, if not, which spread should be chosen for forecasting purposes.

The remainder of the paper has two main goals. First, I fill a gap in the empirical literature and establish the predictive power of the whole term structure of credit spreads for different rating classes in a simple OLS regression framework as opposed to investigating the forecasting power of

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[6] The Treasury term spread is defined as the difference between interest rates on long and short maturity government debt. See Stock and Watson (2003a) for a comprehensive survey.

[7] See, for example, Dotsey (1998).

[8] Boivin and Giannoni (2006) also provide evidence that the reduced effect of monetary policy shocks is largely due to an increase in the Federal Reserve's responsiveness to inflation expectations.

[9] Stock and Watson (2003b) find mixed evidence for the junk bond spread as a leading indicator as it falsely predicted a slowdown in 1998 although it still outperforms other indicators in a one-by-one comparison.

one arbitrary credit spread. Second, I seek to understand what drives the predictive power. This requires decomposing the credit spreads into components that may or may not reflect the external finance premium and thus be related to future GDP growth. To achieve this, I need to go beyond the OLS framework and estimate a macro-finance term structure model, which allows identifying the drivers of the credit spreads.

The macro-finance model is estimated without the underpinnings of a structural macroeconomic model. Consequently, even though the model allows identifying latent factors that are unrelated to observed macro variables it is not possible to pinpoint exactly what the actual causal relationships are between the state variables in the model. However, as mentioned in Section 2.1, the financial accelerator theory is ultimately agnostic about the source of shocks to the external finance premium. While it may be of independent interest to better understand the shocks to the external finance premium, I focus on the transmission mechanism from the external finance premium to real activity. Thus, a result that links one of the drivers of the predictive power to the external finance premium would be consistent with the financial accelerator mechanism.

3 Forecasting Regressions

This section examines the in-sample predictive content of credit spreads using OLS regressions. Over the 1992:2–2005:4 sample period, I document the strong predictive relationship between real activity and credit spreads across the whole term structure, even when adding contemporaneous and lagged GDP growth and inflation, and the 5-year term spread as control variables.[10]

3.1 Data and Methodology

Denote the annualized log real GDP growth from t to $t+k$ expressed at a quarterly frequency as

$$g_{t,k} = \frac{400}{k} \log \left(\frac{GDP_{t+k}}{GDP_t} \right) = \frac{1}{k} \sum_{i=1}^{k} g_{t+i}. \tag{1}$$

Using this notation, $g_{t,1} = g_{t+1}$. Furthermore, denote the credit spread for a rating class i and maturity τ as $CS_t^i(\tau) = y_t^i(\tau) - y_t^T(\tau)$, where $y_t^i(\tau)$ and $y_t^T(\tau)$ are the corporate and Treasury yields,

[10] Some robustness checks using an extended sample period are performed in Appendix C.

respectively. The Treasury yields used are unsmoothed Fama-Bliss zero coupon bond prices for maturities ranging from three months up to ten years.[11] Zero coupon corporate bond yields for the same maturities and rating classes AAA, BBB and B are taken from Bloomberg. Credit spreads are calculated as the difference between the corporate and the Treasury yields. GDP data are available through the FRED database (Federal Reserve Bank of St. Louis). A detailed description of the data is provided in Appendix A.

The predictive power of the credit spreads can be examined in the following regressions:

$$g_{t,k} = \alpha_k^i(\tau) + \beta_k^i(\tau) CS_t^i(\tau) + controls + u_{t+k}. \tag{2}$$

Future GDP growth for the next k quarters is regressed on the credit spread for rating class i and maturity τ. I am careful to avoid overstating the predictability by using Hodrick (1992) (1B) standard errors, which appropriately account for heteroskedasticity and moving average error terms u_{t+k}.

Since GDP growth is serially correlated, its own past values are themselves useful predictors. This means, the *controls* in the regression equation (2) should include current and lagged GDP values in order to determine whether the credit spreads have predictive content for real activity over and beyond what is contained in past values. Furthermore, GDP growth and inflation are negatively related.[12] To answer the question whether the term structures of credit spreads contain relevant information that is not already included in the history of GDP growth and inflation itself, current and lagged values of inflation, π, should also be added as control variables.[13]

Historically, the term structure of Treasury yields and the term spread in particular has been a good predictor of real activity. In order to verify that the predictive power of credit spreads is not driven by information already contained in Treasury yields, I also include the 5-year term spread and the short rate as a control variable.

In addition to running the regression (2), I also run the following regression:

$$g_{t,k} = \alpha_k + \delta_k(L) g_t + \eta_k(L) \pi_t + u_{t+k}, \tag{3}$$

where $\delta(L)$ and $\eta(L)$ denote lag polynomials such that $\delta(L) = \delta^{(1)} g_t + \delta^{(2)} g_{t-1} + ... + \delta^{(p)} g_{t-p+1}$ and p is the number of lagged values of GDP growth included (g_t is a lagged value relative to the forecasted

[11] I thank Rob Bliss for providing me with the Treasury yield data.

[12] See, for example, Fischer (1993), or Bruno and Easterly (1998).

[13] Inflation is calculated as the growth rate in CPI, available through the FRED database (Federal Reserve Bank of St. Louis).

variable). Unless otherwise noted, regression (2) with controls and regression (3) are performed with $p = 2$, which means current and lagged GDP growth and inflation are included.

3.2 Credit Spread Regressions

This section reports the results from regressing future GDP growth on credit spreads. To summarize, I find the following: (1) Credit spreads across the whole spectrum of rating classes and maturities (only with the exception of short maturity AAA spreads) have predictive power, even when controlling for the information contained in the history of the macro variables and the term structure of Treasury yields; (2) longer maturity spreads perform better than short maturity spreads for the same rating class in terms of R^2s; (3) combining spreads of different maturities and rating classes in a single regression helps improving adjusted R^2s suggesting that the forecasting power may be driven by more than a single factor.

3.2.1 Univariate Regressions

Table 1, panel A contains the results for the $\beta_k^i(\tau)$ coefficients in the simple univariate credit spread regression without controls for the sample period 1992:2–2005:4. Apart from short-term AAA spreads, almost all $\beta_k^i(\tau)$ coefficients are significantly different from zero. Panel B in Table 1 displays the same $\beta_k^i(\tau)$ coefficients for the credit spread regressions including control variables. All coefficients that are significant in the univariate regressions are also significant in the full multivariate regressions with all the controls. Current and lagged GDP values are insignificant in general, whereas coefficients for current and lagged inflation are significantly negative for forecast horizons one year and above, confirming the documented negative relationship between inflation and real activity.[14] The coefficient for the term spread is insignificant in general. The addition of the history of macro variables has a positive effect on both, R^2s and adjusted R^2s, thus suggesting that macro variables are indeed relevant for explaining future GDP growth.[15]

While overall, the results clearly indicate that credit spreads have significant forecasting power, there are differences across rating classes and maturities. In general, longer maturity spreads perform

[14] Coefficients other than those for the credit spreads are not reported.

[15] Adding more lags of the macro variables does not qualitatively change the results for the credit spread coefficients, i.e. the significant coefficients remain significant; however, adjusted R^2s do not improve further.

better than shorter maturity spreads for the same rating class. 1-year AAA spreads for example are not significant, and R^2s for 10-year BBB spreads are much higher than those for 1-year spreads. The only exceptions to this regularity are horizons below one year for forecasting regressions using B spreads. At the same time, the results for B spreads are very robust to the choice of maturity—the discrepancy in terms of R^2s is very small.

Despite exhibiting consistent forecasting power across the whole term structure, B spreads are not the best predictor based on the R^2. Investment grade credits can reach R^2s of over 60%, whereas the maximum R^2 for the 10-year B spread is a mere 28%. This result seems to contradict Gertler and Lown (2000) who argue that high yield spreads are particularly suitable for forecasting GDP growth because lower rated firms face a higher external finance premium and are more likely to suffer from financial market frictions. Alternatively, the results could also be driven by the fact that the credit spreads are a polluted measure of the external finance premium in the first place.

Panel C in Table 2 summarizes the R^2s from the full regressions using all control variables. In addition, the table contains the R^2s from regressing future GDP growth on (1) the history of macro variables only (panel A) and (2) the history of macro variables and the short rate and various term spreads (panel B), respectively. This allows to assess the impact of adding variables to the regression with macro variables only. The results in panel B reveal that including either the short rate or various term spreads in regression (1) leaves R^2s basically unaffected (with the exception of short horizon forecasts using the 1-year spread). This lack of an effect is consistent with the demise of the term structure of Treasury yields as a predictor of real activity after the period of monetary tightening under Chairman Paul Volcker ended in the mid-1980s. The full regression results using Treasury yields documenting the declining predictive power of the short rate and the term spread are reported in Appendix B.1.

Only the inclusion of the credit spreads (panel C) improves R^2s significantly (again, with the exception of short maturity AAA spreads). This result implies that credit spreads do contain relevant information not present in past GDP growth, inflation or the Treasury yield curve. As an additional exercise to corroborate this conclusion I estimate simple VARs that include the 10-year B spread in addition to GDP, inflation and the short rate. Shocks to the credit spread that are orthogonal to the short rate, GDP and the price level have a significant effect on the future path of the economy (see Appendix B.2 for detailed results).

3.2.2 Multivariate Regressions

To further examine whether the whole term structure of credit spreads is relevant, I use multiple spreads for a rating class in a single regression; namely, I choose to combine information from the "level" and the "slope" of the term structure of credit spreads. In analogy to terminology used for Treasury yields, the level is given by the 3-month spread and the slope is defined as the difference between the 3-month and the 10-year spread for a given rating class i, respectively. The results for the multivariate regressions using both the level and the slope are displayed in Table 1, panels C (without controls) and D (including controls). Again, the controls do not drive the results.

Adding another piece of information to the regression improves the R^2s for all rating classes and horizons by up to 4 percentage points. Moreover, coefficients on the slope and level are both significant for AAA spreads for horizons between two and three years and for BBB spreads for horizons two quarters and above. In the case of B spreads, all relevant information is picked up by the level. This suggests that at least for investment grade credits, different maturity spreads contain different relevant information. Thus, there seems to be a benefit in using several different credit spreads as opposed to arbitrarily picking one.

Obviously, spreads can also be combined across rating classes. Depending on the forecast horizon, a different, seemingly arbitrary combination of spreads results in the highest R^2s.[16] This can be taken as evidence that the whole term structure of credit spreads across the whole rating spectrum contains relevant information for forecasting future GDP growth. Unfortunately, the regression framework does not allow to systematically analyze which spreads are most informative and which combination is the right one for a given horizon. At the same time, knowing the right combination would not give us much insight as to what is actually driving the forecasting power. Being able to attribute the forecasting power of the credit spreads to a number of underlying factors will also give us some additional confidence in the validity and persistence of the spreads as leading indicators for future real activity.

Section 4 introduces a macro-finance model, which allows to disentangle and pin down the factors that drive credit spreads and that are responsible for the predictive power. The model will also be helpful in understanding the break-down of the term spread as a leading indicator since the mid-1980s.

[16] Results for this exercise are not reported.

4 A Macro-Finance Term Structure Model

The macro-finance term structure model described in this section helps disentangling the different sources of predictability found in the term structure of credit spreads. The model builds on the macro-finance literature starting with Ang and Piazzesi (2003) that links the dynamics of the term structure of Treasury yields with macro factors by adding credit spreads as observable data.

Duffee (1999) and Driessen (2005) estimate a no-arbitrage term structure model with credit spreads but they do not include macro variables. Wu and Zhang (2005) is the first paper to examine the joint behavior of macro variables and credit spreads in a three-factor model with observable factors only. Amato and Luisi (2006) estimate a version that combines observable and latent factors but they do not allow for the latent variables to influence the macro factors. The model presented in this section is more general and specifically allows to investigate how shocks to latent factors can feed back into the real economy.

4.1 State Variables

The model is set in discrete time at quarterly frequency. I assume that the joint behavior of the Treasury yields and corporate bond spreads is captured by the state vector $z_t = [\ m_t \quad x_t\ ]'$. The vector of macroeconomic variables contains GDP growth and inflation and is given by $m_t = [\ g_t \quad \pi_t\ ]'$. Even though the focus of the paper is on forecasting GDP growth, inflation is explicitly included as an observable state variable because of its importance in determining monetary policy. Therefore, I am interested in separating out the effect of inflation from other information contained in credit spreads. x_t denotes the vector of latent factors in the model and can contain lags of m_t, any other macro variables not explicitly modeled, or any unknown variables. This means that z_t fully reflects the available information at time t.

The state vector follows a VAR(1) process under the physical probability measure $\mathbb{P}$,

$$z_t = \mu + \Phi z_{t-1} + \Sigma \epsilon_t, \tag{4}$$

where $\epsilon_t \sim N(0, I)$.

4.2 Treasury yields

The short-term interest rate r_t is assumed to be a linear function of the state variables:

$$r_t = \delta_0 + \delta_z' z_t = \delta_0 + \delta_m' m_t + \delta_x' x_t. \tag{5}$$

In order to value the assets, the model needs to be completed by specifying the stochastic discount factor ξ_t :

$$\xi_t = -r_{t-1} - \frac{1}{2}\Lambda_{t-1}' \Lambda_{t-1} - \Lambda_{t-1}\epsilon_t, \tag{6}$$

where the market prices of risk follow the essentially affine specification (Duffee (2002)):

$$\Lambda_t = \Lambda_0 + \Lambda_z z_t. \tag{7}$$

Under these assumptions, yields on zero coupon Treasury bonds are linear in the state variables:

$$\begin{aligned} y_t^T(\tau) &= a^{\mathbb{Q}}(\tau) + b^{\mathbb{Q}}(\tau)' z_t \\ &= a^{\mathbb{Q}}(\tau) + b_m^{\mathbb{Q}}(\tau)' m_t + b_x^{\mathbb{Q}}(\tau) x_t && (8) \\ &\triangleq \underbrace{a^{\mathbb{P}}(\tau) + b^{\mathbb{P}}(\tau)' z_t}_{\text{Short rate expectations}} + \underbrace{a^{TP}(\tau) + b^{TP}(\tau)' z_t}_{\text{Term premium}} && (9) \end{aligned}$$

where τ is the respective maturity and $a^{\mathbb{Q}}$ and $b^{\mathbb{Q}}$ solve well-known recursive equations with boundary conditions $a^{\mathbb{Q}}(1) = \delta_0$ and $b^{\mathbb{Q}}(1) = \delta_z$.[17] In particular, this means that $y_t^T(1) = r_t$; using quarterly data, the nominal risk-free rate is the 3-month Treasury yield.

The second line of equation (8) decomposes the yields into the expectations of the future short rate and the term premium. The first component can be calculated using the usual factor loadings and assuming zero market prices of risk.

4.3 Corporate Bond Spreads

Duffie and Singleton (1999) show that defaultable bonds can be valued as if they were risk-free by replacing the short rate r_t with a default adjusted rate $r_t + s_t$, where s_t can be interpreted as the product of the risk-neutral default probability and loss given default and is called the "instantaneous default spread."

[17] For the recursive equations see Ang and Piazzesi (2003).

If we assume the instantaneous spread to be a linear function of the state variables:

$$s_t^i = \gamma_0^i + \gamma_z^{i\prime} z_t = \gamma_0^i + \gamma_m^{i\prime} m_t + \gamma_x^{i\prime} x_t, \tag{10}$$

yields on zero coupon corporate bonds for a given rating class $i = \{AAA, BBB, B\}$ will also be linear in the state variables.

$$y_t^i(\tau) = \tilde{a}^{i,\mathbb{Q}}(\tau) + \tilde{b}^{i,\mathbb{Q}}(\tau)' z_t. \tag{11}$$

Credit spreads can then be calculated as the difference between the yields on defaultable and default-free bonds and decomposed into expectations and term premia just as Treasury yields.

$$\begin{aligned}
CS_t^i(\tau) &\triangleq y_t^i(\tau) - y_t^T(\tau) \\
&= (\tilde{a}^{i,\mathbb{Q}}(\tau) - a^{\mathbb{Q}}(\tau)) + (\tilde{b}^{i,\mathbb{Q}}(\tau) - b^{\mathbb{Q}}(\tau))' z_t \\
&\triangleq a^{i,\mathbb{Q}}(\tau) + b^{i,\mathbb{Q}}(\tau)' z_t \\
&= a^{i,\mathbb{Q}}(\tau) + b_m^{i,\mathbb{Q}}(\tau)' m_t + b_x^{i,\mathbb{Q}}(\tau) x_t && (12) \\
&\triangleq \underbrace{a^{i,\mathbb{P}}(\tau) + b^{i,\mathbb{P}}(\tau)' z_t}_{\text{Short rate expectations}} + \underbrace{a^{i,TP}(\tau) + b^{i,TP}(\tau)' z_t}_{\text{Term premium}} && (13)
\end{aligned}$$

5 Econometric Methodology

The model parameters of the term structure model are estimated jointly via maximum likelihood with Kalman filter following Bikbov and Chernov (2006), Duffee and Stanton (2004), and de Jong (2000), among others.

5.1 Observation Equations

GDP growth and inflation represent the two observable state variables in the model. Treasury yields and credit spreads are the observable data, which help estimating the parameters of the model. GDP and inflation data are taken from the FRED database (Federal Reserve Bank of St. Louis), Treasury yields are unsmoothed Fama-Bliss zero coupon bond prices provided by Rob Bliss and credit spreads are calculated as the difference between zero coupon corporate bond yields taken from Bloomberg and the zero coupon Treasury yields. All yields are available for three and six months, and one, two, three, five, seven and ten year maturities. A detailed description of the data is provided in Appendix A.

The macro variables are assumed to be observed without errors. Furthermore, I allow for estimation errors for both Treasury yields and corporate credit spreads. This assumption is necessary to be able to specify the model in state-space form. In addition, this specification means that the latent factors are not per se associated with a predetermined set of yield maturities that could be used to solve for the latent factors directly.

The state equation in the model is defined by equation (4). In addition, we have the observed asset prices, which represent the observation equations as follows:

$$y_t^T(\tau) = a^{\mathbb{Q}}(\tau) + b_m^{\mathbb{Q}}(\tau)' m_t + b_x^{\mathbb{Q}}(\tau)' x_t + \varepsilon_t \tag{14}$$

and

$$CS_t^i(\tau) = a^{i,\mathbb{Q}}(\tau) + b_m^{i,\mathbb{Q}}(\tau)' m_t + b_x^{i,\mathbb{Q}}(\tau)' x_t + \varepsilon_t^i, \tag{15}$$

where y_t^T represents the Treasury yields for maturity τ and CS_t^i stands for the corporate bond spread for rating class i and maturity τ. The right-hand side of equations (14) and (15) are expanded versions of equations (8) and (12).

The estimation errors are denoted by ε_t and ε_t^i, respectively. I assume that the Treasury yield estimation errors are i.i.d normal with standard deviation σ_ε. The credit spread estimation errors are also assumed to be i.i.d normal with standard deviation σ_ε^i.

5.2 Number of Factors and Identification

Jointly fitting a total of eight Treasury yields and twenty-four credit spreads (three rating classes, eight spreads each) with a parsimonious term structure model is a daunting task. In addition, two of the factors are already given by the observable macro variables in the model. A principal components analysis of the yields and credit spreads reveals that at least three latent factors are needed to capture around 92% of the variation in the data not explained by the macro variables. Two latent factors would explain significantly less variation, whereas adding a fourth factor would only explain an additional 2.4%. Adding more factors is also problematic because the number of parameters increases disproportionally. In order to achieve a manageable dimensionality of the parameter space, one either needs to restrict the number of state variables or impose restrictions on certain parameters.

I choose to impose only restrictions needed for identification and thus allow for the richest possible set of interactions amongst the factors. This decision implies however, that the number of factors needs to be limited to a reasonable number. Therefore, I choose to have three latent factor and estimate a five-factor model. Then, the vector of latent factors x_t is equal to $[\ x_{1,t} \quad x_{2,t} \quad x_{3,t}\ ]'$.

Comparing various existing models in the literature with the macro-finance model presented in this paper confirms that the chosen specification is indeed parsimonious given the set of observable variables. Modeling only macro variables and Treasury yields, Ang and Piazzesi (2003) also estimate a five-factor model with two observable and two latent factors. Bikbov and Chernov (2006) show that at least a total of four factors are needed to capture the slope of the Treasury yield curve in a macro-finance model with two observable macro factors. Driessen (2005) uses four latent factors to capture the dynamics of the Treasury yield curve and the common variation in credit spreads in addition to one latent factor per firm in the sample. With only three firms (or three rating classes) this would result in a seven-factor model. Finally, Amato and Luisi (2006) estimate a macro-finance model with three observable and three latent factors but they use credit spreads from only two rating classes.

Identification of the model needs to take into account that there is a mixture of macro and latent variables. Define $\mu = [\ \mu_m \quad \mu_x\ ]'$. I let μ_m, Φ, δ_0 and δ_m be free. μ_x is restricted such that the long-run mean of the latent factors is equal to zero, i.e.:

$$e_i' = (I - \Phi)\mu = 0, \tag{16}$$

where e_i is a vector of zeros with a one in the position of the respective latent factor. Furthermore, $\delta_{1x} = \delta_{2x} = \delta_{3x} = 1$. Finally, the matrix Σ, controlling the variance in the state equation (4), is given by:

$$\Sigma = \begin{bmatrix} \sigma_{gg} & 0 & 0 & 0 & 0 \\ \sigma_{\pi g} & \sigma_{\pi\pi} & 0 & 0 & 0 \\ \sigma_{1g} & \sigma_{1\pi} & \sigma_{11} & 0 & 0 \\ \sigma_{2g} & \sigma_{2\pi} & 0 & \sigma_{22} & 0 \\ \sigma_{3g} & \sigma_{3\pi} & 0 & 0 & \sigma_{33} \end{bmatrix} \tag{17}$$

5.3 Additional Considerations

Risk Premia. Despite being identified in the model, risk premia are very hard to estimate in practice. Also, a rich specification of risk premia bears the danger of overfitting the data. I follow Bikbov and Chernov (2006) and augment the standard log-likelihood function, $\mathcal{L}$, with a penalization term which is proportional to the variation of the term premium in (9) and (13):

$$\begin{aligned}\mathcal{L}_p &= \mathcal{L} - \frac{1}{2\sigma_p^2}\sum_{\tau}(a^{TP}(\tau))^2 + b^{TP}(\tau)' \cdot \text{Diag}(\text{var}(z_t)) \cdot b^{TP}(\tau) \\ &- \frac{1}{2\sigma_p^2}\sum_{i,\tau}(a^{i,TP}(\tau))^2 + b^{i,TP}(\tau)' \cdot \text{Diag}(\text{var}(z_t)) \cdot b^{i,TP}(\tau), \end{aligned} \tag{18}$$

where σ_p controls the importance of the penalization term, and the "Diag" operator creates a diagonal matrix out of a regular one. If market prices of risk are equal to zero, the term premia will be equal to zero as well. Therefore, $\mathcal{L}_p$ imposes an extra burden on the model to use the risk premia as a last resort in fitting the yields. This helps to stabilize the likelihood and simplifies the search for the global optimum. In particular, this setup helps avoiding very large values of risk premia.

Fitting Credit Spreads and Choice of Estimation Period. Treasury yields and macro variables are available starting in 1971:3. Credit spreads for the whole term structure and all rating classes only become available in 1992:2.[18] Theoretically, it is possible to estimate the macro-finance model using all available data. It is relatively straightforward to deal with the many missing credit spreads in the early sample period in the Kalman filter framework by only partially updating whenever observations are missing (see Harvey (1989)). However, I choose to estimate the model only over the common sample period 1992:2–2005:4 as the focus of the paper is on extracting information from credit spreads, not Treasury yields. Estimating the model over the common sample period results in a better fit of the credit spreads compared to a specification for the whole sample. Truncating the sample is also an approach to deal with time-varying predictive relations as noted by Stock and Watson (2003a).

The fit of credit spreads can be improved further by imposing appropriate restrictions on the estimation errors. I use the following restrictions to make the estimation errors roughly proportional to the level of the yields and credit spreads:

$$\varepsilon^2 = \frac{1}{2}(\varepsilon^{AAA})^2 = \frac{1}{2}(\varepsilon^{BBB})^2 = (\varepsilon^{B})^2. \tag{19}$$

[18] See Appendix A for a detailed description of data availability.

While this modification slightly improves the fit of credit spreads it does not drive the results, meaning that filtered latent factors are highly correlated to those from an unrestricted estimation.

Optimization. I need to estimate 92 parameters in the model. There is a large cross-section of observations available, which should help in pinning these parameters down. However, the relative short time series of 14 years of quarterly data leaves a concern of whether a global optimum can be found. I use a very large and efficient set of starting values to ensure that the global optimum is found. The grid search is extremely costly in a multi-dimensional space, and, in practice, limits the extent of the global search. The computational costs can be reduced by using the Sobol' quasi-random sequences to generate the starting points (see, e.g., Press, Teukovsky, Vetterling, and Flannery (1992)). I evaluate the likelihood for two billion sets of starting values, and then optimize using the best twenty thousand points as starting values. I optimize alternating between simplex and SQP algorithms and eliminating half of the likelihoods at each stage.

6 Estimation Results and Sources of Predictive Power

This section presents the results from estimating the macro-finance term structure model described in Section 4. Section 6.1 describes the model fit and verifies that the model implied spreads are able to pick up the predictive power observed in the data. Section 6.2 examines whether expectations, term premia or both together drive the forecasting ability. Section 6.3 decomposes the credit spreads into components attributable to the observable macro and the unobservable finance factors and examines their contributions to the overall predictive power.

6.1 The Predictive Power of Model Implied Spreads

6.1.1 Model Fit

The model fit is directly relevant to the question whether it is possible to capture the information that drives the predictive power of the credit spreads with the specification proposed in Section (4). As I am interested in examining the sources of the forecasting power, the model implied yields and spreads must also forecast GDP growth. If the implied spreads do not exhibit any predictive power, we are unable to make any statement about the sources of the predictive relationship with real activity other than recognizing that we need to introduce more factors into the model.

Using a fairly parsimonious model we cannot expect to be able to fit the whole term structures of Treasury yields and credit spreads for different rating classes perfectly. The results in Section 3 suggest that there is relevant information contained in a wide variety of different spreads except in short maturity AAA spreads. Furthermore, long maturity spreads seem to be more informative in general. Hence, the better we are able to fit long maturity spreads for all rating classes and lower grade spreads for all maturities, the better we can expect the model to perform in producing implied spreads that contain the same forecasting power.

Other than describing the model fit, the paper does not report the technical details of the estimation results such as parameter values, or tests of their statistical significance. There are too many parameters to discuss, and most of them are hard to interpret.

Treasury Yields. The model fits Treasuries very well. R^2s for levels are above 97% and mean absolute pricing errors are between 9 and 20 basis points (or between 2.5% and 8.2% expressed as a fraction of yield levels). At the same time, the model also fits the slope reasonably well with an R^2 of about 93%, while the curvature is fit with an R^2 of 79%. The R^2s are displayed in Table 3 along with the results for the fit of the corporate spreads. Figure 1 plots the actual and implied slope (Panel A) and curvature (Panel B).

Corporate Yields and Credit Spreads. The model fits B spreads almost as well as Treasury yields with R^2s close to or above 97% for almost all maturities. For BBB spreads, R^2s range between around 60% for short maturities and up to 80% for longer maturities. AAA spreads display the greatest disparity with an R^2 as low as 13% for the short spread, while the 10-year spreads are fitted well with an R^2 of almost 80%. The actual and implied spreads for selected maturities are displayed in Figure 2. The standard deviations of the errors in the observation equation (15) are 0.15 for AAA and BBB spreads and 0.22 for B spreads. This implies that the model values the high grade spreads within just under 30 basis points and the B spreads within about 44 basis points ($2\sigma_{\varepsilon^i}$). The mean absolute errors range between 6 and 11 basis points for AAA spreads, between 12 and 16 for BBB spreads and between 12 and 25 for B spreads. Expressed in fractions of the actual spread levels, the average errors for AAA spreads range between 15% and 58%, for BBB spreads between 15% and 23%, and for B spreads between 4% and 9%.

6.1.2 Implied Spreads and Estimation Errors

To test whether the model is able to capture the predictive power apparent in the real data I rerun the predictive regressions from Section 3 using the model implied spreads. Namely, I replicate Panel A from Table 1 using the implied credit spreads (Table 4, panel A) and the estimation errors (Table 4, panel B). The results confirm that overall, the implied spreads are performing satisfactorily. The coefficient for the estimation error is only significant for 10-year AAA and BBB spreads at forecast horizons two and three years. This means that only long maturity high grade spreads might contain additional information that can be used for forecasting GDP growth at long horizons, which the model is not able to capture.

Other than that, the implied spreads produce roughly the same R^2s as the actual spreads for the various horizons with exception of short-term AAA spreads. The model implied spreads have marginally significant forecasting power, whereas the actual spreads do not forecast GDP growth. This is not really surprising given the poor performance of the model in fitting short maturity AAA spreads. However, this could also be evidence for a problem with the actual data. The average value of AAA short maturity spreads is around 35 basis points. Since they are calculated as the difference between Treasury and corporate bond yields, noise in either of the time series directly translates into noise in the spread time series with an order of magnitude that is similar to the spread level itself. It is even possible that the implied spreads are a cleaner and thus better measure for the risk of AAA rated firms than the observed spreads.

6.2 Expectations and Term Premia

The state variables affect the credit spreads and Treasury yields through the expectations about the future short rate and through the term premia. Having estimated a full model, it is easy to decompose the credit spreads and investigate the role of the term premia in forecasting GDP growth in detail. The part of the credit spreads that is driven by the expectations about the future short rate can be computed by setting the risk parameters to zero in the equations for the Treasury yields and credit spreads, equations (8) and (12). The difference between the a credit spread under the $\mathbb{Q}$- and under the $\mathbb{P}$-measure is defined as the credit spread term premium

Figure 3, rows one through three, shows the implied credit spreads under the risk neutral measure, the spreads under the $\mathbb{P}$-measure and the term premia. For shorter maturities, expectations about the future short rate drive most of the variation in credit spreads. For longer maturities, spreads under the $\mathbb{P}$-measure flatten out and almost all the variation comes from the term premia, this effect being even more pronounced for higher grade credits. The same pattern can be observed for Treasury yields (see Figure 3, row four). By definition, the term premium starts at zero for the 3-month spreads, thus implying that all the forecasting power of the shortest maturity spreads is attributed to the $\mathbb{P}$-measure by default. Consequently, one would conjecture that, as maturity increases and the implied spreads based on expectations about the short rate flatten out, the importance of the term premia would increase.

Table 5 displays the coefficient estimates from running multivariate predictive regressions using the term premia and the credit spreads under the $\mathbb{P}$-measure. The results are not entirely in line with what would be expected. For AAA spreads, expectations are never significant, whereas term premia are for all horizons; the forecasting power of AAA appears to be solely driven by term premia. For BBB and B however, the $\mathbb{P}$-measure component is mostly significant for short maturity spreads while term premia are relevant for longer maturity spreads. This result implies, that it is not possible to determine what drives the forecasting power in the case of lower grade credit spreads as both, expectations and term premia are important depending on the maturity of the spreads.[19] Therefore, it is necessary to further decompose the implied spreads and explicitly consider the contributions of the state variables.

6.3 The Determinants of Credit Spreads and the Drivers of Forecasting Power

6.3.1 Macro Variables and Latent Factors

Apart from decomposing credit spreads (and Treasury yields) into expectations and term premia, it is also possible to directly assess the contributions of the five state variables to the predictive power of the credit spreads. Specifically, I am interested in disentangling the information in credit spreads

[19] Hamilton and Kim (2002) decompose the Treasury term spread in a similar fashion. They also conclude that both components matter. In addition, they find that the contribution of the expectations piece is significantly larger than that of the term premium.

that is not related to the macro variables. Even given the factor loadings in equations (12) and (8), separating out the contribution of the macro variables is not straightforward because they are correlated with the latent factors.

In order to extract all information related to GDP growth and inflation from the latent factors, I use the projection method introduced by Bikbov and Chernov (2006). This allows decomposing each latent factor x_i into a component explained by GDP growth and inflation, and a residual piece f_i which is orthogonal to the history of the observable macro variables, $M_t = \{m_t, m_{t-1}, ..., m_0\}$:

$$f_t = x_t - \hat{x}(M_t), \tag{20}$$

$$\hat{x}(M_t) = c(\Theta) + \sum_{j=0}^{t} c_{t-j}(\Theta) m_{t-j}, \tag{21}$$

where the matrices c are functions of parameters $\Theta = (\mu, \Phi, \Sigma)$ that control the dynamics of the state variables. The details of the procedure are provided in Appendix D.

The residuals f from the projection are not unique. Dai and Singleton (2000) show that for a given set of bond prices there are multiple equivalent combinations, or rotations, of the factors. However, this property can be exploited by choosing a specific rotation that is useful for interpreting the residuals f. I rotate the factors such that they are orthogonal to each other and f_1 and f_2 are interpreted as a "credit" and a "level" factor, respectively. The credit factor is designed to capture common variation in credit spreads not driven by the macro variables while the level factor picks up the variation on the short end of the Treasury yield curve. The details of the procedure are provided in Appendix E. The third factor f_3 is interpreted as a "slope" factor.

Panel A in Figure 5 graphs the credit factor f_1 with the B 3-month and 10-year spreads. The correlations are 70% and 57%, respectively. For BBB spreads, the correlations are slightly lower with 61% and 54%, whereas correlations with AAA spreads on the long and the short end reach 50% and 18%, respectively (50% and 40% if the correlations are measured with implied spreads). As already indicated by the factor loadings, Treasury yields are virtually uncorrelated with the credit factor (below 5%).

The credit factor is strongly associated with the index of tighter loan standards from the Federal Reserve's quarterly Senior Loan Officer Opinion Survey, as the correlation between the two is 62%.[20] A plot of the two series is provided in Figure 5, panel B. The relationship between f_1 and the index

[20] The survey can be obtained from the Federal Reserve website (Board of Governors of the Federal Reserve System).

of tighter loan standards further supports the interpretation of f_1 as a credit factor as it is not only a relevant determinant of credit spreads but also directly related to a proxy for credit conditions.

The level factor f_2 is highly correlated with Treasury yields of all maturities. Figure 6, panel A, graphs f_2 with the 3-month and 10-year Treasury yields. The correlations between f_2 and the Treasury yields are 77% and 53%, respectively. Moreover, the level factor is also strongly associated with the Federal funds target rate; the two series are plotted in Figure 6, panel B, the correlation is 67%.[21] Since the Federal funds rate is often considered as an indicator of monetary policy, f_2 can also be interpreted as a "monetary policy" factor.

6.3.2 Factor Loadings

Figure 4 plots the normalized loadings of credit spreads and Treasury yields. This allows visualizing the initial impact of a shock to the state variables on the yields or spreads for different maturities. To make them comparable, the loadings are normalized by the standard deviation of the factors and the credit spreads or yields, respectively; the figure shows the contemporaneous impact of a one standard deviation shock to any of the factors on the financial variables measured in standard deviations.

The plotted loadings on the macro variables take into account that GDP and inflation are correlated with the latent factors x_t by modifying the original factor loadings $b_m^{\mathbb{Q}}$ given in equations (9) and (13) and adding $c_t(\Theta)b_x^{\mathbb{Q}}$, where $c_t(\Theta)$ is taken from equation (21). As such, the loadings represent the true contemporaneous impact of variations in either GDP or inflation on Treasury yields and credit spreads. Positive shocks to GDP cause spreads to narrow, although the effect on AAA short maturity spreads is only minor. Inflation appears to have almost no effect on either spreads or Treasuries.[22]

The normalized factor loadings for the two residual factors f_1 and f_2 in Figure 4 illustrate the effect of the chosen rotation. Credit spreads load heavily on the credit factor, whereas Treasury yields are only marginally exposed. The largest loadings on f_1 occur for short maturity BBB and B spreads; the relevance of f_1 slightly decreases with maturity but the credit factor is an important

To be specific, the correlation is measured between factor f_1 and the prewithened index of tighter loan standards. I prewithen the time series by regressing it on eight lags of GDP growth and inflation.

[21] The Federal funds target rate is available through the FRED database (Federal Reserve Bank of St. Louis).

[22] Note that the factor loadings only reflect the immediate effect of shocks to the state variables and do not take into account the influence of lagged inflation.

determinant for credit spreads across all classes and maturities. Almost the reverse is true for the level factor f_2: Treasury yields for all maturities consistently and strongly load on the level factor f_2 while the loadings of credit spreads are very small (with the exception of short maturity AAA spreads).

While the credit factor can be attributed to credit spreads and the level factor is almost exclusively a driver of Treasury yields, the third factor f_3 affects both. However, it seems to work mainly on the long end and in opposite directions for Treasury yields and credit spreads. Long maturity Treasury yields load positively on f_3 while long maturity credit spreads for all rating classes have negative loadings. Therefore, f_3 can be thought of as a slope factor. Correlations with short dated Treasury yields and credit spreads are virtually zero, whereas the correlation with 10-year Treasury yields is almost 74% and correlations with long maturity credit spreads are also high in absolute terms but negative, ranging between −48% to −58%.

Even though factor loadings differ between credit spreads of different rating classes it is noteworthy that the shapes of the term structure of factor loadings in Figure 4 are very similar for all credit spreads, implying that credit spreads are driven by common factors. This is consistent with findings by Collin-Dufresne, Goldstein, and Martin (2001) who conclude that most of the variation of credit spread changes for individual bonds is explained by an aggregate common factor.[23]

6.3.3 The Forecasting Power of Credit Spread Components

The projection procedure described in Section 6.3.1 allows to single out the component of the credit spreads driven by movements in the macro variables:

$$CS^i_{M,t}(\tau) \quad = \quad a^{i,\mathbb{Q}}(\tau) + b^{i,\mathbb{Q}}_m(\tau)' m_t + b^{i,\mathbb{Q}}_x(\tau)' \hat{x}(M_t) \tag{22}$$

Similarly, the components of the credit spreads attributable to the residuals f_j can be calculated as the product of the respective factor loading times the realization of the factor, $CS^i_{f_j,t}(\tau) = b^{i,\mathbb{Q}}_x(\tau)' f_j$ for $j = \{1, 2, 3\}$. Thus, the implied spreads $\widehat{CS^i_t}(\tau)$ can be decomposed into its components according

[23] In contrast, Driessen (2005) estimates a model that assumes firm-specific factors to begin with and Amato and Luisi (2006) conclude that one dominant latent factor per rating category drives most of the variation in credit spreads.

to a variation of equation (12):

$$\begin{aligned}\widehat{CS}_t^i(\tau) &= a^{i,\mathbb{Q}}(\tau) + b_m^{i,\mathbb{Q}}(\tau)' m_t + b_x^{i,\mathbb{Q}}(\tau)'\hat{x}(M_t) + b_x^{i,\mathbb{Q}}(\tau)' f_t \\ &\triangleq CS^i_{M,t}(\tau) + CS^i_{f_1,t}(\tau) + CS^i_{f_2,t}(\tau) + CS^i_{f_3,t}(\tau). \end{aligned} \tag{23}$$

Figure 7 graphs the implied spreads and its various components, macro variables including the projection (and including the constant), credit factor f_1, level factor f_2 and slope factor f_3. A reflection of Figure 4, the f_2-component is only marginal for all credit spreads. The part that can directly be attributed to the observable macro variables either directly or via projection seems to account for a large part of the variation in the implied credit spreads.

To examine the predictive content of the components of the credit spreads, I run two sets of univariate regressions. First, I regress future GDP growth on the standardized values of $CS^i_{M,t}(\tau)$ to investigate the contribution of the macro variables. Second, I regress future GDP growth on the standardized credit, level and slope factors, respectively.

Panel A in Table 6 reports the coefficient estimates from the first set of regressions. Macro variables are relevant contributors to the forecasting power for horizons up to two years for longer maturity credit spreads. However, the macro factors do not contribute to predicting GDP for short maturity spreads.

The results of the second set of regressions are reported in Table 6, panel B. The credit factor f_1 has significant forecasting power at all horizons and R^2s range between 7% and 54% for the one quarter and three year horizons, respectively. The level and slope factors on the other hand do not have any predictive content. In the case of the slope factor, the lack of predictive power is notable as credit spreads at the long end load quite heavily on f_3. This means that while shocks to f_3 may significantly move credit spreads they contain no information as to the future direction of the economy.

Compared with actual credit spreads, the R^2s for the credit factor regressions are usually higher than those for short maturity spreads and below the numbers for longer maturities. This supports the conclusion that the credit factor accounts for a large part but not all of the forecasting power.

Table 7 displays the results from regressing future GDP growth on all the components of the implied spreads in equation (23). The results from the univariate regressions mostly carry over to the multivariate case. The significant effect of the credit factor f_1 largely remains intact but it is driven out by the contribution of the macro factors for short horizon forecasts (one and two quarters). The factors f_2 and f_3 are still insignificant, except for short maturity AAA spreads at one and two quarter horizons.

Excluding the factors f_2 and f_3 from the full regression often results in better adjusted R^2s compared to the full set of regressors, especially for lower grade spreads and longer forecast horizons (results not reported). This provides further evidence that only the macro variables and the credit factor are relevant for forecasting GDP growth.

6.4 The Sources of Forecasting Power and the External Finance Premium

To summarize, first, I showed that a five-factor macro-finance model is capable of picking up the predictive power contained in the actual data, which justifies decomposing the implied spreads and further investigating the sources of the forecasting ability. Second, disentangling the expectations from the term premia does not provide a lot of insight as both components contribute to the predictive power of the credit spreads. Finally, decomposing credit spreads into components based on the state variables in the model helps discovering the drivers of the predictive power.

Of the five factors in the model, only the two macro variables and the credit factor are relevant for forecasting GDP growth. The relevance of the credit factor in predicting future real activity is consistent with the existence of a transmission channel from borrowing conditions to real activity along the lines of a financial accelerator. Namely, it seems that the credit factor picks up disturbances in the financial markets that are manifested in changing credit conditions and ultimately affect the external finance premium. Within the given empirical framework it is not possible to determine where shocks to the credit factor originate. This should be further investigated in a structural model with no-arbitrage restrictions such as the models of Rudebusch and Wu (2003) and Hordahl, Tristani, and Vestin (2006).

Contrary to credit spreads, Treasury yields are largely driven by factors that do not have any forecasting power. Specifically, the level or monetary policy factor is the main driver of the short rate, which explains its lack of predictive power in the sample period considered.

7 Conclusion

Credit spreads over the whole spectrum of rating classes are suited to predict future GDP growth up to a horizon of three years. However, within a simple OLS regression framework, it is not possible to further investigate the predictive power and identify its sources.

A macro-finance term structure model estimated jointly for Treasury yields and credit spreads is able to capture the predictive power of credit spreads reasonably well. A shock to inflation positively affects both, Treasury yields and spreads for all rating classes, albeit in most cases only marginally. Innovations to GDP growth have a positive impact on the term structure of Treasury yields, especially on the shorter end, while credit spreads narrow for all rating classes, with larger declines for longer maturity spreads. All credit spreads load heavily on a credit factor, which can be linked to the index of tighter loan standards and thus can be interpreted as a proxy for credit conditions. In contrast, Treasury yields load strongly on a level factor, which is associated with the Fed funds target rate and therefore can also be interpreted as a monetary policy factor.

Disentangling term premia and expectations does not answer the question what drives the predictive power inherent in credit spreads as both components are important depending on forecast horizon and maturity of the credit spreads. Decomposing the spreads into contributions from the state variables on the other hand, yields more insights about the drivers of forecasting power. The most important contributor to the predictability of credit spreads is a credit factor, which is independent of the observed macro variables and can be interpreted as a proxy for credit conditions and explains between 50% and 100% of the overall predictive power. Current and past realizations of GDP growth and inflation contribute significantly to the forecasting power of spreads from all rating classes at short horizons. The macro factors and the credit factor account for virtually all predictive power found in credit spreads. Shocks to credit spreads that are not related to these factors are irrelevant for forecasting purposes. In particular, the level or monetary policy factor has no forecasting power. Consequently, the short rate, which loads heavily on the level factor, does not predict future real activity. This finding does not imply that monetary policy has no impact on output but can be explained by a stabilizing monetary policy regime over the sample period. The high predictive power of the credit factor lends support to the existence of a transmission channel from borrowing conditions to real activity consistent with the financial accelerator theory.

Appendix

A Data Description

This section provides a detailed description of the data used in this paper. GDP growth and inflation represent the two observable state variables in the model. Treasury yields and credit spreads are the observable data, which help estimating the parameters of the model.

A.1 Macro Variables

Since I intend to evaluate out-of-sample forecasts, it is necessary to pay close attention to when the data becomes available in order to avoid introducing a look-ahead bias. I use quarterly time series of real GDP and seasonally adjusted CPI available through the FRED database (Federal Reserve Bank of St. Louis). Real GDP is a three decimal time series in bn of chained 2000 USD, seasonally adjusted annual rate and CPI is the consumer price index for all urban consumers, all items.The annualized quarterly log changes in these two variables proxy for g_t and π_t, respectively.

GDP numbers are subject to several revisions. In the first month after the end of a quarter, an "advance" estimate is released, in the second month a "preliminary" and in the third month a "final," with the final number often being further revised in later releases.[24] I use the revised figures instead of the real-time dataset for two reasons. First of all, a good estimate of the final GDP number is available in the third month after a quarter (the "final" estimate) and second, GDP numbers are not available in the real time dataset in the early periods of the full sample.[25] However, I do try to avoid a look ahead bias by shifting the GDP time series by one period to account for the fact that in quarter t we only have information available about quarter $t-1$. Thus, implicitly I assume that the final revised figures are the same as those of the "final" release by the BEA in the third month of the following quarter.

$$g_t = 400 \times log\left(\frac{GDP_t}{GDP_{t-1}}\right), \tag{A-1}$$

where GDP_t is the GDP number for quarter $t-1$, which is released in the third month of quarter t.

I perform a similar adjustment with the CPI numbers, which are released with a one month lag. For any given quarter I am using the CPI numbers that are released in the third month, which are

[24] More information can be found on the Bureau of Economic Analysis (BEA) website.
[25] An overview of the available real time data sets can be found on the Federal Reserve Bank of Philadelphia website.

CPI numbers for the middle month of the quarter. Hence,

$$\pi_t = 400 \times log\left(\frac{P_t}{P_{t-1}}\right), \tag{A-2}$$

where P_t is the price level in the second month of quarter t, which is released in the third month of quarter t.

A.2 Treasury Yields

I use quarterly time series of continously compounded zero coupon yields from 1971:3 to 2005:4 with maturities three and six months and one, two, three, five, seven and ten years.

There are several potential sources for Treasury yields, all of which have some benefits and costs. Cochrane and Piazzesi (2006) use the well known Fama-Bliss dataset available from CRSP, which is not smoothed across maturities but which only has zero coupon bond prices with maturities up to 5 years. In order to incorporate longer maturities they also work with the new Guerkaynak, Sack, and Wright (2006) dataset, which has smoothed zero coupon yields.[26] Cochrane and Piazzesi (2006) point out that even small amounts of smoothing across maturities have the potential to lose a lot of information.

It is certainly more desirable to work with unsmoothed yields. However, measuring the whole yield curve, i.e. using maturities longer than five years is also very important as the slope of the curve is correlated with the macro environment (Estrella and Hardouvelis (1991); Estrella and Mishkin (1998); and Ang, Piazzesi, and Wei (2006)) and can be used to forecast GDP, a fact that is particularly relevant for this paper as well.

In short, neither the Guerkaynak, Sack, and Wright (2006) nor the Fama-Bliss dataset satisfy all needs. For the most part of the sample period I use a proprietary dataset of unsmoothed Fama-Bliss approximation of the zero coupon bond prices, which has yields for all desired maturities, i.e. up to ten years.[27] The starting point of my sample period is determined by the first quarter in which the ten year yield is available. However, this dataset has not been updated since 2002:4 so the data has to be augmented by using yields from other sources for the last part or the sample period. From 2003:1 to 2005:4 I use data from CRSP. The three month risk free rate is taken from the Fama Risk

[26] The data are available from the Federeal Reserve Board website (`www.federalreserve.gov/pubs/feds/2006`, last accessed November 22, 2007).

[27] I thank Robert Bliss for providing me with the data

Free Rates file, the six month yield is taken from the Fama T-bill structure file and the yields up to five years are taken from the Fama-Bliss dataset. All are continously compounded.

Thus, yields for seven and ten years are still missing for the last two years in the sample. Instead of treating those as missing observations I choose to complete my data by using yields from the Guerkaynak, Sack, and Wright (2006) dataset.

A.3 Credit Spreads

Credit spreads are calculated as the difference between the zero coupon corporate bond yields and the zero coupon Treasury yields described above. Yields for AAA, BBB and B rated bonds are taken from Bloomberg. Again, the data collection is not straightforward as there are different sources of data with different starting points. I use the zero coupon yields for industrials that are derived by stripping Bloomberg's fair market value (FMC) par coupon curves. These yields are available starting in 1989:2 for AAA bonds, and in 1993:3 for bonds rated BBB and B. In addition, Bloomberg provides zero coupon yields that are derived by stripping a swap curve for the same rating categories. For BBB and B rated bonds these data are available before 1993:3, so I augment my dataset accordingly by adding the additional data points. As a result, data on bonds rated BBB start in 1991:2, B yields are available from 1992:2. The chosen maturities are the same as those of the Treasury yields. Figure (8) displays Treasury yields and credit spreads for 3-month, 1-year and 10-year maturities.

Unfortunately, data for the whole term structure of corporate yields is not available before 1992:2. However, there are a few corporate bond indices available starting in the early 1970s, such as the Lehman Brothers corporate bond indices for investment grade bonds. For each rating class $i = \{AAA, BBB\}$ there is an index for "long" (normally above 10 years) and "intermediate" (between 1 and 10 years) maturities. Using redemption yields and the corresponding Treasury bond indices, it is possible to construct approximate credit spreads for different maturities. This in turn allows calculating a credit spread slope by taking the difference of the two. Lehman Brothers also provides a high yield bond index but only starting in 1987:1. The high yield bond index with the longest maturity that is available through Datastream is the "Merill Lynch US High Yield 100," which starts in 1980:1. For both yield indices I calculate a high yield spread using the redemption yield of the Lehman Brothers Treasury index (all maturities). The additional spread data, while unsuitable to use in a term-structure model, are used to perform robustness checks for the results in Section 3.2

and can be found in Appendix C.

B The Forecasting Power of Treasury Yields

B.1 Treasury Yield Regressions

In this section, I document the declining importance of the short rate and the term spread in forecasting real activity since the mid-1980s. Analogous to regression equation (2), I run the following regressions to examine the predictive power of the short rate and the term spread, respectively:

$$g_{t,k} = \alpha_k(1) + \gamma_k(1) y_t^T(1) + controls + u_{t+k}, \tag{B-3}$$

$$g_{t,k} = \alpha_k(\tau) + \gamma_k(\tau)(y_t^T(\tau) - y_t^T(1)) + controls + u_{t+k} \tag{B-4}$$

In the existing literature, the predictive regressions are usually run without control variables. However, adding the controls does not qualitatively change the results. I report the results without control variables to demonstrate that they are not responsible for the disappearing predictive relationship between the term spread and real activity.

The $\gamma_k(\tau)$ coefficients for the term spread regressions presented in Table 8, panels A and B, are significant for horizons between one and three years in the full and in the pre-1992:2 sample. R^2s range between 20% and 36% in the full sample and go up to 50% in the early sample for the 5-year term spread. In the post-1992:2 sample period (Table 8, panel C), the term spread loses its predictive power. Coefficients are not significant anymore and R^2s are basically zero.

My findings for the early and the full sample are in line with Estrella and Hardouvelis (1991) and Plosser and Rouwenhorst (1994) who find empirical evidence that the long end of the yield curve contains relevant information that is independent of monetary policy and thus, the term spread should be preferred to the short rate alone. The coefficient for the short rate in regression equation (B-3) is only significant for a one year forecast horizon. This result is not consistent with Bernanke and Blinder (1992) who find that the short rate is particularly informative about future movements of real activity, and with Ang, Piazzesi, and Wei (2006) who conclude that the nominal short rate dominates the term spread in forecasting GDP growth.

Apart from using slightly different sample periods, both papers also employ different methodologies. Bernanke and Blinder (1992) for example use Granger-causality tests and estimate VARs, while Ang, Piazzesi, and Wei (2006) draw their conclusions from a macro-finance term structure model. Although the macro-finance model presented in this paper is not the same as the one used in Ang, Piazzesi, and Wei (2006) (the largest difference being that they do not consider credit spreads), the results presented in Section 6.3.3 along with the regression results presented in this section suggest that the findings of Ang, Piazzesi, and Wei (2006) could also be driven by a strong predictive relationship between the Treasury yield curve and economic activity pre-1980. Appendix B.2 provides some additional results from simple VAR specifications, which (1) provide evidence that the effect found by Bernanke and Blinder (1992) is present in the data used in this paper during the early but not during the late sample period and (2) reconfirm the finding that the Treasury yield curve has lost its predictive power since the mid-1980s.

The subsamples for the Treasury yield regressions in Table 8, panels B and C, are chosen such that the late sample coincides with the availability of the corporate bond yield data. Consequently, the cutoff point is rather arbitrary. Estrella, Rodrigues, and Schich (2003) and Jardet (2004) both test for the stability of the predictive relationship between the term spread and economic activity and they find evidence for a structural break around 1984. In panel D, the predictive term spread regressions are repeated for the sample period 1985:1–2005:4, which excludes the period of monetary policy tightening under Paul Volcker. The results are in line with those reported in panel C, namely that the term spread no longer exhibits predictive power. The declining importance of the term spread in predicting GDP growth is consistent with a monetary policy regime that has been more concerned with inflation since the mid-1980s.

B.2 Evidence from VARs

Bernanke and Blinder (1992) and Bernanke and Gertler (1995) use VAR specifications to investigate the credit channel transmission mechanism of monetary policy. They both find that a shock to the Fed funds rate is followed by sustained declines in real GDP.

This section has two purposes. First, using simple bivariate VAR specifications it provides a robustness check for the regression results. The main results of Sections 3 and B.1 are confirmed, namely that the term spread has lost its importance in the late sample period 1992:2–2005:4, whereas information that manifests itself in credit spreads significantly affects future GDP. Second, estimating appropriate VARs allows comparing the results for my data with those reported in Bernanke and

Blinder (1992) and Bernanke and Gertler (1995). For the pre-1992:2 sample, I find results that are consistent with the theory of a credit channel—an unanticipated tightening of monetary policy, represented by a shock to the short rate, results in economic slowdown. In the late sample period however, this effect disappears, suggesting that the findings reported by Bernanke and Blinder (1992) and Bernanke and Gertler (1995) need to be interpreted with caution in the current environment.

To confirm the results from Section 3, I estimate simple bivariate reduced form VARs using log real GDP and term or credit spreads for the full sample, as well as for the pre- and post-1992:2 sample. Figure 9 plots the impulse-response functions for a 100bp shock to the 5-year term spread (panels A to C for the full, late and early sample periods) or the 10-year B spread (panel D), respectively. A negative shock to the term spread only has a negative effect on real GDP in the full and early sample; during the late sample period, GDP is practically unaffected by movements in the term. An unanticipated positive shock to the high yield spread however, leads to a significant decline in output.

To further gauge the effect of monetary policy shocks and to compare the results with those of Bernanke and Blinder (1992) and Bernanke and Gertler (1995), I consider a slightly more complicated VAR using the short rate as the monetary policy instrument, and including the logs of real GDP and of CPI in the estimation.[28] The lag length is chosen to be two, based on Bayes information criterion, and the short rate is ordered last in the VAR. The impulse response functions for a 100bp increase in the short rate are displayed in Figure 10, panels A through C. The results exhibit a "price puzzle," i.e. prices react positively to a shock in the short rate.[29] Although this effect is counterintuitive, I do not attempt to fix this by adding other time series to the VAR since this is not the focus of my paper. The response path for GDP however, is in line with the results for the simple bivariate VARs. In the full and in the early sample, output declines following a shock to the short rate. This is consistent with the results reported by Bernanke and Blinder (1992) and Bernanke and Gertler (1995). In the late sample however, the effect of a shock to the short rate almost reverses, again suggesting that the relationship reported in the earlier literature has disappeared.

I add the 10-year B spread to the VAR and order it last in the system. This implies that monetary policy can have a contemporaneous effect on the spread but it is assumed that the Fed does not react

[28] Instead of the Federal funds rate however, I use the 3-month Treasury yield as this is per definition the short rate used in the macro-finance model presented in section 4.

[29] See for example Eichenbaum (1992). Sims (1992) suggests that one potential explanation is that simple VARs omit information about future inflation that is actually available to the Fed. He proposes to include a commodity price index to account for this information.

to current shocks to the spread. The impulse response functions to a 100bp rise in the credit spread are plotted in Figure 10, panel D. GDP and the short rate both react negatively to a positive shock in the high yield spread; CPI is largely unaffected. Again, the results are in line with the findings of Section 3 and consistent with the existence of a financial accelerator: a shock that is orthogonal to the short rate, GDP and the price level and that manifests itself in the credit spread has a significant effect on the future path of the economy.

C Robustness Checks for Credit Spread Regressions

It would be desirable to have a longer history for the full term structure of credit spreads. Unfortunately, the data availability is limited in this regard. However, it is possible, to extend the data set for high grade spreads back to the mid-1970s and for high yield spreads back to the mid-1980s using alternative data from Lehman Brothers and Merrill Lynch (see Appendix A). To check whether the alternative data, which is arguably less rich, yields qualitatively similar results to the ones presented in Section 3.2, I replicate Table 1, panel A using the additional data set. The results in Table 9, panel A indicate that the spreads constructed from the bond indices more or less capture the same variation in future GDP growth as the data available from Bloomberg. In terms of R^2s, the Lehman Brothers high yield spread behaves strikingly similar to the B 10-year spread, whereas the Merill Lynch spread exhibits the same pattern as the B 1-year spread (R^2s are sharply decreasing for longer horizons). The results for the extended sample periods are then presented in Table 9, panels B and C. Panel B displays the regressions using all available data (different starting points depending on data availability) while panel C reports the results for the subsample 1985:1–2005:4 (or 1987:1–2005:4 for the Lehman Brothers high yield index). Comparing results using all and only post-1985:1 data in Table 9, it is apparent that the relationship between real activity and the high yield spread becomes stronger in the late-1980s. The market for high yield debt did not really develop until after the mid-1980s. Before, most high yield debt were bonds that were originally issued by former investment grade firms. This might distort results in the early periods. It is also evident that spreads for investment grade credits become better predictors for real activity over time.

In order to check whether the results for credit spreads are solely driven by the late sample, I also repeat the regressions using pre-1985:1 and a pre-1992:2 only, respectively. The results are weaker but in line with what is reported in Table 9. Long maturity investment grade spreads significantly predict GDP for a horizon up to one year. High yield spreads predict GDP growth well for horizons up to three years in the pre-1992:2 sample. Pre-1985:1 results are either distorted (Merrill Lynch high yield index) or not available (Lehman Brothers high yield index).

In summary, the results reported in Section 3.2 are quite robust to alternative data and extended sample periods, which gives further confidence that the limited availability of the whole term structure of credit spreads is not distorting the overall findings.

D Projection

The model controlling the evolution of state variables z in equation (4) can be rewritten in block representation as:

$$z_t = \begin{bmatrix} \mu_m \\ \mu_x \end{bmatrix} + \begin{bmatrix} \Phi^{mm} & \Phi^{mx} \\ \Phi^{xm} & \Phi^{xx} \end{bmatrix} \begin{bmatrix} m_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \Sigma^{xx} & \Sigma^{xx} \\ \Sigma^{xx} & \Sigma^{xx} \end{bmatrix} \begin{bmatrix} \epsilon_t^m \\ \epsilon_t^x \end{bmatrix} \tag{D-5}$$

This model does not represent a state-space system. Nonetheless, Liptser (1997) and Liptser and Shiryaev (2001) derive the projection of one element of the VAR(1) on the other using the same ideas as in the Kalman filtering. In particular, these authors provide the following expression for the conditional mean, often referred to as "forecast," and variance of the forecast error:

$$\begin{aligned} \hat{x}(M_t) &= \mu^x + \Phi^{xx}\hat{x}(M_{t-1}) + \Phi^{xm}m_{t-1} \\ &+ \left(\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx}P_{t-1}\Phi^{mx\prime}\right)\left(\Sigma^{mx}\Sigma^{mx\prime} + \Sigma^{mm}\Sigma^{mm\prime} + \Phi^{mx}P_{t-1}\Phi^{mx\prime}\right)^{-1} \\ &\times \left(m_t - \mu_m - \Phi^{mx}\hat{x}(M_{t-1}) - \Phi^{mm}m_{t-1}\right) \end{aligned} \tag{D-6}$$

$$\begin{aligned} P_t &= \Phi^{xx}P_{t-1}\Phi^{xx\prime} + \left(\Sigma^{xx}\Sigma^{xx\prime} + \Sigma^{xm}\Sigma^{xm\prime}\right) \\ &- \left(\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx}P_{t-1}\Phi^{mx\prime}\right)\left(\Sigma^{mx}\Sigma^{mx\prime} + \Sigma^{mm}\Sigma^{mm\prime} + \Phi^{mx}P_{t-1}\Phi^{mx\prime}\right)^{-1} \\ &\times \left(\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx}P_{t-1}\Phi^{mx\prime}\right)', \end{aligned} \tag{D-7}$$

where m and x are generically referred to as vectors of observable and latent variables, respectively.

To describe the projection initialization, some additional notations are introduced. The long-run mean of z is:

$$(I - \Phi)^{-1}\mu = \begin{bmatrix} \Theta^m \\ \Theta^x \end{bmatrix}$$

The steady-state matrix P satisfies:

$$\begin{aligned} P &= \Phi^{xx} P \Phi^{xx\prime} + (\Sigma^{xx}\Sigma^{xx\prime} + \Sigma^{xm}\Sigma^{xm\prime}) \\ &- (\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx} P \Phi^{mx\prime}) (\Sigma^{mx}\Sigma^{mx\prime} + \Sigma^{mm}\Sigma^{mm\prime} + \Phi^{mx} P \Phi^{mx\prime})^{-1} \\ &\times (\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx} P \Phi^{mx\prime})' \end{aligned} \quad \text{(D-8)}$$

Then the projection is initialized as follows:

$$\hat{x}(m_0) = \Theta^x + V^{xm}(V^{mm})^{-1}(m_0 - \Theta^m), \ P_0 = P \quad \text{(D-9)}$$

In this case $P_t = P$ and the projection is time-stationary. An alternative strategy is to initialize P_0 at the unconditional variance of z. In this case, the sequence P_t will converge to P.

The lags of the projected x in the expression (D-6) could be recursively substituted out so that the current projection is expressed as a distributed-lag function of macro variables:

$$\hat{x}(M_t) = c(\Theta) + \sum_{j=0}^{t} c_{t-j}(\Theta) m_{t-j}, \quad \text{(D-10)}$$

where the matrices c are functions of parameters $\Theta = (\mu, \Phi, \Sigma)$ that control the dynamics of the state variables z in (4).

E Latent Factor Indeterminacy

Dai and Singleton (2000) point out that identifying restrictions imposed at the estimation stage are not necessarily unique. There are many sets of restrictions, or invariant transformations of the model, such that the yields or inflation expectations are left unchanged. Naturally, when a parameter configuration changes, the respective latent variables change as well by "rotating." This can be exploited by using invariant transformations that are useful for interpreting the latent factors. I use the invariant affine transformation, which scales factors by a matrix. Appendix A of Dai and Singleton (2000) describes how such a transformation affects model parameters.

The first rotation, $\mathcal{O}$, ensures that the three factors are orthogonal to each other. I define a rotation $\mathcal{O} = \mathcal{R}x_t$, so that the variance-covariance matrix of x becomes diagonal. The matrix $\mathcal{R}$ is not unique; i.e., the rotation of type $\mathcal{O}$ can generate many triples of orthogonal factors x. The second proposed rotation, $\mathcal{M}$, can be applied after any of the rotations from the class $\mathcal{O}$ resolves this type of indeterminacy. Define $\mathcal{M} = \mathcal{U}x_t$, where the matrix $\mathcal{U}$ is the orthogonal matrix; i.e., $\mathcal{U}\mathcal{U}' = I$, that preserves the correlation structure between the factors. In the three-dimensional case, the matrix $\mathcal{U}$ is determined by two parameters, which are established by maximizing the loading of the 3-month B spread on x_1. After the second rotation, the first latent factor, x_1, is identified. Define $x_t^{(1)} = [\ x_{2,t} \quad x_{3,t}\ ]'$, the vector of latent variables excluding $x_{1,t}$. Further define the third rotation, $\mathcal{N} = \mathcal{S}x_t^{(1)}$, where $\mathcal{S}$ again is the orthogonal matrix. In the two-dimensional case the matrix $\mathcal{S}$ is determined by a single parameter, which is established by maximizing the factor loading of the Treasury short rate on x_2.

References

Amato, Jeffery, and Maurizio Luisi, 2006, Factors in the term structure of credit spreads, BIS Working Paper No. 203.

Ang, Andrew, and Monika Piazzesi, 2003, A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables, *Journal of Monetary Economics* 50, 745–787.

——— , and Min Wei, 2006, What does the yield curve tell us about GDP growth?, *Journal of Econometrics* 131, 359–403.

Bernanke, Ben, 2007a, The financial accelerator and the credit channel, Speech delivered at the Credit Channel of Monetary Policy in the Twenty-first Century Conference, Federal Reserve Bank of Atlanta, Atlanta, Georgia, June 15.

——— , 2007b, The recent financial turmoil and its economic and policy consequences, the Economic Club of New York, New York, New York, October 15.

——— , and Alan Blinder, 1992, The federal funds rate and the channels of monetary transmission, *American Economic Review* 82, 901–921.

Bernanke, Ben, and Mark Gertler, 1989, Agency costs, net worth, and business fluctuations, *American Economic Review* 79, 14–31.

——— , 1990, Financial fragility and economic performance, *The Quarterly Journal of Economics* 105, 87–114.

——— , 1995, Inside the black box: The credit channel of monetary policy transmission, *Journal of Economic Perspectives* 9, 27–48.

——— , and Simon Gilchrist, 1996, The financial accelerator and the flight to quality, *The Review of Economics and Statistics* 78, 1–15.

——— , 1999, The financial accelerator in a quantitative business cycle framework, in *Handbook of Macroeconomics*, vol. 1C . pp. 1341–1393 (Amsterdam: Elsevier).

Bikbov, Ruslan, and Mikhail Chernov, 2006, No-arbitrage macroeconomic determinants of the yield curve, Working Paper, Columbia University.

Boivin, Jean, and Marc P. Giannoni, 2006, Has monetary policy become more effective?, *The Review of Economics and Statistics* 88, 445–462.

Bruno, Michael, and William Easterly, 1998, Inflation crises and long-run growth, *Journal of Monetary Economics* 41, 3–26.

Chan-Lau, Jorge A., and Iryna V. Ivaschenko, 2001, Corporate bond risk and real activity: An empirical analysis of yield spreads and their systematic components, IMF Working Paper 01/158.

——— , 2002, The corporate spread curve and industrial production in the United States, IMF Working Paper 02/8.

Cochrane, John, and Monika Piazzesi, 2006, Decomposing the yield curve, Working Paper, University of Chicago.

Collin-Dufresne, Pierre, Robert Goldstein, and Spencer Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177–2207.

Dai, Qiang, and Kenneth Singleton, 2000, Specification analysis of affine term structure models, *Journal of Finance* 55, 1943–1978.

de Jong, Frank, 2000, Time series and cross-section information in affine term-structure models, *Journal of Business and Economic Statistics* 18, 300–314.

Dotsey, Michael, 1998, The predictive content of the interest rate term spread for future economic growth, *Federal Reserve Board of Richmond Quarterly Review* 84/3, 30–51.

Driessen, Joost, 2005, Is default event risk priced in corporate bonds?, *Review of Financial Studies* 18, 165–195.

Duffee, Gregory R., 1999, Estimating the price of default risk, *Review of Financial Studies* 12, 197–226.

——— , 2002, Term premia and interest rate forecasts in affine models, *Journal of Finance* 57, 405–443.

——— , and Richard Stanton, 2004, Estimation of dynamic term structure models, Working Paper, University of California at Berkeley.

Duffie, Darrell, and Ken Singleton, 1999, Modeling term structures of defaultable bonds, *Review of Financial Studies* 12, 687–720.

Eichenbaum, Martin, 1992, Comments on interpreting the macroeconomic time series facts: The effect of monetary policy, *European Economic Review* 36, 1001–1011.

Estrella, Arturo, and Gikas A. Hardouvelis, 1991, The term structure as a predictor of real economic activity, *Journal of Finance* 46, 555–576.

Estrella, Arturo, and Frederic S. Mishkin, 1998, Predicting U.S. recessions: Financial variables as leading indicators, *Review of Economics and Statistics* 80, 45–61.

Estrella, Arturo, Anthony P. Rodrigues, and Sebastian Schich, 2003, How stable is the predictive power of the yield curve? Evidence from Germany and the United States, *Review of Economics and Statistics* 85, 629–644.

Fischer, Stanley, 1993, The role of macroeconomic factors in growth, *Journal of Monetary Economics* 32, 485–512.

Gertler, Mark, and Cara S. Lown, 2000, The information in the high yield bond spread for the business cycle: Evidence and some implications, NBER Working Paper No. 7549.

Guerkaynak, Refet, Brian Sack, and Jonathan Wright, 2006, The US treasury yield curve: 1961 to the present, Manuscript, Federal Reserve Board of Governors.

Hamilton, James D., and Don H. Kim, 2002, A reexamination of the predictability of economic activity using the yield spread, *Journal of Money, Credit, and Banking* 34, 340–360.

Harvey, Andrew C., 1989, *Forecasting, Structural Time Series Models and the Kalman Filter* (Cambridge University Press: Cambridge, UK).

Hodrick, Robert J., 1992, Dividend yields and expected stock returns: Alternative procedures for influence and measurement, *Review of Financial Studies* 5, 357–386.

Hordahl, Peter, Oreste Tristani, and David Vestin, 2006, A joint econometric model of macroeconomic and term structure dynamics, *Journal of Econometrics* 131, 405–444.

Jardet, Caroline, 2004, Why did the term structure of interest rates lose its predictive power?, *Economic Modelling* 21, 509–524.

Liptser, Robert S., 1997, Stochastic control, Lecture Notes, Tel Aviv University.

——— , and Albert N. Shiryaev, 2001, *Statistics of Random Processes: I. General Theory* (Springer: Berlin Heidelberg) 2nd edn.

Mishkin, Frederic S., 2007a, Financial instability and monetary policy, Speech delivered at the Risk USA 2007 Conference, New York, New York, November 5, 2007.

——— , 2007b, Financial instability and the Federal Reserve as a liquidity provider, Speech delivered at the Museum of American Finance Commemoration of the Panic of 1907, New York, New York, October 26.

Mody, Ashoka, and Mark P. Taylor, 2004, Financial predictors of real activity and the financial accelerator, *Economics Letters* 82, 167–172.

Morris, Charles, Robert Neal, and Douglas S. Rolph, 2000, Interest rates and credit spread dynamics, Working Paper, Federal Reserve Bank of Kansas City.

Plosser, Charles I., and K. Geert Rouwenhorst, 1994, International term structures and real economic growth, *Journal of Monetary Economics* 33, 133–155.

Press, William H., Saul A. Teukovsky, William T. Vetterling, and Brian P. Flannery, 1992, *Numerical Recipies in C* (Cambridge University Press: Cambridge) second edn.

Rudebusch, Glenn D., and Tao Wu, 2003, A macro-finance model of the term structure, monetary policy, and the economy, Working Paper, Federal Reserve Bank of San Francisco.

Sims, Chris A., 1992, Interpreting the macroeconomic time series facts: The effect of monetary policy, *European Economic Review* 36, 975–1000.

Stock, James H., and Mark W. Watson, 2003a, Forecasting output and inflation: The role of asset prices, *Journal of Economic Literature* 41, 788–829.

——— , 2003b, How did leading indicator forecasts perform during the 2001 recession?, *Federal Reserve Bank of Richmond Economic Quarterly* 89/3, 71–90.

Wu, Liuren, and Frank X. Zhang, 2005, A no-arbitrage analysis of economic determinants of the credit spread curve, Working Paper, Federal Reserve Board.

Table 1. Credit spread regressions

Panel A reports the slope coefficient $\beta_k^i(\tau)$, and the R^2 and $\bar{R}^2$ (adjusted R^2) from regressing future GDP growth $g_{t,k}$ for k quarters on credit spreads, $CS_t^i(\tau)$, for rating class i and maturity τ:

$$g_{t,k} = \alpha_k^i(\tau) + \beta_k^i(\tau) CS_t^i(\tau) + u_{t+k}.$$

Panel C reports the coefficients β_k^1 and $\beta_k^{i,SL}$, and the R^2 and $\bar{R}^2$ from the regression

$$g_{t,k} = \alpha_k(\tau) + \beta_k^{i,SL}(CS_t^i(40) - CS_t^i(1)) + \beta_k^i(1) CS_t^i(1) + u_{t+k},$$

where $CS_t^i(\tau) = y_t^i(\tau) - y_t^T(\tau))$, and $y_t^i(\tau)$ and $y_t^T(\tau)$ denote the respective corporate bond and Treasury yields. Panels B and D report the same quantities for the regressions above including the following control variables: short rate, 5-year term spread, and current and lagged GDP growth and inflation. Hodrick (1992) (1B) standard errors are in parentheses. * denotes significantly different from zero at 5% level. The sample period is 1992:2–2005:4, GDP data is included up to 2007:3.

Panel A: Univariate credit spread regressions

	AAA **1 yr**		*AAA* **10 yrs**		*BBB* **1 yr**		*BBB* **10 yrs**		*B* **1 yr**		*B* **10 yrs**	
Horizon (Obs.)	$\beta_k^i(4)$	R^2 / $\bar{R}^2$	$\beta_k^i(40)$	R^2 / $\bar{R}^2$	$\beta_k^i(4)$	R^2 / $\bar{R}^2$	$\beta_k^i(40)$	R^2 / $\bar{R}^2$	$\beta_k^i(4)$	R^2 / $\bar{R}^2$	$\beta_k^i(40)$	R^2 / $\bar{R}^2$
1 qrt	-1.09	0.01	-2.39	0.13	-1.62	0.08	-1.37	0.11	-0.53	0.17	-0.67	0.15
(55)	(2.02)	-0.01	(1.07)*	0.11	(0.65)*	0.07	(0.59)*	0.10	(0.15)*	0.15	(0.22)*	0.13
2 qrts	-1.98	0.04	-2.38	0.23	-1.73	0.17	-1.47	0.23	-0.51	0.27	-0.60	0.21
(55)	(1.60)	0.02	(0.98)*	0.21	(0.57)*	0.16	(0.53)*	0.22	(0.13)*	0.26	(0.19)*	0.19
1 yr	-1.67	0.04	-2.41	0.34	-1.57	0.21	-1.47	0.35	-0.41	0.26	-0.57	0.28
(55)	(1.23)	0.02	(0.86)*	0.33	(0.51)*	0.20	(0.50)*	0.34	(0.14)*	0.25	(0.17)*	0.26
2 yrs	-1.18	0.03	-2.35	0.52	-1.18	0.18	-1.36	0.47	-0.27	0.18	-0.41	0.22
(54)	(0.78)	0.01	(0.71)*	0.51	(0.50)*	0.17	(0.44)*	0.46	(0.13)*	0.16	(0.15)*	0.21
3 yrs	-1.25	0.04	-2.07	0.58	-1.13	0.24	-1.30	0.63	-0.22	0.15	-0.39	0.27
(50)	(0.65)	0.02	(0.63)*	0.57	(0.47)*	0.22	(0.41)*	0.62	(0.14)	0.14	(0.16)*	0.26

Panel B: Univariate credit spread regressions with controls

	AAA **1 yr**		*AAA* **10 yrs**		*BBB* **1 yr**		*BBB* **10 yrs**		*B* **1 yr**		*B* **10 yrs**	
Horizon (Obs.)	$\beta_k^i(4)$	R^2 / $\bar{R}^2$	$\beta_k^i(40)$	R^2 / $\bar{R}^2$	$\beta_k^i(4)$	R^2 / $\bar{R}^2$	$\beta_k^i(40)$	R^2 / $\bar{R}^2$	$\beta_k^i(4)$	R^2 / $\bar{R}^2$	$\beta_k^i(40)$	R^2 / $\bar{R}^2$
1 qrt	-2.75	0.21	-2.16	0.26	-1.68	0.24	-0.99	0.22	-0.49	0.27	-0.61	0.26
(55)	(1.90)	0.09	(1.09)	0.15	(0.86)	0.12	(0.62)	0.11	(0.16)*	0.16	(0.22)*	0.15
2 qrts	-2.94	0.25	-2.36	0.35	-1.92	0.32	-1.36	0.33	-0.50	0.36	-0.56	0.31
(55)	(1.64)	0.14	(1.01)*	0.25	(0.75)*	0.22	(0.56)*	0.23	(0.14)*	0.26	(0.20)*	0.21
1 yr	-2.06	0.24	-2.82	0.54	-1.87	0.38	-1.73	0.53	-0.44	0.38	-0.67	0.45
(55)	(1.30)	0.13	(0.80)*	0.47	(0.68)*	0.29	(0.50)*	0.47	(0.13)*	0.29	(0.17)*	0.37
2 yrs	-1.74	0.23	-2.81	0.71	-1.54	0.38	-1.64	0.66	-0.29	0.30	-0.48	0.39
(54)	(0.88)	0.11	(0.62)*	0.67	(0.54)*	0.28	(0.42)*	0.60	(0.12)*	0.20	(0.15)*	0.30
3 yrs	-2.11	0.25	-2.48	0.73	-1.73	0.48	-1.62	0.78	-0.29	0.27	-0.52	0.42
(50)	(0.68)	0.13	(0.55)*	0.69	(0.48)*	0.39	(0.39)*	0.74	(0.13)*	0.15	(0.16)*	0.32

Panel C: Bivariate credit spread regressions

		AAA			*BBB*			*B*		
Horizon (Obs.)		Coeff.	S.E.	R^2 / $\bar{R}^2$	Coeff.	S.E.	R^2 / $\bar{R}^2$	Coeff.	S.E.	R^2 / $\bar{R}^2$
1 qrt	$\beta_1^i(1)$	-0.71	(1.77)	0.15	-1.99	(0.77)*	0.13	-0.72	(0.21)*	0.17
(55)	$\beta_1^{i,SL}$	-2.58	(1.02)*	0.12	-1.16	(0.64)	0.10	-0.44	(0.31)	0.14
2 qrts	$\beta_2^i(1)$	-0.85	(1.71)	0.26	-2.08	(0.68)*	0.26	-0.65	(0.19)*	0.26
(55)	$\beta_2^{i,SL}$	-2.56	(0.91)*	0.23	-1.26	(0.57)*	0.23	-0.33	(0.28)	0.23
1 yr	$\beta_4^i(1)$	-1.79	(1.30)	0.35	-2.07	(0.57)*	0.39	-0.60	(0.17)*	0.31
(55)	$\beta_4^{i,SL}$	-2.48	(0.83)*	0.33	-1.26	(0.53)*	0.37	-0.39	(0.26)	0.29
2 yrs	$\beta_8^i(1)$	-2.02	(0.99)*	0.52	-1.62	(0.53)*	0.48	-0.43	(0.16)*	0.24
(54)	$\beta_8^{i,SL}$	-2.39	(0.69)*	0.50	-1.27	(0.46)*	0.46	-0.31	(0.21)	0.21
3 yrs	$\beta_{12}^i(1)$	-1.99	(0.76)*	0.58	-1.48	(0.54)*	0.63	-0.41	(0.17)*	0.28
(50)	$\beta_{12}^{i,SL}$	-2.08	(0.64)*	0.57	-1.24	(0.42)*	0.62	-0.34	(0.20)	0.25

Panel D: Bivariate credit spread regressions with controls

		AAA			*BBB*			*B*		
Horizon (Obs.)		Coeff.	S.E.	R^2 / $\bar{R}^2$	Coeff.	S.E.	R^2 / $\bar{R}^2$	Coeff.	S.E.	R^2 / $\bar{R}^2$
1 qrt	$\beta_1^i(1)$	-0.96	(1.92)	0.27	-1.51	(0.93)*	0.23	-0.62	(0.22)*	0.27
(55)	$\beta_1^{i,SL}$	-2.36	(0.99)*	0.14	-0.69	(0.67)	0.10	-0.41	(0.40)	0.14
2 qrts	$\beta_2^i(1)$	-0.93	(1.72)	0.38	-1.74	(0.85)*	0.34	-0.57	(0.20)*	0.34
(55)	$\beta_2^{i,SL}$	-2.60	(0.93)*	0.27	-1.15	(0.59)	0.23	-0.27	(0.35)	0.22
1 yr	$\beta_4^i(1)$	-2.00	(1.18)	0.55	-1.89	(0.64)*	0.54	-0.67	(0.17)*	0.45
(55)	$\beta_4^{i,SL}$	-2.96	(0.77)*	0.47	-1.64	(0.52)*	0.46	-0.63	(0.29)*	0.36
2 yrs	$\beta_6^i(1)$	-2.40	(0.88)*	0.72	-1.58	(0.50)*	0.66	-0.48	(0.15)*	0.39
(54)	$\beta_6^{i,SL}$	-2.88	(0.60)*	0.67	-1.68	(0.41)*	0.60	-0.50	(0.22)*	0.28
3 yrs	$\beta_{12}^i(1)$	-2.55	(0.61)*	0.73	-1.72	(0.45)*	0.78	-0.52	(0.16)*	0.42
(50)	$\beta_{12}^{i,SL}$	-2.46	(0.57)*	0.68	-1.56	(0.38)*	0.74	-0.53	(0.20)*	0.31

Table 2. Summary of R^2s

Panel A reports the R^2 from regressing future GDP growth $g_{t,k}$ for k quarters on current and lagged macro variables, GDP growth g and inflation π:

$$g_{t,k} = \alpha_k + \delta_k^{(1)} g_t + \delta_k^{(2)} g_{t-1} + \eta_k^{(1)} \pi_t + \eta_k^{(2)} \pi_{t-1} + u_{t+k},$$

In panel B, the short rate or various measures of the term spread are added to the regression. Panel C adds the 5-year term spread and various credit spreads. The sample period for all regressions is 1992:2–2005:4, GDP data is included up to 2007:3.

	Horizon	1 qrt	2 qrts	1 yr	2 yrs	3 yrs
Panel A	Macro	0.15	0.18	0.19	0.17	0.05
Panel B	short rate r_t	0.15	0.18	0.19	0.17	0.07
	1-yr term spread	0.24	0.24	0.20	0.17	0.09
	5-yr term spread	0.16	0.18	0.19	0.17	0.07
	10-yr term spread	0.15	0.18	0.19	0.18	0.08
Panel C	AAA 1 yr	0.17	0.22	0.23	0.21	0.13
	AAA 10 yr	0.24	0.35	0.54	0.71	0.71
	BBB 1 yr	0.23	0.32	0.38	0.38	0.47
	BBB 10 yr	0.22	0.33	0.51	0.64	0.78
	B 1 yr	0.27	0.36	0.37	0.30	0.27
	B 10 yr	0.24	0.31	0.45	0.39	0.40

Table 3. Model fit: R^2s for implied yields and spreads

The table reports the R^2s of the implied yields and credit spreads. The sample period is 1992:2–2005:4, GDP data is included up to 2007:3.

	Maturity				
	1 qrt	1 yr	10 yrs	Slope	Curvature
Treasuries	0.979	0.992	0.979	0.932	0.785
AAA	0.132	0.206	0.790	0.593	0.251
BBB	0.592	0.669	0.817	0.722	0.431
B	0.981	0.990	0.921	0.829	0.771

Table 4. Implied credit spread regressions

Panel A reports the slope coefficient $\beta_k^i(\tau)$, and the R^2 and $\bar{R}^2$ (adjusted R^2) from regressing future GDP growth $g_{t,k}$ for k quarters on implied credit spreads, $\widehat{CS}_t^i(\tau)$, for rating class i and maturity τ:

$$g_{t,k} = \alpha_k^i(\tau) + \beta_k^i(\tau)\widehat{CS}_t^i(\tau) + u_{t+k},$$

where $\widehat{CS}_t^i(\tau) = \widehat{y}_t^i(\tau) - \widehat{y_t^T}(\tau))$ and all the yields are model implied instead of actual yields. In panel B, $\widehat{CS}_t^i(\tau)$ is replaced by the estimation error given by $CS_t^i(\tau) - \widehat{CS}_t^i(\tau)$, the difference between the actual and the implied credit spread. Hodrick (1992) (1B) standard errors in parentheses. * denotes significantly different from zero at 5% level. The sample period is 1992:2–2005:4, GDP data is included up to 2007:3.

Panel A: Implied credit spreads

	AAA **1 yr**		*AAA* **10 yrs**		*BBB* **1 yr**		*BBB* **10 yrs**		*B* **1 yr**		*B* **10 yrs**	
Horizon (Obs.)	$\beta_k^i(4)$	R^2 $\bar{R}^2$	$\beta_k^i(40)$	R^2 $\bar{R}^2$	$\beta_k^i(4)$	R^2 $\bar{R}^2$	$\beta_k^i(40)$	R^2 $\bar{R}^2$	$\beta_k^i(4)$	R^2 $\bar{R}^2$	$\beta_k^i(40)$	R^2 $\bar{R}^2$
1 qrt	-5.89	0.05	-2.86	0.13	-2.68	0.16	-1.75	0.16	-0.55	0.16	-0.74	0.16
(55)	(3.64)	0.03	(1.10)*	0.12	(0.75)*	0.14	(0.56)*	0.15	(0.15)*	0.15	(0.24)*	0.15
2 qrts	-6.75	0.12	-2.74	0.22	-2.59	0.26	-1.63	0.25	-0.53	0.27	-0.73	0.28
(55)	(3.48)	0.10	(1.03)*	0.20	(0.69)*	0.25	(0.53)*	0.24	(0.14)*	0.26	(0.22)*	0.27
1 yr	-7.27	0.21	-2.47	0.26	-2.24	0.29	-1.40	0.28	-0.45	0.29	-0.65	0.33
(55)	(3.14)*	0.19	(0.92)*	0.25	(0.71)*	0.28	(0.48)*	0.26	(0.15)*	0.28	(0.19)*	0.32
2 yrs	-5.27	0.17	-2.05	0.28	-1.51	0.20	-1.15	0.29	-0.30	0.20	-0.49	0.30
(54)	(2.65)	0.15	(0.74)*	0.27	(0.67)*	0.19	(0.40)*	0.28	(0.14)*	0.19	(0.16)*	0.28
3 yrs	-4.97	0.17	-1.91	0.35	-1.29	0.19	-1.07	0.36	-0.25	0.19	-0.45	0.34
(50)	(2.45)*	0.15	(0.69)*	0.33	(0.71)	0.17	(0.39)*	0.35	(0.14)	0.17	(0.16)*	0.32

Panel B: Estimation errors

	AAA **1 yr**		*AAA* **10 yrs**		*BBB* **1 yr**		*BBB* **10 yrs**		*B* **1 yr**		*B* **10 yrs**	
Horizon (Obs.)	$\beta_k^i(4)$	R^2 $\bar{R}^2$	$\beta_k^i(40)$	R^2 $\bar{R}^2$	$\beta_k^i(4)$	R^2 $\bar{R}^2$	$\beta_k^i(40)$	R^2 $\bar{R}^2$	$\beta_k^i(4)$	R^2 $\bar{R}^2$	$\beta_k^i(40)$	R^2 $\bar{R}^2$
1 qrt	0.75	0.00	-1.48	0.01	0.55	0.00	0.85	0.01	-2.36	0.04	0.12	0.00
(55)	(2.35)	-0.02	(2.25)	-0.01	(1.27)	-0.02	(0.96)	-0.01	(1.55)	0.02	(0.94)	-0.02
2 qrts	-0.06	0.00	-1.90	0.03	0.06	0.00	-0.28	0.00	-2.02	0.05	0.95	0.04
(55)	(1.86)	-0.02	(2.22)	0.01	(1.13)	-0.02	(0.99)	-0.02	(1.16)	0.03	(0.70)	0.02
1 yr	0.52	0.00	-2.95	0.11	-0.20	0.00	-1.35	0.05	0.43	0.00	0.39	0.01
(55)	(1.49)	-0.02	(1.70)	0.09	(1.01)	-0.02	(0.90)	0.04	(0.98)	-0.02	(0.52)	-0.01
2 yrs	0.44	0.00	-4.17	0.34	-0.49	0.01	-1.97	0.18	0.86	0.02	0.61	0.04
(54)	(0.77)	-0.02	(1.29)*	0.32	(0.67)	-0.01	(0.75)*	0.17	(0.75)	0.00	(0.31)	0.02
3 yrs	-0.02	0.00	-3.74	0.37	-0.97	0.06	-2.15	0.30	1.17	0.05	0.37	0.02
(50)	(0.45)	-0.02	(1.06)*	0.36	(0.52)	0.04	(0.63)*	0.29	(0.63)	0.03	(0.21)	-0.00

Table 5. Implied credit spread regressions: term premia and spreads under $\mathbb{P}$-measure

The table reports the coefficients $\beta_k^{i,TP}(\tau)$ and $\beta_k^{i,\mathbb{P}}(\tau)$, and the R^2 and $\bar{R}^2$ (adjusted R^2) from the regression

$$g_{t,k} = \alpha_k(\tau) + \beta_k^{i,TP}(\tau) CS^i_{TP,t}(\tau) + \beta_k^{i,\mathbb{P}} CS^i_{\mathbb{P},t}(\tau) + u_{t+k},$$

where $g_{t,k}$ denotes future GDP growth for k quarters and $CS^i_{\mathbb{P},t}(\tau)$ and $CS^i_{TP,t}(\tau)$ denote the expectations and term premium components of the implied credit spread for rating class i and maturity τ, $\widehat{CS}^i_t(\tau)$, respectively. Hodrick (1992) standard errors in parentheses. * denotes significantly different from zero at 5% level. The sample period is 1992:2–2005:4, GDP data is included up to 2007:3.

Panel A		*AAA* **1 yr**			*AAA* **10 yrs**		
Horizon (Obs.)		Coeff.	S.E.	R^2 $\bar{R}^2$	Coeff.	S.E.	R^2 $\bar{R}^2$
1 qrt	$\beta_1^{i,TP}(\tau)$	-17.12	(4.80)*	0.19	-2.70	(1.13)*	0.14
(55)	$\beta_1^{i,\mathbb{P}}(\tau)$	-1.39	(3.77)	0.16	5.41	(11.21)	0.11
2 qrts	$\beta_2^{i,TP}(\tau)$	-15.78	(4.35)*	0.28	-2.72	(1.05)*	0.22
(55)	$\beta_2^{i,\mathbb{P}}(\tau)$	-3.13	(3.76)	0.25	-1.56	(11.36)	0.19
1 yr	$\beta_4^{i,TP}(\tau)$	-13.82	(4.06)*	0.33	-2.57	(0.92)*	0.27
(55)	$\beta_4^{i,\mathbb{P}}(\tau)$	-4.65	(3.21)	0.31	-7.27	(9.88)	0.24
2 yrs	$\beta_8^{i,TP}(\tau)$	-10.59	(3.63)*	0.30	-2.07	(0.74)*	0.28
(54)	$\beta_8^{i,\mathbb{P}}(\tau)$	-3.13	(2.45)	0.27	-3.14	(7.53)	0.26
3 yrs	$\beta_{12}^{i,TP}(\tau)$	-10.25	(3.60)*	0.37	-1.85	(0.66)*	0.35
(50)	$\beta_{12}^{i,\mathbb{P}}(\tau)$	-2.68	(2.15)	0.34	0.27	(6.77)	0.32
Panel B		*BBB* **1 yr**			*BBB* **10 yrs**		
Horizon (Obs.)		Coeff.	S.E.	R^2 $\bar{R}^2$	Coeff.	S.E.	R^2 $\bar{R}^2$
1 qrt	$\beta_1^{i,TP}(\tau)$	-5.12	(2.24)*	0.18	-1.75	(0.56)*	0.17
(55)	$\beta_1^{i,\mathbb{P}}(\tau)$	-1.85	(0.88)*	0.15	-2.96	(2.24)	0.13
2 qrts	$\beta_2^{i,TP}(\tau)$	-3.56	(2.15)	0.27	-1.63	(0.52)*	0.28
(55)	$\beta_2^{i,\mathbb{P}}(\tau)$	-2.26	(0.87)*	0.24	-4.20	(2.25)	0.25
1 yr	$\beta_4^{i,TP}(\tau)$	-2.35	(2.09)	0.29	-1.41	(0.47)*	0.36
(55)	$\beta_4^{i,\mathbb{P}}(\tau)$	-2.21	(0.83)*	0.26	-4.66	(1.96)*	0.33
2 yrs	$\beta_8^{i,TP}(\tau)$	-2.32	(1.72)	0.21	-1.15	(0.39)*	0.32
(54)	$\beta_8^{i,\mathbb{P}}(\tau)$	-1.22	(0.78)	0.18	-2.72	(1.58)	0.29
3 yrs	$\beta_{12}^{i,TP}(\tau)$	-2.71	(1.66)	0.23	-1.08	(0.38)*	0.37
(50)	$\beta_{12}^{i,\mathbb{P}}(\tau)$	-0.64	(0.98)	0.20	-1.77	(1.77)	0.34
Panel C		*B* **1 yr**			*B* **10 yrs**		
Horizon (Obs.)		Coeff.	S.E.	R^2 $\bar{R}^2$	Coeff.	S.E.	R^2 $\bar{R}^2$
1 qrt	$\beta_1^{i,\mathbb{P}}(\tau)$	-0.83	(0.72)	0.16	-0.79	(0.25)*	0.17
(55)	$\beta_1^{i,TP}(\tau)$	-0.50	(0.18)*	0.13	-0.47	(0.52)	0.14
2 qrts	$\beta_2^{i,\mathbb{P}}(\tau)$	-0.41	(0.70)	0.27	-0.72	(0.24)*	0.28
(55)	$\beta_2^{i,TP}(\tau)$	-0.55	(0.17)*	0.24	-0.78	(0.53)	0.26
1 yr	$\beta_4^{i,\mathbb{P}}(\tau)$	-0.04	(0.65)	0.31	-0.60	(0.22)*	0.35
(55)	$\beta_4^{i,TP}(\tau)$	-0.52	(0.16)*	0.28	-0.92	(0.46)*	0.32
2 yrs	$\beta_8^{i,\mathbb{P}}(\tau)$	-0.14	(0.53)	0.21	-0.49	(0.18)*	0.30
(54)	$\beta_8^{i,TP}(\tau)$	-0.33	(0.15)*	0.18	-0.51	(0.36)	0.27
3 yrs	$\beta_{12}^{i,\mathbb{P}}(\tau)$	-0.20	(0.49)	0.19	-0.47	(0.18)*	0.34
(50)	$\beta_{12}^{i,TP}(\tau)$	-0.27	(0.17)	0.15	-0.31	(0.41)	0.31

Table 6. The forecasting power of determinants of credit spreads

Panel A reports the coefficient $\beta_k^{i,M}(\tau)$, the R^2 and $\bar{R}^2$ (adjusted R^2) from regressing future GDP growth, $g_{t,k}$, for k quarters on the component of credit spreads that can be attributed to the observable macro variables, $\hat{CS}^i_M(\tau)$:

$$g_{t,k} = \alpha_k(\tau) + \beta_k^{i,M}(\tau) CS^i_{M,t}(\tau) + u_{t+k}.$$

Panel B reports the coefficient $\beta_k^{f_j}$, R^2 and $\bar{R}^2$ (adjusted R^2) from the regression

$$g_{t,k} = \alpha_k + \beta_k^{f_j} f_{j,t} + u_{t+k},$$

for $j = \{1,2,3\}$ and f_j denotes the credit, level and slope factors, respectively.
The orthogonalised residuals f and the credit spread component driven by the macro variables, $CS^i_M(\tau)$, are standardized to facilitate interpretation of the results. Hodrick (1992) (1B) standard errors in parentheses. * denotes significantly different from zero at 5% level. The sample period is 1992:2–2005:4, GDP data is included up to 2007:3.

Panel A: Projection component

	AAA **1 yr**		*AAA* **10 yrs**		*BBB* **1 yr**		*BBB* **10 yrs**		*B* **1 yr**		*B* **10 yrs**	
Horizon (Obs.)	$\beta_k^{i,M}(4)$	R^2 $\bar{R}^2$	$\beta_k^{i,M}(40)$	R^2 $\bar{R}^2$	$\beta_k^{i,M}(4)$	R^2 $\bar{R}^2$	$\beta_k^{i,M}(40)$	R^2 $\bar{R}^2$	$\beta_k^{i,M}(4)$	R^2 $\bar{R}^2$	$\beta_k^{i,M}(40)$	R^2 $\bar{R}^2$
1 qrt	-0.50	0.07	-0.50	0.07	-0.49	0.07	-0.56	0.09	-0.48	0.06	-0.56	0.09
(55)	(0.26)	0.05	(0.24)*	0.05	(0.26)	0.05	(0.22)*	0.07	(0.26)	0.05	(0.21)*	0.07
2 qrts	-0.48	0.11	-0.54	0.14	-0.44	0.09	-0.59	0.17	-0.45	0.10	-0.58	0.17
(55)	(0.24)*	0.10	(0.23)*	0.13	(0.25)	0.08	(0.20)*	0.16	(0.25)	0.08	(0.20)*	0.15
1 yr	-0.42	0.13	-0.47	0.16	-0.28	0.06	-0.49	0.18	-0.29	0.06	-0.45	0.15
(55)	(0.20)*	0.11	(0.19)*	0.15	(0.25)	0.04	(0.17)*	0.16	(0.25)	0.04	(0.17)*	0.14
2 yrs	-0.29	0.09	-0.38	0.16	-0.06	0.00	-0.36	0.15	-0.07	0.01	-0.29	0.10
(54)	(0.15)	0.08	(0.16)*	0.15	(0.24)	0.02	(0.15)*	0.14	(0.24)	0.01	(0.15)	0.08
3 yrs	-0.11	0.02	-0.26	0.10	0.13	0.03	-0.22	0.07	0.12	0.02	-0.12	0.02
(50)	(0.13)	0.00	(0.14)	0.08	(0.22)	0.01	(0.14)	0.05	(0.22)	0.00	(0.15)	0.00

Panel B: Orthogonalized residuals

	f_1		f_2		f_3	
Horizon (Obs.)	$\beta_k^{f_1}$	R^2 $\bar{R}^2$	$\beta_k^{f_2}$	R^2 $\bar{R}^2$	$\beta_k^{f_3}$	R^2 $\bar{R}^2$
1 qrt	-0.50	0.07	0.37	0.04	0.36	0.04
(55)	(0.25)*	0.05	(0.23)	0.02	(0.24)	0.02
2 qrts	-0.52	0.13	0.22	0.02	0.27	0.04
(55)	(0.25)*	0.12	(0.23)	0.00	(0.23)	0.02
1 yr	-0.54	0.21	0.07	0.00	0.23	0.04
(55)	(0.21)*	0.20	(0.20)	0.01	(0.21)	0.02
2 yrs	-0.48	0.26	0.15	0.03	0.20	0.05
(54)	(0.18)*	0.24	(0.15)	0.01	(0.16)	0.03
3 yrs	-0.64	0.54	0.25	0.10	0.26	0.11
(55)	(0.18)*	0.53	(0.13)	0.08	(0.16)	0.09

Table 7. Implied credit spread regressions: full decomposition

The table reports the coefficients $\beta_k^{i,M}(\tau)$ and $\beta_k^{i,f}(\tau)$, and the R^2 and $\bar{R}^2$ (adjusted R^2) from regressing future GDP growth, $g_{t,k}$, for k quarters on the various components of the credit spreads:

$$g_{t,k} = \alpha_k(\tau) + \beta_k^{i,M}(\tau) CS_{M,t}^i(\tau) + \beta_k^{i,f_1}(\tau) CS_{f_1,t}^i(\tau) + \beta_k^{i,f_2}(\tau) CS_{f_2,t}^i(\tau) + \beta_k^{i,f_3}(\tau) CS_{f_1,t}^i(\tau) + u_{t+k},$$

where $CS_M^i(\tau)$ and $\hat{CS}_f^i(\tau)$ denote the components of the credit spreads that can be attributed to the observable macro variables and its lags M, and the various orthogonalized residuals f_1, f_2 and f_3, respectively. The implied credit spread, $\widehat{CS_t^i}(\tau)$, is the sum of the four components. Hodrick (1992) (1B) standard errors in parentheses. * denotes significantly different from zero at 5% level. The sample period is 1992:2–2005:4, GDP data is included up to 2007:3.

Panel A		*AAA* **1 yr**			*AAA* **10 yrs**		
Horizon (Obs.)		Coeff.	S.E.	R^2 / $\bar{R}^2$	Coeff.	S.E.	R^2 / $\bar{R}^2$
1 qrt	$\beta_1^{i,M}(\tau)$	-24.18	(5.60)*	0.27	-4.07	(1.39)*	0.21
(55)	$\beta_1^{i,f_1}(\tau)$	-4.15	(5.02)	0.22	-3.49	(3.66)	0.14
	$\beta_1^{i,f_2}(\tau)$	19.85	(7.19)*		162.90	(77.81)*	
	$\beta_1^{i,f_3}(\tau)$	-57.20	(21.16)*		-2.44	(1.29)	
2 qrts	$\beta_2^{i,M}(\tau)$	-19.75	(5.05)*	0.35	-3.88	(1.23)*	0.31
(55)	$\beta_2^{i,f_1}(\tau)$	-6.43	(5.19)	0.29	-4.59	(3.81)	0.25
	$\beta_2^{i,f_2}(\tau)$	12.96	(7.52)		105.40	(80.13)	
	$\beta_2^{i,f_3}(\tau)$	-42.41	(20.84)*		-1.80	(1.26)	
1 yr	$\beta_4^{i,M}(\tau)$	-14.43	(4.46)*	0.38	-2.90	(1.04)*	0.35
(55)	$\beta_4^{i,f_1}(\tau)$	-8.56	(4.19)*	0.33	-6.01	(3.07)	0.30
	$\beta_4^{i,f_2}(\tau)$	6.19	(6.56)		42.36	(68.88)	
	$\beta_4^{i,f_3}(\tau)$	-31.56	(18.86)		-1.36	(1.15)	
2 yrs	$\beta_8^{i,M}(\tau)$	-10.92	(2.87)*	0.41	-2.47	(0.69)*	0.42
(54)	$\beta_8^{i,f_1}(\tau)$	-7.50	(2.83)*	0.37	-5.20	(2.08)*	0.37
	$\beta_8^{i,f_2}(\tau)$	7.40	(3.97)		64.95	(44.07)	
	$\beta_8^{i,f_3}(\tau)$	-25.44	(16.09)		-1.12	(0.98)	
3 yrs	$\beta_{12}^{i,M}(\tau)$	-5.38	(2.96)	0.62	-1.59	(0.76)*	0.65
(50)	$\beta_{12}^{i,f_1}(\tau)$	-11.45	(3.31)*	0.58	-7.84	(2.44)*	0.62
	$\beta_{12}^{i,f_2}(\tau)$	5.73	(3.61)		58.80	(40.74)	
	$\beta_{12}^{i,f_3}(\tau)$	-18.36	(17.72)		-0.93	(1.06)	

Table 7. Implied credit spread regressions: full decomposition (cont.)

Panel B		*BBB* **1 yr**			*BBB* **10 yrs**		
Horizon (Obs.)		Coeff.	S.E.	R^2 $\bar{R}^2$	Coeff.	S.E.	R^2 $\bar{R}^2$
1 qrt	$\beta_1^{i,M}(\tau)$	-2.59	(1.13)*	0.19	-2.33	(0.70)*	0.21
(55)	$\beta_1^{i,f_1}(\tau)$	-2.17	(1.07)	0.13	-2.10	(1.94)	0.15
	$\beta_1^{i,f_2}(\tau)$	-88.39	(81.32)		-9.42	(5.09)	
	$\beta_1^{i,f_3}(\tau)$	-21.21	(14.79)		-1.23	(0.70)	
2 qrts	$\beta_2^{i,M}(\tau)$	-2.47	(1.13)*	0.28	-2.27	(0.64)*	0.32
(55)	$\beta_2^{i,f_1}(\tau)$	-2.44	(1.03)*	0.22	-2.63	(1.98)	0.27
	$\beta_2^{i,f_2}(\tau)$	-27.88	(81.23)		-5.77	(5.20)	
	$\beta_2^{i,f_3}(\tau)$	-14.32	(13.89)		-0.89	(0.68)	
1 yr	$\beta_4^{i,M}(\tau)$	-1.78	(1.17)	0.32	-1.69	(0.55)*	0.36
(55)	$\beta_4^{i,f_1}(\tau)$	-2.57	(0.90)*	0.27	-3.30	(1.61)*	0.31
	$\beta_4^{i,f_2}(\tau)$	19.71	(71.80)		-1.91	(4.49)	
	$\beta_4^{i,f_3}(\tau)$	-10.86	(12.87)		-0.67	(0.63)	
2 yrs	$\beta_8^{i,M}(\tau)$	-0.49	(1.19)	0.30	-1.28	(0.45)*	0.40
(54)	$\beta_8^{i,f_1}(\tau)$	-2.10	(0.72)*	0.24	-2.95	(1.13)*	0.35
	$\beta_8^{i,f_2}(\tau)$	-28.06	(49.81)		-3.33	(2.97)	
	$\beta_8^{i,f_3}(\tau)$	-8.77	(10.47)		-0.53	(0.53)	
3 yrs	$\beta_{12}^{i,M}(\tau)$	0.45	(1.06)	0.59	-0.72	(0.51)	0.63
(50)	$\beta_{12}^{i,f_1}(\tau)$	-2.50	(0.80)*	0.55	-4.29	(1.27)*	0.59
	$\beta_{12}^{i,f_2}(\tau)$	-50.50	(42.56)		-3.12	(2.72)	
	$\beta_{12}^{i,f_3}(\tau)$	-8.68	(11.59)		-0.44	(0.57)	
Panel C		*B* **1 yr**			*B* **10 yrs**		
Horizon (Obs.)		Coeff.	S.E.	R^2 $\bar{R}^2$	Coeff.	S.E.	R^2 $\bar{R}^2$
1 qrt	$\beta_1^{i,M}(\tau)$	-0.49	(0.22)*	0.19	-0.94	(0.26)*	0.22
(55)	$\beta_1^{i,f_1}(\tau)$	-0.46	(0.23)*	0.12	-0.59	(0.47)	0.16
	$\beta_1^{i,f_2}(\tau)$	-3.37	(3.14)		5.97	(3.39)	
	$\beta_1^{i,f_3}(\tau)$	-2.61	(1.85)		-0.78	(0.42)	
2 qrts	$\beta_2^{i,M}(\tau)$	-0.49	(0.22)*	0.28	-0.91	(0.24)*	0.33
(55)	$\beta_2^{i,f_1}(\tau)$	-0.52	(0.22)*	0.22	-0.71	(0.47)	0.28
	$\beta_2^{i,f_2}(\tau)$	-0.99	(3.13)		3.52	(3.44)	
	$\beta_2^{i,f_3}(\tau)$	-1.75	(1.74)		-0.57	(0.41)	
1 yr	$\beta_4^{i,M}(\tau)$	-0.36	(0.23)	0.32	-0.65	(0.22)*	0.36
(55)	$\beta_4^{i,f_1}(\tau)$	-0.55	(0.19)*	0.27	-0.85	(0.38)*	0.31
	$\beta_4^{i,f_2}(\tau)$	0.82	(2.76)		1.00	(2.98)	
	$\beta_4^{i,f_3}(\tau)$	-1.33	(1.61)		-0.43	(0.38)	
2 yrs	$\beta_8^{i,M}(\tau)$	-0.11	(0.23)	0.30	-0.42	(0.19)*	0.37
(54)	$\beta_8^{i,f_1}(\tau)$	-0.45	(0.16)*	0.24	-0.77	(0.28)*	0.32
	$\beta_8^{i,f_2}(\tau)$	-1.04	(1.92)		1.92	(2.00)	
	$\beta_8^{i,f_3}(\tau)$	-1.09	(1.31)		-0.33	(0.31)	
3 yrs	$\beta_{12}^{i,M}(\tau)$	0.08	(0.21)	0.58	-0.19	(0.21)	0.60
(50)	$\beta_{12}^{i,f_1}(\tau)$	-0.54	(0.17)*	0.55	-1.06	(0.30)*	0.56
	$\beta_{12}^{i,f_2}(\tau)$	-1.92	(1.64)		1.86	(1.80)	
	$\beta_{12}^{i,f_3}(\tau)$	-1.09	(1.45)		-0.26	(0.34)	

Table 8. Term spread and short rate regressions

The table reports the slope coefficient $\gamma_k(\tau)$, the R^2 and the $\bar{R}^2$ from regressing future GDP growth, $g_{t,k}$, for k quarters on the short rate and various term spreads, respectively:

$$g_{t,k} = \alpha_k(\tau) + \gamma_k(\tau)(y_t^T(\tau) - y_t^T(1)) + u_{t+k}$$

for different sample periods. In the first column, the term spread is replaced by the short rate in the regression. Hodrick (1992) (1B) standard errors are in parentheses. * denotes significantly different from zero at 5% level. GDP data is included up to 2007:3.

Panel A: 1971:3–2005:4								
	short rate r_t		**1 year**		**5 years**		**10 years**	
Horizon (Obs.)	$\gamma_k(1)$	R^2 / $\bar{R}^2$	$\gamma_k(4)$	R^2 / $\bar{R}^2$	$\gamma_k(20)$	R^2 / $\bar{R}^2$	$\gamma_k(40)$	R^2 / $\bar{R}^2$
1 qrt	-0.09	0.01	1.26	0.03	0.42	0.02	0.26	0.01
(138)	(0.10)	-0.00	(0.83)	0.03	(0.23)	0.02	(0.17)	0.01
2 qrts	-0.16	0.03	0.98	0.03	0.57	0.07	0.41	0.05
(138)	(0.11)	0.03	(0.63)	0.02	(0.22)*	0.06	(0.17)*	0.04
1 yr	-0.22	0.09	1.38	0.10	0.80	0.20	0.60	0.17
(138)	(0.11)*	0.09	(0.48)*	0.09	(0.23)*	0.19	(0.18)*	0.16
2 yrs	-0.16	0.09	1.36	0.18	0.78	0.35	0.57	0.28
(137)	(0.10)	0.09	(0.40)*	0.17	(0.23)*	0.34	(0.18)*	0.27
3 yrs	-0.08	0.04	0.88	0.13	0.56	0.33	0.40	0.24
(133)	(0.10)	0.03	(0.33)*	0.13	(0.20)*	0.32	(0.16)*	0.23
Panel B: 1971:3–1992:1								
	short rate r_t		**1 year**		**5 years**		**10 years**	
Horizon (Obs.)	$\gamma_k(1)$	R^2 / $\bar{R}^2$	$\gamma_k(4)$	R^2 / $\bar{R}^2$	$\gamma_k(20)$	R^2 / $\bar{R}^2$	$\gamma_k(40)$	R^2 / $\bar{R}^2$
1 qrt	-0.20	0.02	1.13	0.03	0.50	0.03	0.39	0.02
(83)	(0.17)	0.01	(0.99)	0.01	(0.29)	0.02	(0.25)	0.01
2 qrts	-0.33	0.08	0.91	0.03	0.73	0.09	0.64	0.09
(83)	(0.18)	0.07	(0.75)	0.01	(0.28)*	0.08	(0.23)*	0.08
1 yr	-0.44	0.21	1.59	0.12	1.06	0.30	0.93	0.29
(83)	(0.17)*	0.20	(0.58)*	0.11	(0.29)*	0.29	(0.25)*	0.28
2 yrs	-0.30	0.18	1.66	0.25	1.00	0.51	0.83	0.45
(83)	(0.16)	0.17	(0.51)*	0.24	(0.28)*	0.50	(0.24)*	0.44
3 yrs	-0.12	0.06	1.02	0.17	0.70	0.45	0.55	0.36
(83)	(0.14)	0.05	(0.42)*	0.16	(0.25)*	0.45	(0.21)*	0.35
Panel C: 1992:2–2005:4								
	short rate r_t		**1 year**		**5 years**		**10 years**	
Horizon (Obs.)	$\gamma_k(1)$	R^2 / $\bar{R}^2$	$\gamma_k(4)$	R^2 / $\bar{R}^2$	$\gamma_k(20)$	R^2 / $\bar{R}^2$	$\gamma_k(40)$	R^2 / $\bar{R}^2$
1 qrt	0.17	0.02	2.02	0.12	0.14	0.00	-0.00	0.00
(55)	(0.17)	0.00	(0.61)*	0.11	(0.25)	-0.01	(0.20)	-0.02
2 qrts	0.11	0.02	1.40	0.10	0.07	0.00	-0.01	0.00
(55)	(0.16)	-0.00	(0.64)*	0.09	(0.25)	-0.02	(0.19)	-0.02
1 yr	0.05	0.00	0.59	0.03	0.00	0.00	-0.01	0.00
(55)	(0.15)	-0.01	(0.62)	0.01	(0.24)	-0.02	(0.18)	-0.02
2 yrs	0.03	0.00	0.24	0.01	0.07	0.01	0.06	0.01
(54)	(0.14)	-0.02	(0.36)	-0.01	(0.21)	-0.01	(0.17)	-0.01
3 yrs	0.04	0.01	0.47	0.04	0.13	0.02	0.09	0.02
(50)	(0.11)	-0.01	(0.34)	0.02	(0.19)	0.00	(0.16)	-0.00
Panel D: 1985:1–2005:4								
	short rate r_t		**1 year**		**5 years**		**10 years**	
Horizon (Obs.)	$\gamma_k(1)$	R^2 / $\bar{R}^2$	$\gamma_k(4)$	R^2 / $\bar{R}^2$	$\gamma_k(20)$	R^2 / $\bar{R}^2$	$\gamma_k(40)$	R^2 / $\bar{R}^2$
1 qrt	0.04	0.00	2.24	0.15	0.30	0.02	0.10	0.00
(84)	(0.10)	-0.01	(0.47)*	0.14	(0.20)	0.01	(0.16)	-0.01
2 qrts	-0.01	0.00	1.73	0.15	0.28	0.03	0.13	0.01
(84)	(0.10)	-0.01	(0.49)*	0.14	(0.20)	0.02	(0.15)	-0.00
1 yr	-0.07	0.01	1.21	0.10	0.29	0.04	0.19	0.03
(84)	(0.10)	0.00	(0.48)*	0.09	(0.19)	0.03	(0.15)	0.02
2 yrs	-0.11	0.05	0.80	0.07	0.35	0.10	0.25	0.10
(83)	(0.10)	0.04	(0.33)*	0.06	(0.20)	0.09	(0.16)	0.08
3 yrs	-0.10	0.06	0.52	0.05	0.33	0.13	0.24	0.12
(79)	(0.09)	0.04	(0.26)*	0.03	(0.17)	0.12	(0.14)	0.11

Table 9. Credit spread regressions: Lehman and Merrill Lynch bond indices

The table reports the slope coefficient $\beta_k^i(\tau)$ and R^2 from regressing future GDP growth $g_{t,k}$ for k quarters on credit spreads, $CS_t^i(\tau)$, for rating class i and maturity τ:

$$g_{t,k} = \alpha_k^i(\tau) + \beta_k^i(\tau) CS_t^i(\tau) + u_{t+k},$$

where $CS_t^i(\tau) = y_t^i(\tau) - y_t^T(\tau))$ and $y_t^i(\tau)$ and $y_t^T(\tau)$ denote the respective corporate bond and Treasury yields . Hodrick (1992) (1B) standard errors in parentheses. * denotes significantly different from zero at 5% level.

Panel A: 1992:2–2005:4												
	AAA **IM**		*AAA* **L**		*BBB* **IM**		*BBB* **L**		**LB** *HY*		**ML** *HY*	
Horizon (Obs.)	$\beta_k^{AAA}(IM)$	R^2	$\beta_k^{AAA}(L)$	R^2	$\beta_k^{BBB}(IM)$	R^2	$\beta_k^{BBB}(L)$	R^2	β_k^{HY}	R^2	β_k^{HY}	R^2
1 qrt	-1.55	0.06	-1.68	0.12	-0.94	0.15	-1.34	0.17	-0.42	0.19	-0.52	0.23
(54)	(0.74)*		(0.67)*		(0.27)*		(0.42)*		(0.11)*		(0.11)*	
2 qrts	-1.54	0.10	-1.75	0.22	-0.93	0.26	-1.36	0.30	-0.41	0.31	-0.48	0.34
(53)	(0.77)*		(0.68)*		(0.25)*		(0.41)*		(0.10)*		(0.10)*	
1 yr	-1.44	0.12	-1.70	0.31	-0.83	0.30	-1.32	0.42	-0.37	0.37	-0.41	0.35
(51)	(0.82)		(0.64)*		(0.26)*		(0.39)*		(0.10)*		(0.10)*	
2 yrs	-0.99	0.09	-1.54	0.40	-0.60	0.25	-1.06	0.43	-0.30	0.36	-0.27	0.23
(47)	(0.73)		(0.55)*		(0.26)*		(0.34)*		(0.10)*		(0.11)*	
3 yrs	-1.26	0.17	-1.39	0.45	-0.53	0.28	-0.88	0.43	-0.25	0.38	-0.21	0.21
(43)	(0.78)		(0.55)*		(0.25)*		(0.34)*		(0.10)*		(0.11)	
Panel B: all available data												
	1973:1–2005:4										**1980:1–2005:4**	
	AAA **IM**		*AAA* **L**		*BBB* **IM**		*BBB* **L**				**ML** *HY*	
Horizon	$\beta_k^{AAA}(IM)$	R^2 (Obs.)	$\beta_k^{AAA}(L)$	R^2 (Obs.)	$\beta_k^{BBB}(IM)$	R^2 (Obs.)	$\beta_k^{BBB}(L)$	R^2 (Obs.)			β_k^{HY}	R^2 (Obs.)
1 qrt	-1.77	0.04	-3.03	0.09	-1.46	0.12	-2.15	0.17			-0.34	0.07
	(0.86)*	(131)	(0.76)*	(131)	(0.31)*	(131)	(0.44)*	(131)			(0.15)*	(103)
2 qrts	-1.17	0.03	-3.00	0.14	-1.18	0.12	-2.06	0.24			-0.29	0.07
	(0.77)	(130)	(0.71)*	(130)	(0.28)*	(130)	(0.44)*	(130)			(0.16)	(102)
1 yr	-0.05	0.00	-2.29	0.13	-0.48	0.03	-1.44	0.18			-0.22	0.07
	(0.73)	(128)	(0.63)*	(128)	(0.27)*	(128)	(0.41)*	(128)			(0.14)	(100)
2 yrs	0.73	0.03	-0.83	0.03	0.22	0.01	-0.43	0.03			-0.12	0.04
	(0.60)	(124)	(0.57)	(124)	(0.23)	(124)	(0.34)	(124)			(0.12)	(96)
3 yrs	0.52	0.02	-0.32	0.01	0.25	0.02	-0.05	0.00			-0.14	0.08
	(0.61)	(120)	(0.51)	(120)	(0.19)	(120)	(0.26)	(120)			(0.07)	(92)
Panel C: 1985:1–2005:4												
	AAA **IM**		*AAA* **L**		*BBB* **IM**		*BBB* **L**		**LB** *HY*		**ML** *HY*	
Horizon	$\beta_k^{AAA}(IM)$	R^2 (Obs.)	$\beta_k^{AAA}(L)$	R^2 (Obs.)	$\beta_k^{BBB}(IM)$	R^2 (Obs.)	$\beta_k^{BBB}(L)$	R^2 (Obs.)	β_k^{HY}	R^2 (Obs.)	β_k^{HY}	R^2 (Obs.)
1 qrt	-1.47	0.05	-1.38	0.06	-0.89	0.11	-1.35	0.13	-0.53	0.32	-0.58	0.34
	(0.62)*	(83)	(0.58)*	(83)	(0.25)*	(83)	(0.39)*	(83)	(0.09)*	(75)	(0.09)*	(83)
2 qrts	-1.53	0.08	-1.53	0.12	-0.85	0.16	-1.37	0.21	-0.52	0.49	-0.55	0.49
	(0.60)*	(82)	(0.56)*	(82)	(0.23)*	(82)	(0.35)*	(82)	(0.09)*	(74)	(0.09)*	(82)
1 yr	-1.21	0.07	-1.50	0.17	-0.63	0.12	-1.25	0.25	-0.45	0.52	-0.45	0.45
	(0.59)*	(80)	(0.51)*	(80)	(0.21)*	(80)	(0.31)*	(80)	(0.08)*	(72)	(0.08)*	(80)
2 yrs	-0.39	0.01	-1.19	0.17	-0.27	0.04	-0.84	0.19	-0.32	0.40	-0.27	0.27
	(0.53)	(76)	(0.48)*	(76)	(0.22)	(76)	(0.30)*	(76)	(0.07)*	(68)	(0.07)*	(76)
3 yrs	-0.35	0.01	-1.04	0.18	-0.19	0.03	-0.66	0.17	-0.24	0.35	-0.19	0.19
	(0.51)	(72)	(0.46)*	(72)	(0.21)	(72)	(0.28)*	(72)	(0.07)*	(64)	(0.07)*	(72)

Figure 1. Treasury yields: actual and implied slope and curvature

The figure shows the actual and model implied slope and curvature of the Treasury yields.

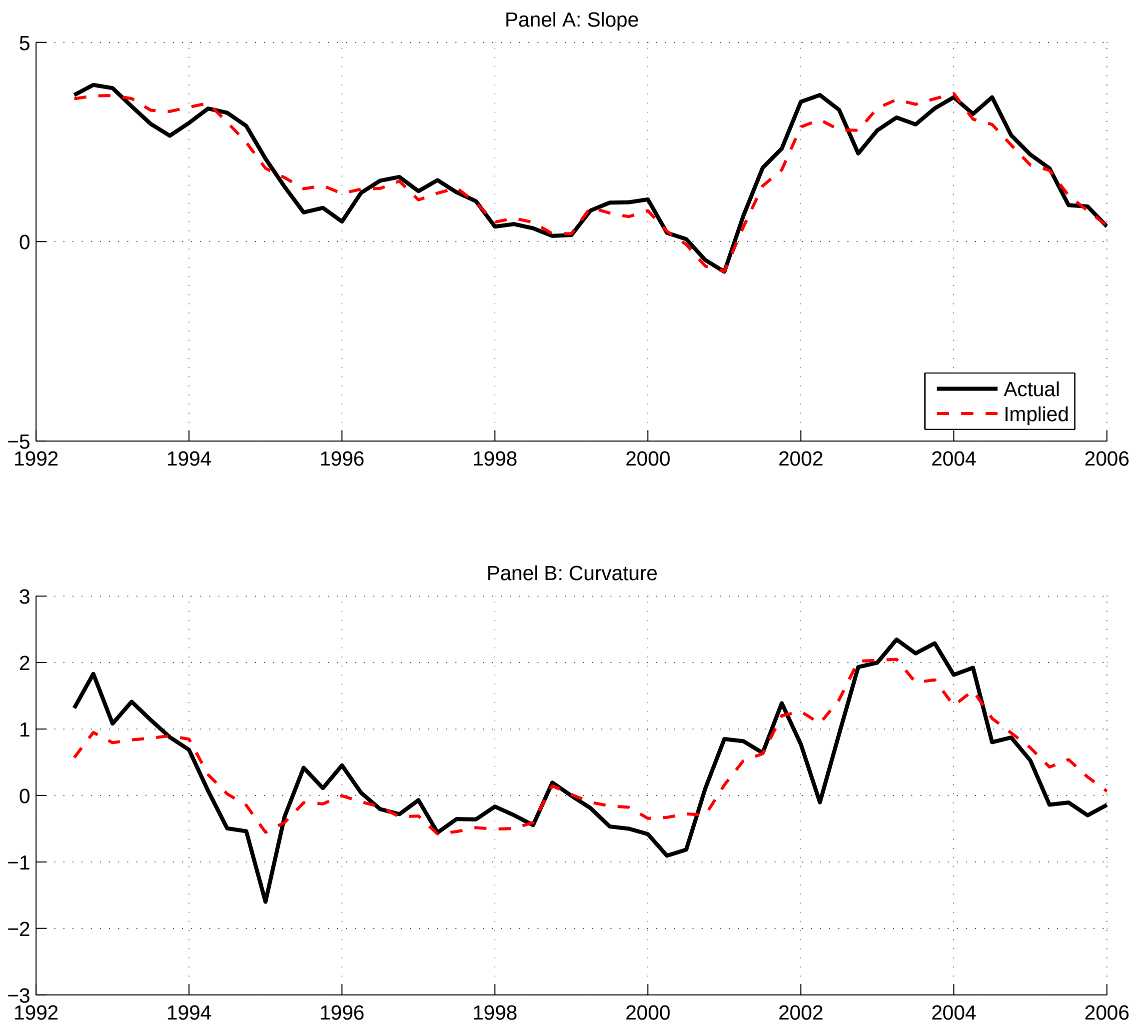


Figure 2. Credit spreads: actual and implied levels

The figure shows the fit of the credit spreads levels. I plot actual and model implied 1- and 10-year credit spreads for AAA, BBB and B credits.

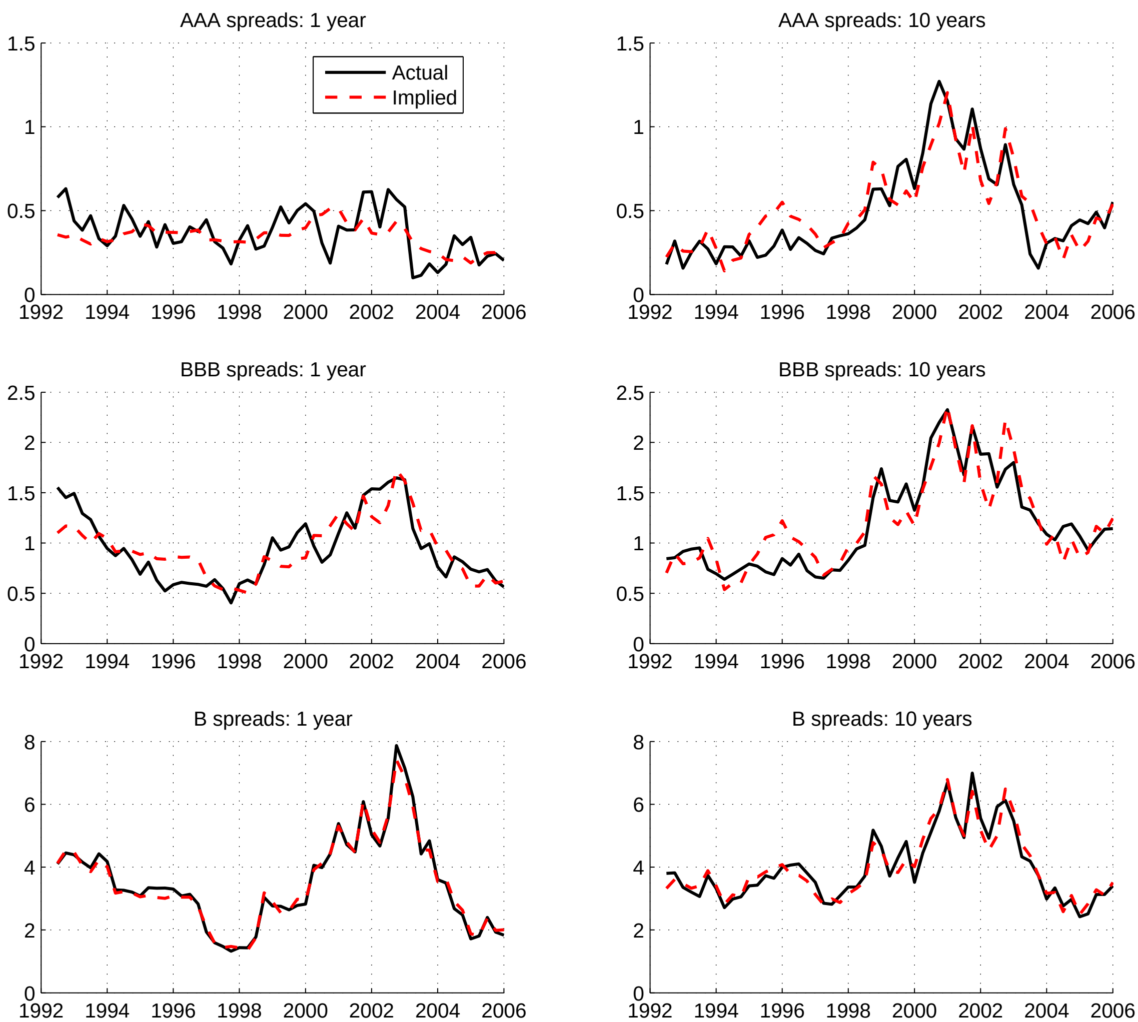


Figure 3. Implied spreads and Treasury yields, and term premia

The figure shows the decomposition of the implied credit spreads (thin black line) and Treasury yields into a part based on expectations about the future short rate (thick blue line) and a term premium (thick green line).

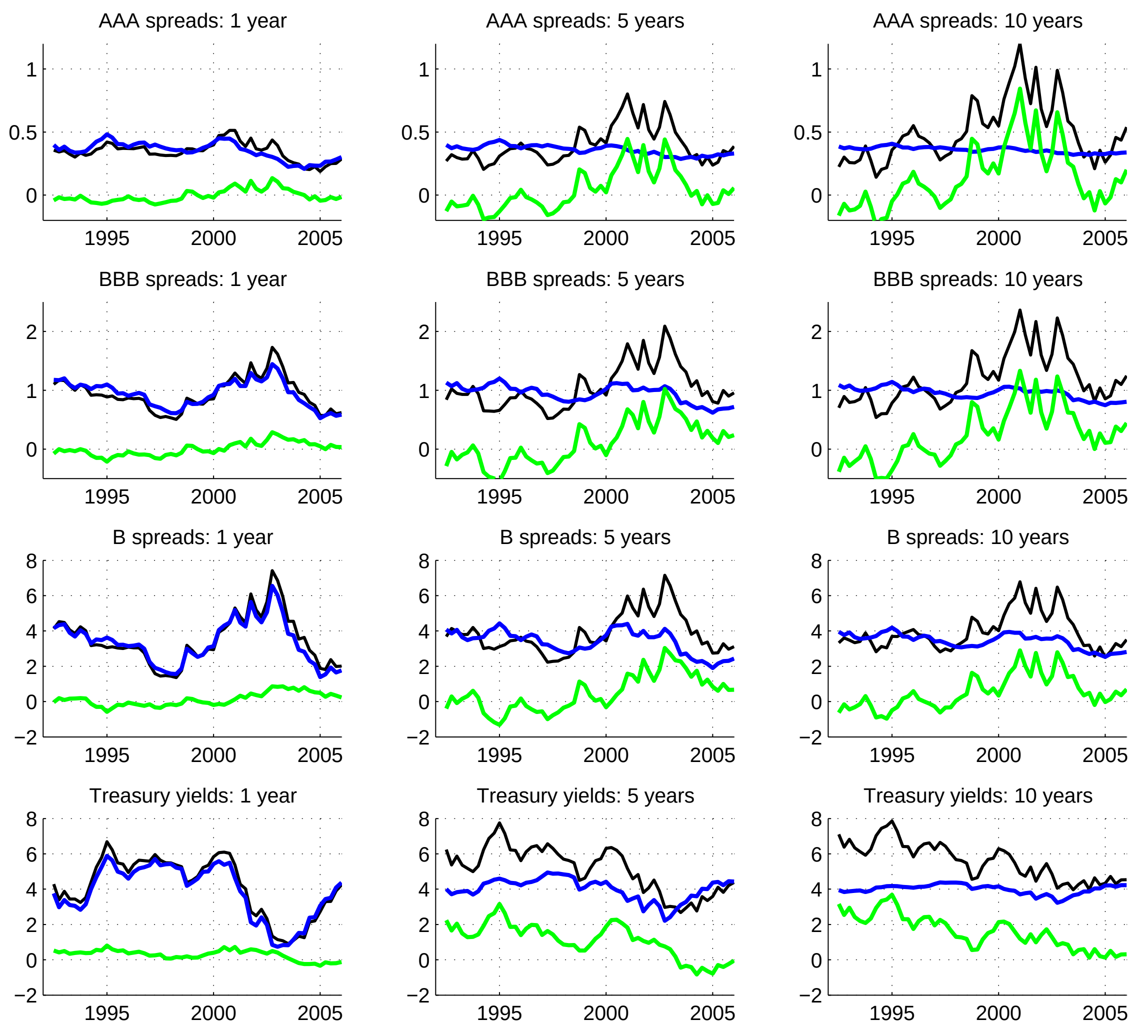


Figure 4. Normalized factor loadings

The figure shows how Treasury yields and credit spreads change in response to a one standard deviation change in any of the state variables. The responses are also expressed in standard deviations to facilitate comparison and gauge the relevance of the various state variables.

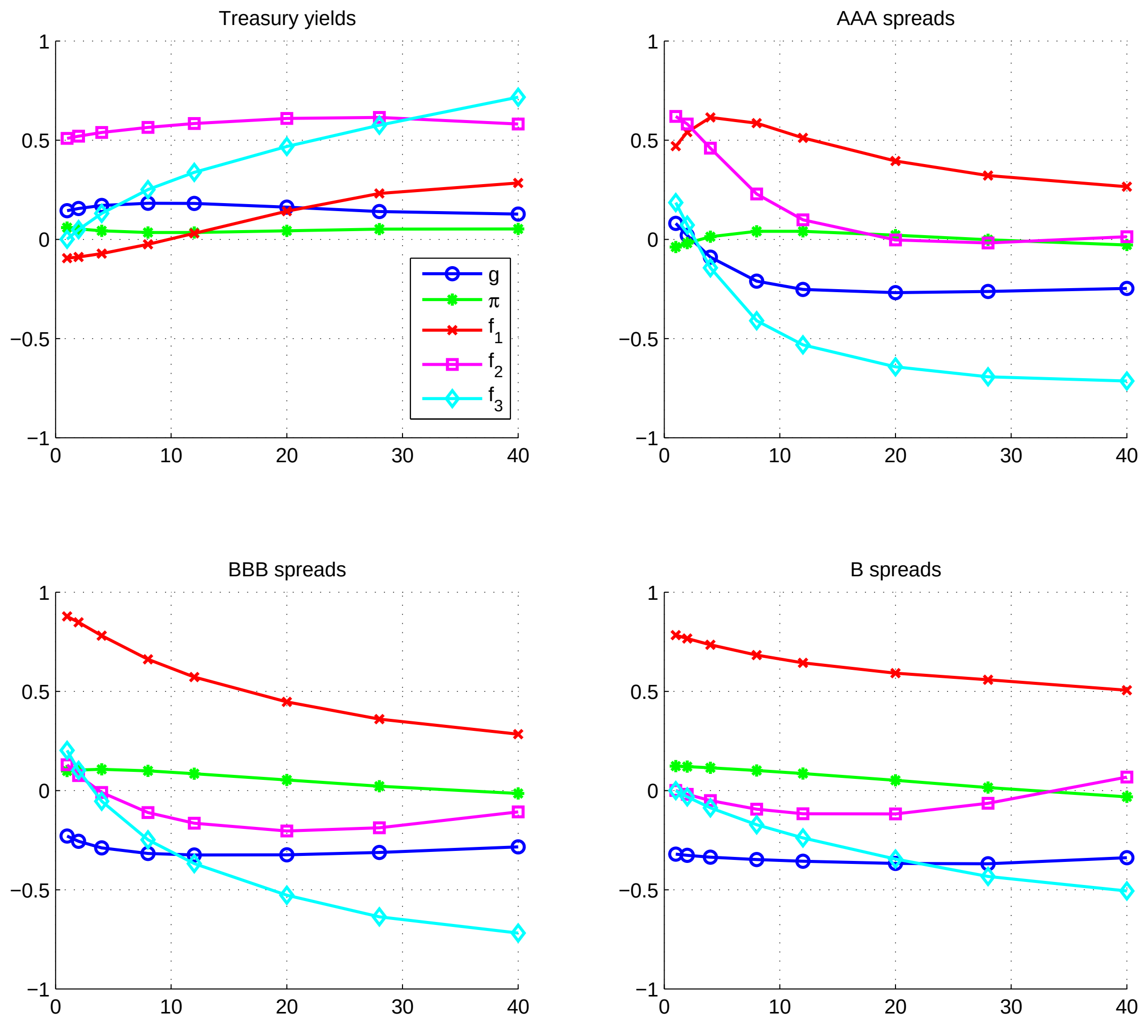
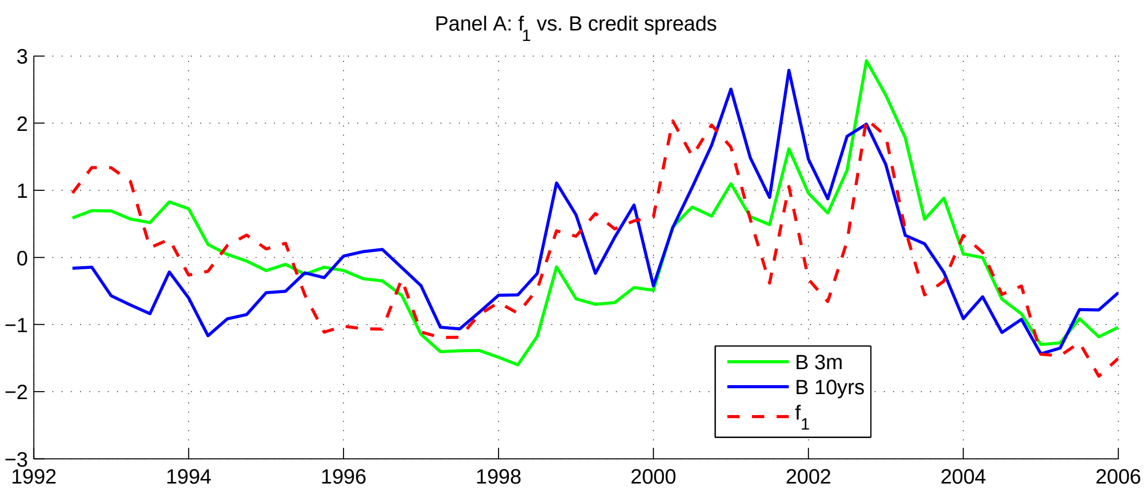


Figure 5. Factor f_1, B spreads and index of tighter loan standards

Panel A plots the quarterly time series of the estimated factor f_1 against 3-month and 10-year B spreads. Correlations between f_1 and the credit spreads are 70% and 57%, respectively. Panel B plots the factor f_1 against the prewithened index of tighter loan standards from the Senior Loan Officer Opinion Survey. The prewithened series are residuals from regressing the original series on eight lags of inflation and real activity. The correlation between the two series is 62%. All series are normalized to facilitate comparison.



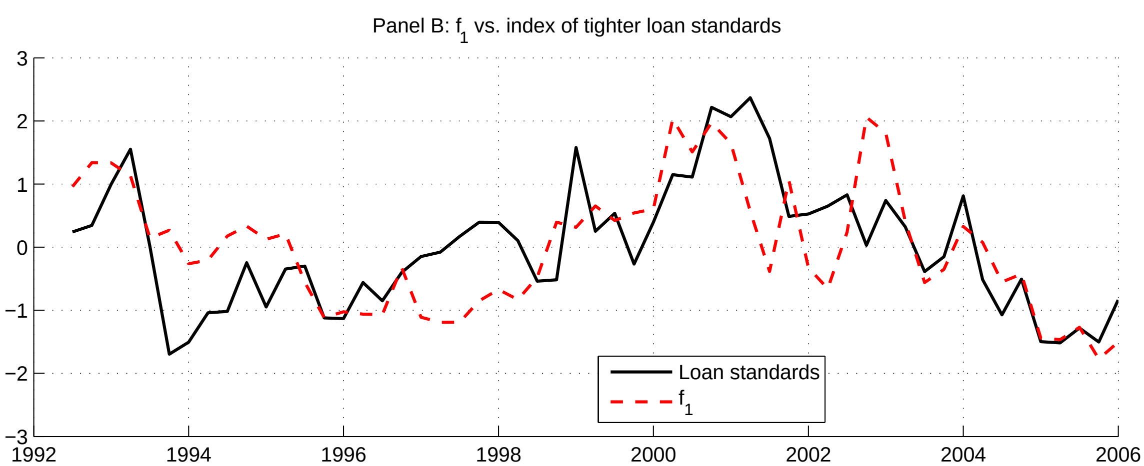
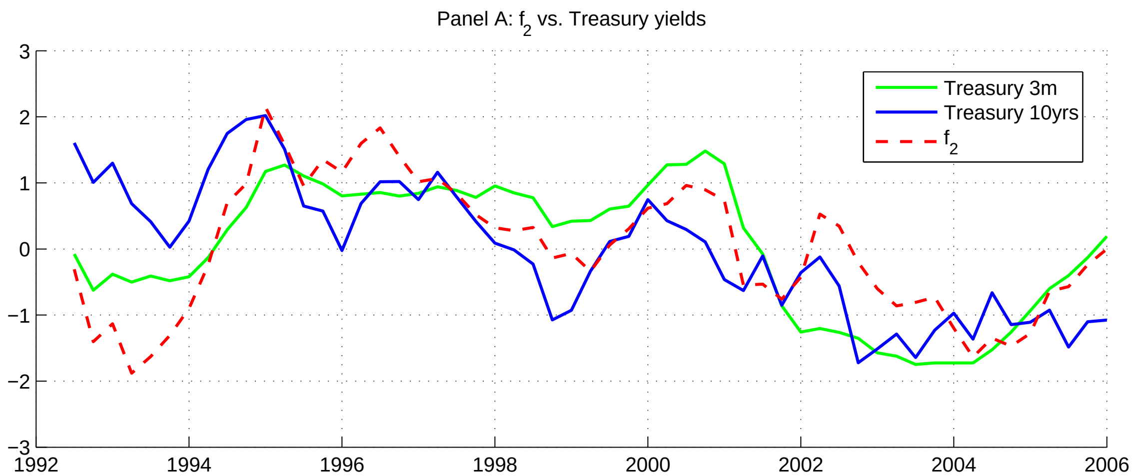


Figure 6. Factor f_2, Treasury yields and Federal funds target rate

Panel A plots quarterly time series of the estimated factor f_2 against 3-month and 10-year Treasury yields. Correlations between f_2 and the Treasury yields are 77% and 52%, respectively. Panel B plots the factor f_2 against the prewithened Federal funds target rate. The prewithened series are residuals from regressing the original series on eight lags of inflation and real activity. The correlation between the two series is 68%. All series are normalized to facilitate comparison.



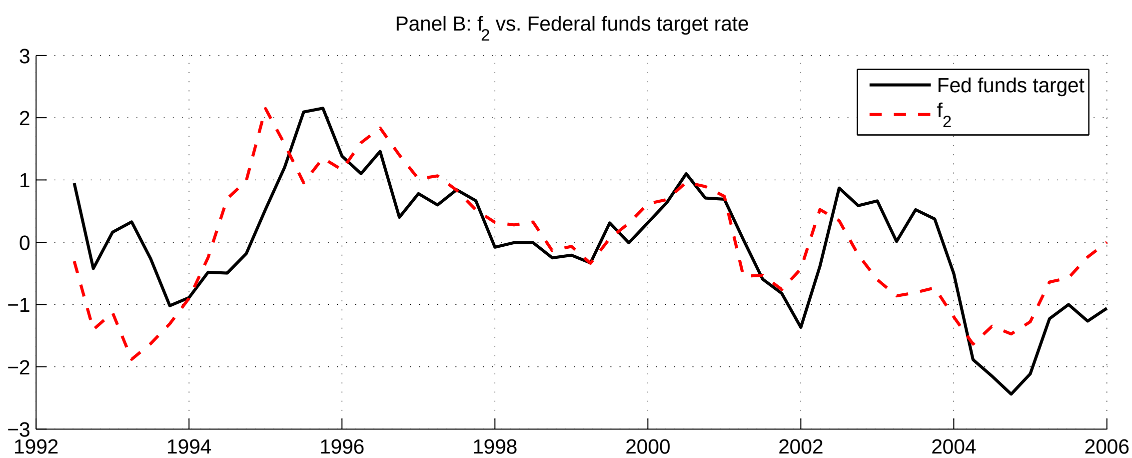


Figure 7. Decomposition of implied spreads

The figure shows the implied credit spreads and the decompositions thereof into the contributions from the various factors. The projection piece includes the constant, the direct contribution of the macro variables and the projection. The contribution of the orthogonalized factors is calculated by multiplying the factor loading by the realizations.

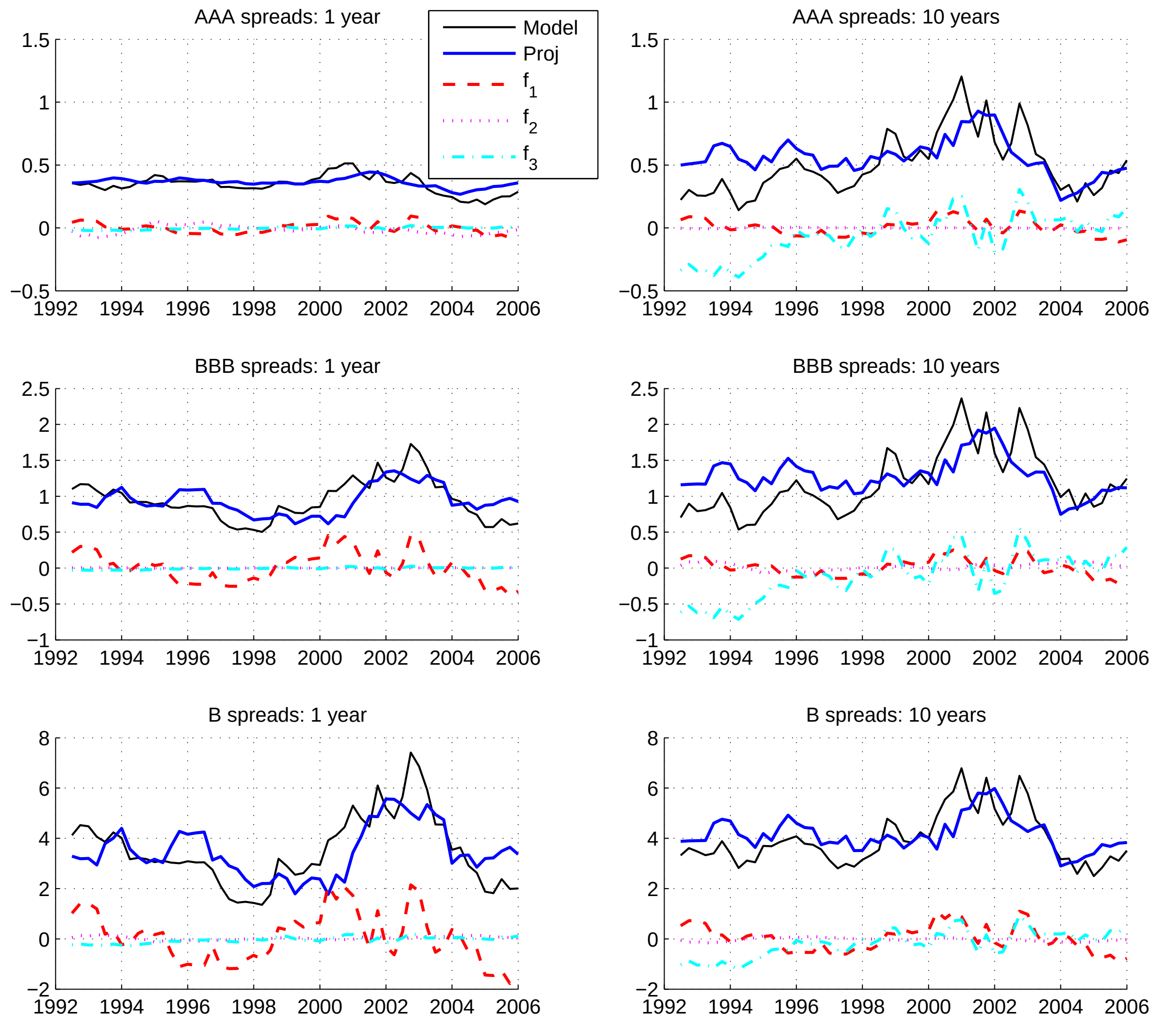


Figure 8. Treasury yields and credit spreads

Panel A shows the 3-month, 1-year and 1-year Treasury yields, and 10-year corporate bond yields Panels B through D show the 3-month, 1-year and 10-year credit spreads, respectively for AAA, BBB and B credits.

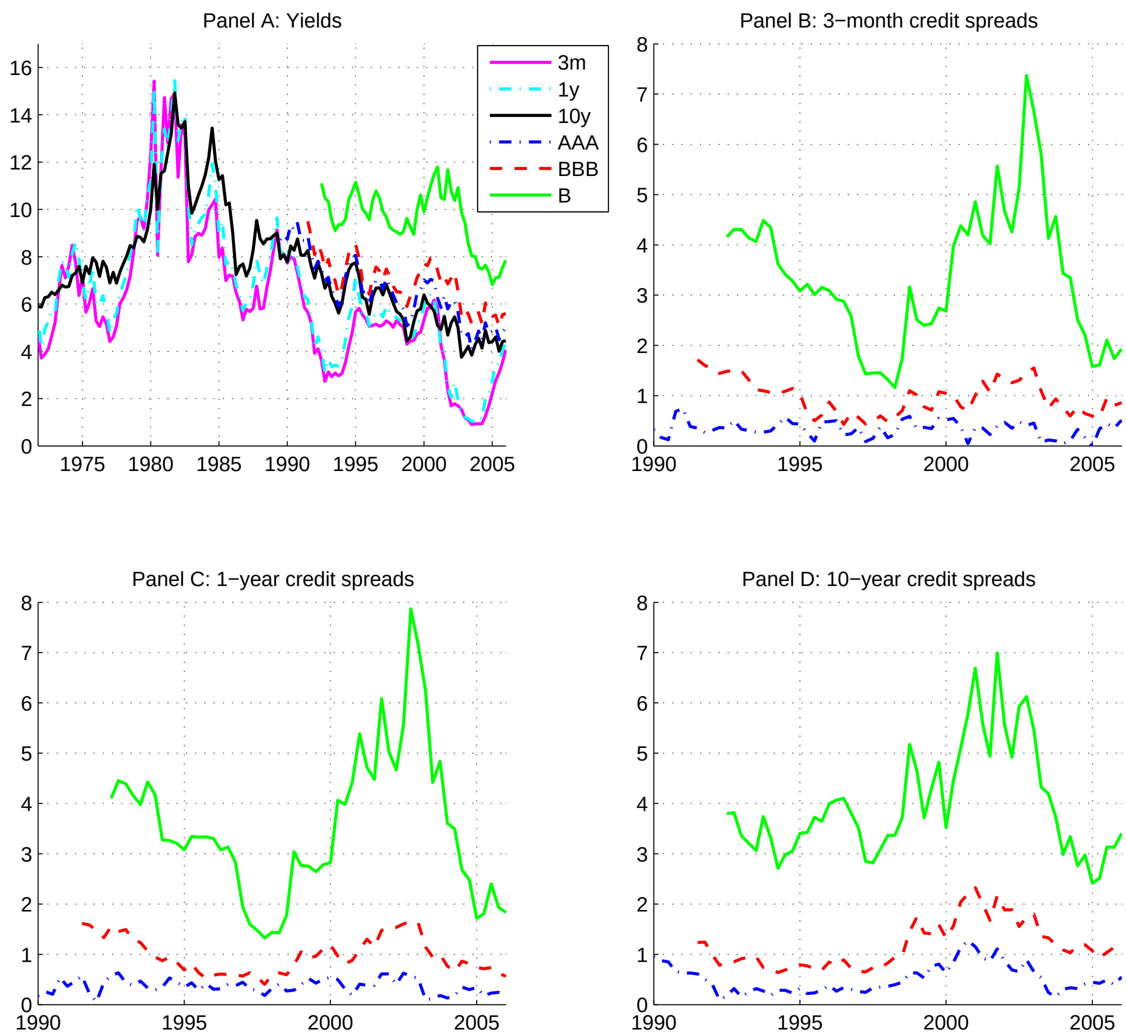


Figure 9. Impulse response functions for bivariate VARs

I plot the impulse response functions for simple bivariate VARs with lag length equal to four quarters. Panels A through C show the impulse response functions of real GDP and the term spread to a 100bp shock in the term spread for different sample periods. Panel D plots the impulse response functions for GDP and the 10-year B spread to a 100bp shock in the B spread. The lag length is determined using Bayes criterion.

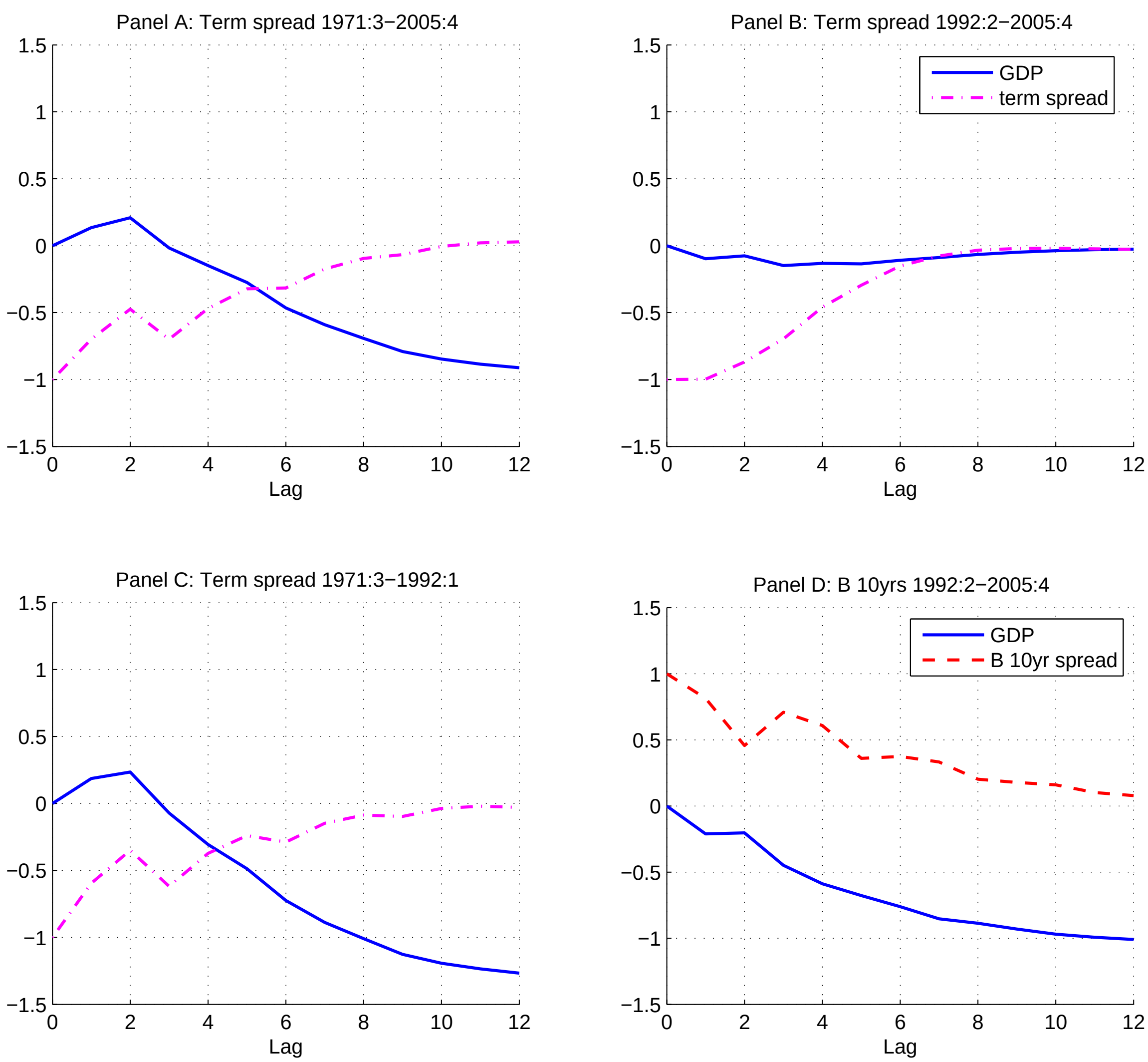


Figure 10. Impulse response functions for VARs

I plot the impulse response functions for multivariate VARs with lag length equal to two quarters. Panels A through C show the impulse response functions of real GDP, inflation and the short rate to a 100bp shock in the short rate for different sample periods. Panel D plots the impulse response functions for GDP, inflation, the short rate and the 10-year B spread to a 100bp shock in the B spread. The lag length is determined using Bayes criterion.