Credit Spreads and Real Activity\*  

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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, while 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 show that there is a pure credit component orthogonal to macroeconomic information that accounts for 50% to 65% of the forecasting power of credit spreads. 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. Using data from 2006–2008, I capture the ongoing crisis during which credit conditions have heavily tightened. As of year-end 2008, the model predicts a contraction of $-2\%$ in real GDP growth for 2009, which is more pessimistic than concurrent forecasts available from surveys.

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1 Introduction

Starting with the August 2007 Federal Open Market Committee (FOMC) statement, the Federal Reserve has continuously expressed concern about strains in the financial markets and the link between tightening credit conditions, financial instability and economic growth.\(^1\) Disturbances in the financial sector, if allowed to develop fully, could have severe negative consequences for real activity. By easing interest rates and providing liquidity to the financial system, the Fed tried to contain the problems in the financial markets and prevent a spillover effect into the overall economy.

In this paper, I explore the transmission of credit conditions into the real economy. An implication of the link between credit markets and the economy is that credit spreads—i.e., the difference between corporate bond 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 help predict 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 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. While the external finance premium is not directly observable, credit spreads are a useful proxy.

Empirically, I motivate my approach with a set of regression results. Using simple OLS regressions of future GDP growth on credit spreads, I find that credit spreads across the whole term structure and for rating categories ranging from AAA to B have predictive content above and beyond that contained in the the term structure of Treasury yields and the history of GDP growth and inflation.

However, it is important to note that not every factor that affects credit spreads needs to be related to future GDP growth. Moreover, 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 linear regression 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.

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\(^1\) See, for example, Bernanke (2007a, 2007b, 2009) and Mishkin (2007a, 2007b).

\(^2\) Credit spread term premia are defined as the difference between the credit spreads calculated under the risk neutral pricing measure and the credit spreads calculated assuming zero prices of risk.
A natural framework that does allow identifying and disentangling the sources of predictive power is a macro-finance term structure model.\textsuperscript{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 jointly 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 spread 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.\textsuperscript{4} Namely, I am able to quantify the contributions of expectations vs. term premia, and the relative importance of various factors in the model.

Decomposing the spreads into an expectations and a term premia piece I find that both are relevant for predicting GDP growth. The expectations piece is important for higher grade long maturity spreads, whereas the term premia piece is an important contributor for a wide variety of spreads and all forecast horizons.

Separating spreads into contributions from the various factors yields further insights. 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, explaining between 50% and 60% of the overall 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.

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. This is noteworthy as there are no restrictions on the factor loadings of credit spreads and Treasury yields in the macro-finance model that would predetermine such an outcome. 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.

The credit factor is constructed to be independent of current and past innovations in inflation and

\textsuperscript{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.”

\textsuperscript{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 my knowledge, the first to examine the predictive content of the term structure of credit spreads in a no-arbitrage framework.
GDP growth, the observable macro state variables. The strong predictive power of the credit factor provides evidence for the existence of a transmission channel from credit conditions to real activity. According to the impulse responses, a one standard deviation shock to the credit factor results in a contraction in real GDP of $-0.6\%$ over a one year period. This finding is 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.

In order to capture more information about the real economy than contained in GDP growth and inflation alone, I estimate the macro-finance model using the first two principal components of a large macro data set as observable factors. While the correlations between the new observable factors and GDP growth and inflation, respectively, are very low, the credit factor remains largely unchanged and the conclusions from the base case model hold.

This robustness check is similar to the factor-augmented vector autoregression (FAVAR) approach that relates a large panel of economic indicators and individual price series to a relatively small number of estimated common factors. In a concurrent study, Gilchrist, Yankov, and Zakrajšek (2009) use the FAVAR framework to identify shocks to bond spreads that are orthogonal to other contemporaneous information. Consistent with the results in this paper, they find that shocks to corporate bond spreads can explain a sizable fraction of the variation in future economic activity. To identify their credit factor, they assume that Treasury yields and other financial variables do not load on the credit factor whereas my no-arbitrage setup allows to separate out the credit component without assuming orthogonality. In further contrast to their study, this paper focuses on the determinants of credit spreads and the linkage between credit conditions and real activity, thus providing an interpretation for the latent credit factor identified in the macro-finance model.

The paper is organized as follows. Section 2 reviews the relevant literature in regard 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 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. Section 7 compares out-of-sample GDP growth expectations with survey forecasts and section 8 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

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5 The data is taken from Boivin, Giannoni, and Mihov (2007).
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. This 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.\footnote{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.}

Because fluctuations in the external finance premium can be reflected in either risk-free interest 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.\footnote{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.} 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.\footnote{See, for example, Dotsey (1998).} 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.\footnote{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.}

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 (1999) 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.\footnote{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.} 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. Gilchrist, Yankov, and Zakrajšek (2009) construct expected default risk based portfolios and conclude that credit spreads on senior unsecured corporate debt have substantial forecasting power for future economic activity. 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 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.\textsuperscript{11} 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 1992:2–2006:1 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, the short rate and the 5-year term spread as control variables.\textsuperscript{12}

3.1 Data and Methodology

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

$$g_{t,k} = \frac{400}{k} \log \left( \frac{GDP_{t+k}}{GDP_t} \right) = \frac{1}{k} \sum_{i=1}^{k} g_{t+i}.$$ \hspace{2cm} (1)

Using this notation, $g_{t,1} = g_{t+1}$. Furthermore, denote the credit spread for a rating class $i$ and maturity $\tau$ as $CS^i_t(\tau) = y^i_t(\tau) - y^T_t(\tau)$, where $y^i_t(\tau)$ and $y^T_t(\tau)$ are the corporate bond and Treasury yields, respectively. Treasury yields are continuously compounded zero coupon bond prices for maturities ranging from three months up to ten years taken from the Guerkyanak, Sack, and Wright (2006) dataset. 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 bond and the Treasury yields. GDP data are available through the FRED database (Federal Reserve Bank of St. Louis).\textsuperscript{13}

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

$$g_{t,k} = \alpha^i_k(\tau) + \beta^i_k(\tau)CS^i_t(\tau) + \Gamma_k'CON_t + u_{t+k}.$$ \hspace{2cm} (2)

\textsuperscript{11} Two examples of DSGE models that incorporate credit market imperfections are Christiano, Motto, and Rostagno (2008), and Cirdia and Woodford (2008).

\textsuperscript{12} Some robustness checks using an extended sample period are performed in appendix C.

\textsuperscript{13} A detailed description of the data is provided in appendix A.
Future GDP growth for the next $k$ quarters is regressed on the credit spread for rating class $i$ and maturity $\tau$ and a vector of control variables $CON_t$. 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 $CON_t$ 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.\(^{14}\) 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, $\pi$, should also be added as control variables.\(^{15}\)

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, $r_t$, as a control variable.

### 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 $R^2$; (3) combining spreads of different maturities and rating classes in a single regression helps improving adjusted $R^2$ suggesting that the forecasting power may be driven by more than a single factor.

### 3.2.1 Univariate Regressions

Table 1, panels A and B contain the results for the $\beta^i_k(\tau)$ coefficients in the regression equation 2 with and without controls for the sample period 1992:2–2006:1.\(^{16}\) Apart from very short-term AAA spreads (less than one year), almost all $\beta^i_k(\tau)$ coefficients are significantly different from zero. All coefficients that are significant in the univariate regressions are also significant in the specification 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

\(^{14}\) See, for example, Fischer (1993), or Bruno and Easterly (1998).

\(^{15}\) Inflation is calculated as the growth rate in CPI, available through the FRED database (Federal Reserve Bank of St. Louis).

\(^{16}\) The tables contain selected result for expositional clarity. Results additional forecast horizons and maturities are available on the author’s website in the online appendix or upon request.
documented negative relationship between inflation and real activity.\textsuperscript{17} The coefficient for the term spread is insignificant in general. The addition of the history of macro variables has a positive effect on both, $R^2$ and adjusted $R^2$, thus suggesting that macro variables are indeed relevant for explaining future GDP growth.\textsuperscript{18}

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 better than shorter maturity spreads for the same rating class.\textsuperscript{19}

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 $R^2$ of over 60\%, whereas the maximum $R^2$ for the 10-year $B$ spread is a mere 26\%. This is consistent with recent findings by Gilchrist, Yankov, and Zakrajšek (2009) who report that bonds issued by intermediate-risk rather than high-risk firms contain much of the predictive power. However, it seems to contradict Gertler and Lown (1999) 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 $R^2$ from the credit spread regressions using all control variables. In addition, Table 2 contains the $R^2$ 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 Table 2, panel B reveal that including either the short rate or various term spreads in regression (1) leaves $R^2$ 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.\textsuperscript{20}

Only the inclusion of the credit spreads (Table 2, panel C) improves $R^2$ significantly (again, with the exception of very 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

\textsuperscript{17}Coefficients other than those for the credit spreads are not reported.

\textsuperscript{18}Unless otherwise noted, regressions with controls are performed with $p = 2$, which means current and lagged GDP growth and inflation are included. 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 $R^2$ do not improve further.

\textsuperscript{19}$R^2$ for 10-year investment grade spreads are usually 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 $R^2$ is very small.

\textsuperscript{20}The results documenting the declining predictive power of the short rate and the term spread are reported in appendix B.
to the short rate, GDP and the price level have a significant effect on the future path of the economy.\footnote{Detailed results are provided in the online appendix.}

### 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 and D. Compared to the univariate regressions, the $R^2$ are improved by up to four percentage points. Moreover, coefficients on the slope and level are both significant for AAA and BBB spreads for all horizons. In the case of B spreads, most of the 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 $R^2$.\footnote{Results for this exercise are not reported.} 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.

### 4 A Macro-Finance Term Structure Model

The macro-finance term structure model described in this section helps disentangling the 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 no-arbitrage term structure models with credit spreads but they do not include macro variables. Wu and Zhang (2005) 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 here 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 joint behavior of the Treasury yields and corporate bond spreads is captured by the state vector \( z_t = (m'_t, x'_t)' \). The vector of macroeconomic variables contains GDP growth and inflation and is given by \( m_t = (g_t, \pi_t)' \). \( x_t \) 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. Hence, \( z_t \) fully reflects the available information at time \( t \).

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

\[
 z_t = \mu + \Phi z_{t-1} + \Sigma \epsilon_t, \quad \text{where } \epsilon_t \sim \mathcal{N}(0, I). \tag{3}
\]

4.2 Treasury Yields

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

\[
 r_t = \delta_0 + \delta'_m m_t + \delta'_x x_t. \tag{4}
\]

In order to value the assets, the model needs to be completed by specifying the stochastic discount factor \( \xi_t \):

\[
 \log \xi_t = -r_{t-1} - \frac{1}{2} \Lambda'_t \Lambda_t - \Lambda'_t \epsilon_t, \tag{5}
\]

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

\[
 \Lambda_t = \Lambda_0 + \Lambda_z z_t. \tag{6}
\]

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

\[
 y_T^T(\tau) = a^Q(\tau) + b^Q(\tau)' z_t = a^Q(\tau) + b^Q_m(\tau)' m_t + b^Q_x(\tau)' x_t \tag{7}
\]

\[
 = a^P(\tau) + b^P(\tau)' z_t + a^{TP}(\tau) + b^{TP}(\tau)' z_t \tag{8}
\]

where \( \tau \) is the respective maturity and \( a^Q \) and \( b^Q \) solve well-known recursive equations with boundary conditions \( a^Q(1) = \delta_0 \) and \( b^Q(1) = \delta_z \).23 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.

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.

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23 For the recursive equations see Ang and Piazzesi (2003).
4.3 Corporate Bond Spreads

Duffie and Singleton (1999) show that in continuous time 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. In discrete time, the same is approximately true under the recovery of market value assumption.

I model the short maturity (3-month) spread as a linear function of the state variables:

$$s^i_t = \gamma_0^i + \gamma_z^i z_t = \gamma_0^i + \gamma_m^i m_t + \gamma_x^i x_t,$$

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

$$y^i_t(\tau) = \tilde{a}^i(\tau) + \tilde{b}^i(\tau)' z_t.$$

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.

$$CS^i_t(\tau) \triangleq y^i_t(\tau) - y^T_t(\tau) = \left(\tilde{a}^i(\tau) - a^Q(\tau)\right) + \left(\tilde{b}^i(\tau) - b^Q(\tau)\right)' z_t$$

$$= a^Q(\tau) + b^Q(\tau)' z_t = a^Q(\tau) + b^Q_m(\tau)' m_t + b^Q_x(\tau)' x_t$$

$$= a^Q_m(\tau) + a^Q_m(\tau)' m_t + a^Q_x(\tau)' x_t + \xi_t$$

$$= a^Q_m(\tau) + a^Q_m(\tau)' m_t + a^Q_x(\tau)' x_t + \xi_t$$

5 Econometric Methodology

The model parameters of the term structure model are estimated jointly via maximum likelihood with Kalman filter following Bikbov and Chernov (2008), 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. All Treasury yields and credit spreads are available for three and six months, and one, two, three, five, seven and ten year maturities.\(^{24}\)

The state equation in the model is defined by equation (3). The macro variables are assumed to be observed without errors. Furthermore, I allow for estimation errors for both Treasury yields and corporate credit spreads so that the latent factors are not associated with pre-specified observables. Thus, we have the following observation equations:

$$y^T_t(\tau) = a^Q(\tau) + b^Q_m(\tau)' m_t + b^Q_x(\tau)' x_t + \epsilon_t,$$

$$CS^i_t(\tau) = a^i(\tau) + b^i_m(\tau)' m_t + b^i_x(\tau)' x_t + \epsilon^i_t$$

\(^{24}\) A detailed description of the data is provided in appendix A.
where $y_T^T$ represents the Treasury yields for maturity $\tau$ and $CS_i^T$ stands for the corporate bond spread for rating class $i$ and maturity $\tau$, with $\tau$ ranging from three months to ten years. The estimation errors are denoted by $\varepsilon_t$ and $\varepsilon_i^t$, and assumed to be i.i.d. normal with standard deviations $\sigma_\varepsilon$ and $\sigma_i^\varepsilon$, respectively.

### 5.2 Number of Factors

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 96.4% 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 1.5%. Adding more factors is also problematic because the number of parameters increases disproportionately. 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 and I therefore choose to have three latent factors, i.e. $x_t = (x_{1,t}, x_{2,t}, x_{3,t})'$, and estimate a five-factor model.

Given the set of observables, the chosen specification is indeed very parsimonious. Modeling only macro variables and Treasury yields, Ang and Piazzesi (2003) also estimate a five-factor model with two observable and two latent 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.

### 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 augment the standard log-likelihood function, $\mathcal{L}$, with a penalization term, which is proportional to the variation of the term premium in (8) and (12):

$$
\mathcal{L}_p = \mathcal{L} - \frac{1}{2\sigma_p^2} \sum_{\tau} (a^{TP}(\tau))^2 + b^{TP}(\tau)' \cdot \text{Diag}(\text{var}(z_t)) \cdot b^{TP}(\tau) \\
- \frac{1}{2\sigma_i^2} \sum_{i,\tau} (a^{i,TP}(\tau))^2 + b^{i,TP}(\tau)' \cdot \text{Diag}(\text{var}(z_i)) \cdot b^{i,TP}(\tau),
$$

(15)

---

25 In selecting the scheme for identifying parameters, I largely follow Bikbov and Chernov (2008).

26 This approach is also used in Bikbov and Chernov (2008) and Chernov and Mueller (2008).
where $\sigma_p$ 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, $L_p$ 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.\(^{27}\) Theoretically, it is possible to estimate the macro-finance model using all available data.\(^{28}\) However, I choose to estimate the model only over the common sample period 1992:2–2006:1 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 one way to deal with time-varying predictive relations as noted by Stock and Watson (2003a). Finally, the end of the estimation period coincides with the end of the tenure of Alan Greenspan as chairman of the Board of Governors of the Federal Reserve.

In order to deal with the different absolute magnitudes of Treasury yields and corporate bond spreads, I use the following restrictions to make the estimation errors roughly proportional to the level of the yields and credit spreads:\(^{29}\)

$$
\epsilon^2 = \frac{1}{2}(\epsilon^{AAA})^2 = \frac{1}{2}(\epsilon^{BBB})^2 = (\epsilon^B)^2.
$$

**Optimization.** I need to estimate 91 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.\(^{30}\) 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

\(^{27}\) See appendix A for a detailed description of data availability.

\(^{28}\) It is straightforward to deal with the missing credit spreads in the Kalman filter framework by only partially updating whenever observations are missing (see Harvey (1989)).

\(^{29}\) This modification slightly improves the fit of credit spreads but it does not drive the results. Filtered latent factors from an unrestricted estimation are virtually identical.

\(^{30}\) See, for example, Press, Teukovsky, Vetterling, and Flannery (1992).
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 chosen specification. If the implied spreads do not exhibit any forecasting power for GDP growth, 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 very 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.31

Treasury Yields. The model fits Treasuries very well. $R^2$ 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 $R^2$ are displayed in Table 3 along with the results for the fit of the credit spreads. The panels in row one in Figure 1 plot the actual and implied slope and curvature both in- and out-of-sample.

Corporate Yields and Credit Spreads. The model fits B spreads almost as well as Treasury yields with $R^2$ close to or above 98% for almost all maturities. For BBB spreads, $R^2$ range between around 70% for short maturities and above 80% for longer maturities. AAA spreads display the greatest disparity with an $R^2$ as low as 21% for the short spread, while longer maturity spreads are fitted well with $R^2$ of around 70%. The actual and implied spreads for selected maturities are displayed in Figure 1, rows two through four. The standard deviations of the errors in the observation equation (14) are 0.16 for AAA and BBB spreads and 0.25 for B spreads. This implies that the model values the high grade spreads within about 30 basis points and the B spreads within about 50 basis points ($2\sigma_i$). The mean absolute errors range between 7 and 13 basis points (between 18% to 40% expressed as a fraction of the level) for AAA spreads, between 14 and 16 (13% and 21%) for BBB spreads and between 12 and 23 (3% and 6%)

31 Other than describing the model fit, the paper does not report the technical details of the estimation results such as parameter values, or the statistical significance of point estimates. There are too many parameters to discuss, and most of them are hard to interpret. The results are available upon request.
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. Panel A in Table 4 reports the slope coefficient from regressing future GDP growth on the implied spreads, \( CS_i^t(\tau) \) and the vector of control variables for the in-sample period 1992:2–2006:1. Panel B reports the slope coefficient from regressing future GDP growth on the estimation errors given by \( CS_i^t(\tau) - \hat{CS}_i^t(\tau) \), the difference between actual and implied credit spreads.

The results confirm that overall the implied spreads are performing satisfactorily. They capture the predictability of the actual spreads, exhibiting highly significant slope coefficients and high \( R^2 \) for all credit qualities, most maturities and most forecast horizons. Nevertheless, the coefficient for the estimation error turns out to be significant in a few cases, namely for longer maturity higher grade spreads at longer forecast horizon. This means that these spreads might contain additional information that can be used for forecasting GDP growth at long horizons and that the model is not designed to capture.

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 straightforward 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 premia parameters in the equations for the Treasury yields and credit spreads to zero (equations (7) and (11)). The difference between the credit spread under the \( \mathbb{Q} \)- and under the \( \mathbb{P} \)-measure is then defined as the credit spread term premium.

Rows one through three in Figure 2 show the implied credit spreads under the risk neutral \( \mathbb{Q} \)-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 row four in Figure 2). 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 increases.

Regressing future GDP growth on both components of spreads, term premia and spreads under the \( \mathbb{P} \)-measure, allows to investigate whether the predictability can be attributed to either one of them. The term premia component of credit spreads is highly significant across all forecast horizons even for 1-year
credit spreads while the ℙ-component is not relevant at all for short forecast horizons.\textsuperscript{32} This is striking given the comparably small contribution of term premia to the overall variation of short maturity credit spreads. On the other hand, the coefficient for spreads under the ℙ-measure is highly significant for longer horizon forecasts for all short maturity credit spreads and for long maturity high grade spreads. Again, the importance of the long maturity ℙ-component for long horizon forecasts is noteworthy given the lack of variation (see, eg., column three in Figure 2).

Overall, the results suggest that term premia contain more information about future real activity than expectations about the future short rate but depending on the maturity of the credit spreads and the forecast horizon, both components are relevant.\textsuperscript{33} This implies that it is in general not possible to determine what drives the forecasting power as both components—expectations and term premia—are significant. Therefore, it is necessary to further decompose the implied spreads and explicitly consider the contributions of the state variables.

\section*{6.3 Determinants of Credit Spreads and the Drivers of Forecasting Power}

\subsection*{6.3.1 Macro Variables and Latent Factors}

Apart from decomposing credit spreads (and Treasury yields) into expectations and term premia, it is 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 that is not related to the macro variables. Separating out the contribution of the macro variables is not straightforward as 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 (2008). This allows decomposing each latent factor $x_t$ into a component explained by GDP growth and inflation, and a residual piece $f_t$ which is orthogonal to the history of the observable macro variables, $M_t = \{m_t, m_{t-1}, ..., m_0\}$:

\begin{equation}
    f_t = x_t - \hat{x}(M_t),
\end{equation}

\begin{equation}
    \hat{x}(M_t) = c(\Theta) + \sum_{j=0}^{t} c_{t-j}(\Theta)m_{t-j} \triangleq F(\Theta, L)m_t,
\end{equation}

where the matrices $c$ are functions of parameters $\Theta = (\mu, \Phi, \Sigma)$ that control the dynamics of the state variables and $L$ denotes the lag operator.\textsuperscript{34}

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. This property can be exploited by choosing a specific rotation that is useful for interpreting the residuals $f$. I rotate

\textsuperscript{32} The results are provided in the online appendix.

\textsuperscript{33} This is in slight contrast to Hamilton and Kim (2002) who decompose the Treasury term spread in a similar fashion. They also conclude that both components matter but find that the contribution of the expectations piece is significantly larger than that of the term premium.

\textsuperscript{34} The details of the procedure are provided in Bikbov and Chernov (2008), appendix A.
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 in the level of Treasury yields. The details of the procedure are provided in appendix D. Fixing $f_1$ and $f_2$ also pins down $f_3$, which can be interpreted as a “slope” factor.

Panel A in Figure 3 graphs the credit factor $f_1$ with the B 3-month and 10-year spreads. The correlations between $f_1$ and the B spreads are 60% and 67%, respectively. For BBB spreads, the correlations are slightly lower with 41% and 59%, whereas correlations with AAA spreads on the short and the long end reach 18% and 45%, respectively. Treasury yields are virtually uncorrelated with the credit factor (below 8%).

The credit factor is strongly associated with the index of tighter loan standards from the Federal Reserve’s quarterly Senior Loan Officer Opinion Survey; the correlation between the two time series is 64% (panel B in Figure 3). The relationship between $f_1$ and the index 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 other two factors $f_2$ and $f_3$ are not correlated with the index of tighter loan standards (correlation coefficients are −2% and 8%, respectively).

The level factor $f_2$ is highly correlated with Treasury yields of all maturities. Panel A in Figure 4 graphs $f_2$ with the 3-month and 10-year Treasury yields. The correlations between $f_2$ and the Treasury yields are 77% and 85%, respectively. Moreover, the level factor is also strongly associated with the Federal funds target rate; the correlation is 70% (panel B in Figure 4). Since the Federal funds rate is often considered an indicator of monetary policy, $f_2$ can also be interpreted as a “monetary policy” factor.

### 6.3.2 Factor Loadings

Figure 5 plots the normalized loadings of credit spreads and Treasury yields on the state variables $g$ and $\pi$ and the orthogonalized residuals $f_1$, $f_2$ and $f_3$, respectively. This allows visualizing the initial impact of a shock to each of those factors 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 represent the true contemporaneous impact of variations...
in either GDP or inflation on Treasury yields and credit spreads, taking into account that GDP and inflation are correlated with the latent factors $x_t$. Positive shocks to GDP cause spreads to narrow (panel D), while Inflation appears to have almost no effect on either credit spreads or Treasuries (panel E).

The normalized factor loadings for the two residual factors $f_1$ and $f_2$ in Figure 5, panels A and B 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 spreads; the relevance of $f_1$ slightly decreases with maturity but the credit factor is an important 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 in magnitude (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 (panel C). However, it seems to work in opposite directions for Treasury yields and credit spreads. The short rate reacts slightly negative to a shock in $f_3$ while long maturity Treasury yields load positively on $f_3$. Credit spreads for all rating classes load reversely on $f_3$: negative loadings on the short end and positive loadings on the long end. Therefore, $f_3$ can be thought of as a slope factor. In fact, the correlation between $f_3$ and the slope of Treasury yields is roughly 63%.

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 5 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.

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38 The original factor loadings $b_{it}$ given in equations (7) and (11) are modified by adding $c_t(\Theta)b_{xt}$, where $c_t(\Theta)$ is taken from equation (18).

39 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 macro variables.

40 It is important to note however, that this is a result driven by the data and not by ex ante assumption imposed to identify the credit factor.

41 While the factors $f_1$, $f_2$ and $f_3$ are related to the principal components of the credit spreads and Treasury yields, they are not the same. For example, the correlation between $f_1$ and the first principal component of credit spreads is roughly 64%.

42 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.
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:

\[
CS_{M,t}(\tau) = a^i_\cdot \mathcal{Q}(\tau) + b^i_m(\tau)\cdot m_t + b^i_x(\tau)\cdot \hat{x}(M_t) \tag{19}
\]

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, \(CS_{f_j,t}(\tau) = b^i_j(\tau)\cdot f_{j,t}\) for \(j = \{1, 2, 3\}\). Thus, the implied spreads \(\overline{CS}_t(\tau)\) can be decomposed into its components according to a variation of equation (11):

\[
\overline{CS}_t(\tau) = a^i_\cdot \mathcal{Q}(\tau) + b^i_m(\tau)\cdot m_t + b^i_x(\tau)\cdot \hat{x}(M_t) + b^i_f(\tau)\cdot f_t = CS_{M,t}(\tau) + CS_{f_1,t}(\tau) + CS_{f_2,t}(\tau) + CS_{f_3,t}(\tau). \tag{20}
\]

Figure 6 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 5, 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 three sets of regressions with future GDP growth as the regressand. First, the standardized values of \(CS_{M,t}(\tau)\) are used as the regressor in univariate regressions to investigate the contribution of the macro variables. Second, I regress future GDP growth on the standardized credit, level and slope factors, respectively and finally, all components of the implied spreads are used as regressors.

The results of the first two sets of regressions can be summarized as follows.\(^{43}\) First, the contribution of the macro information in the credit spreads depends on the forecast horizon and the maturity of the credit spreads: the coefficients are highly significant for long maturity spreads and for forecast horizons up to two years (\(R^2\) up to 25%).\(^ {44}\) Second, the credit factor \(f_1\) has highly significant forecasting power at all horizons and \(R^2\) range between 10% and 21%. Compared with actual credit spreads, the \(R^2\) for the credit factor are in general smaller for all forecast horizons. This supports the conclusion that the credit factor accounts for a large part, but not all of the forecasting power of the credit spreads. Third, the level and slope factors, \(f_2\) and \(f_3\), do not have any predictive content (with the exception of the level factor for very long forecast horizons) and consequently, \(R^2\) are close to zero. In the case of the slope factor, the lack of predictive power is notable as credit spreads load quite heavily on \(f_3\). This means that while shocks to \(f_3\) may significantly move credit spreads they contain no information about the future direction of the economy.

\(^{43}\) The full results are provided in the online appendix.

\(^{44}\) The macro component of credit spreads is not driven out when current and lagged macro information is included in the regression. This means that credit spreads not only contain information that is relevant for forecasting GDP growth over and above what is contained in the history of macro variables, but that they also make better use of that information compared with a simple regression approach.
Table 5 displays the results from regressing future GDP growth on all the components of the implied spreads in equation (20). The reported results are for regressions without control variables, but they are robust to including macro information directly. The univariate regression results mostly carry over to the multivariate case. The credit factor \( f_1 \) remains significant at all horizons but is slightly weaker at short horizons given the contribution of the macro information through the macro component of credit spreads. The factors \( f_2 \) and \( f_3 \) remain insignificant, again with the exception of \( f_2 \) for long forecast horizons. Excluding the factors \( f_2 \) and \( f_3 \) from the full regression often results in better adjusted \( R^2 \)
compared to the full set of regressors, especially for lower grade spreads and longer forecast horizons. Averaging across forecast horizons, the contribution of the macro variables to the overall predictive power ranges between 25% for short maturity and lower grade spreads and 43% for longer maturity high grade spreads. The credit factor \( f_1 \) contributes between roughly 48% for AAA spreads and 64% for long maturity BBB and B spreads, whereas the level and slope factors account for roughly 8% and 2.5%, respectively. The results are summarized in table 6 and provide further evidence that mainly the macro variables and the credit factor are relevant for forecasting GDP growth as they account for nearly 90% of the predictive power.

### 6.3.4 New Information Response Functions

The shocks to the state variables \( z \) in equation (3), \( \tilde{\epsilon}_t = \Sigma \epsilon_t \), are contemporaneously correlated. Without imposing additional structure, it is not possible to uniquely identify the shocks and consequently, impulse responses will ultimately depend on an arbitrarily chosen orthogonalization scheme. The analysis is further complicated by focussing on the effect of a shock to any of the latent factors \( x_i \) that is uniquely driven by innovations in the respective residuals \( f_i \) while keeping the projection piece \( \hat{x}_i(M_t) \) constant.

Jardet, Monfort, and Pegoraro (2009) propose a generalization of the impulse response function, the new information response function (NIRF), that allows dealing with shocks to filtered variables and isolating the effect of innovations in the respective residuals. The NIRF measures the differential impact on \( z_{t+h} \) (\( h = 1, \ldots, H \)), of new information \( I_t \) at time \( t \), where the new information is some function \( a(\cdot) \) of the shocks to the state variables, i.e. \( I_t = a(\tilde{\epsilon}_t) \). More precisely, the NIRF for a given horizon \( h \geq 0 \) is defined by:

\[
NIRF(h) = E(z_{t+h}|a(\tilde{\epsilon}_t), z_{t-1}) - E(z_{t+h}|z_{t-1}) = \Upsilon(h)E(\tilde{\epsilon}_t|a(\tilde{\epsilon}_t)) = \Upsilon(h)d,
\]

where \( \Upsilon(h) \) is the matrix coefficient of the MA(\( \infty \)) representation of \( z_t \) associated with lag \( h \) and \( d \) represents the new information.

Fortunately, the given setup is particularly convenient to apply the NIRF to innovations in the residuals \( f_i \), which are obtained by applying a linear filter on \( z_t \) according to equations (17) and (18), \( f_t = x_t - F(\Theta,L)m_t \). In addition to being orthogonal to the history of macro factors, the rotation described in appendix D also ensures that the residuals \( f_i \) are orthogonal to each other.
Denote $\epsilon^f_t$ and $\hat{\epsilon}^x_t$ the innovations of $f_t$ and $\hat{x}(M_t)$, respectively. The $3 \times 1$ vector of shocks to $x_t$ is then given by:

$$
\tilde{\epsilon}^x_t = \epsilon^f_t + \epsilon^x_t = \epsilon^f_t + F(\Theta, 0)\tilde{\epsilon}^m_t = \epsilon^f_t + F_1(\Theta, 0)\tilde{\epsilon}^g_t + F_2(\Theta, 0)\tilde{\epsilon}^\pi_t,
$$

where $\tilde{\epsilon}^m_t = (\tilde{\epsilon}^g_t, \tilde{\epsilon}^\pi_t)'$ are the innovations of the macro variables and $F(\Theta, 0)$ is the linear filter on the innovations (without lags).

For a unit shock to the credit factor $f_1$, the new information is:

$$
d = E(\tilde{\epsilon}_t|I_t) = E(\epsilon^f_{t_1} = 1, \epsilon^f_{t_2} = 0, \epsilon^f_{t_3} = 0, \tilde{\epsilon}^m_t = (0, 0)')
$$

Since $\tilde{\epsilon}^m_t = (0, 0)'$, the innovations in the projection part of the latent factors are $\tilde{\epsilon}^x_t = F(\Theta, 0)\tilde{\epsilon}^m_t = (0, 0, 0)'$. This means that $d$ is simply a $5 \times 1$ vector of zeros with one in the third position and the new information response function can easily be calculated according to equation (22) as the third column of $\Upsilon(h)$. To gauge the impact of unit shocks to the level and slope factors, we can simply look at the fourth and fifth column of $\Upsilon(h)$, respectively.

Figure 7 plots the new information responses of GDP growth to one standard deviation shocks in the credit ($f_1$, panel A), level ($f_2$, panel B) and slope ($f_3$, panel C) factors, respectively. The confidence bounds are calculated via parametric bootstrap (Conley, Hansen, and Liu (1997)). Specifically, I simulate 1000 paths from the estimated model and re-estimate it along each path using the original parameters as starting values. It is not surprising that the confidence bounds are rather wide given the estimation procedure, the relatively short sample period, the considerable measurement errors and the number of parameters.

Nevertheless, the impulse responses are consistent with the regression results in the previous section and a positive standard deviation shock to the credit factor has a significantly negative impact on GDP growth in the next four quarters. Shocks to either $f_2$ or $f_3$ on the other hand have no significant impact on future real activity.

### 6.3.5 Robustness of the Credit Factor

While the original rotation is designed to yield a credit factor that captures common variation in credit spreads not driven by the macro variables, it does neither guarantee that $f_1$ is related to the index of tighter loan standards, nor that $f_1$ exhibits any forecasting power. However, given the inherent latent factor indeterminacy, it is possible to choose alternative rotations to achieve these goals.

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45 $F(\Theta, 0)$ is a $3 \times 2$ matrix and $F(\Theta, 0) = (F_1(\Theta, 0), F_2(\Theta, 0))$.

46 In the base model, a one standard deviation shock results in $-0.6\%$ contraction in real GDP over a one year period. The effect is significant over two, three and four quarters at the 99%, 95% and 90% level of significance, respectively. For GDP levels, the effect is significantly negative for up to 12 quarters at the 90% level.
Figures 3 and 4 plot the credit and slope factors (denoted “$f_1$ (corr)” and “$f_2$ (corr)”) from such an alternative rotation that focuses on the link to the index of tighter loan standards. In order to pin down the factors, I first maximize the correlation between $f_1$ and the index of tighter loan standards and then maximize the correlation between $f_2$ and the Federal funds target rate. Even though the original rotation does not depend at all on the the index of tighter loan standards, the maximized correlation is only slightly higher than before with 66%. The correlation of $f_2$ (corr) with the Federal funds target rate remains nearly identical with 69%. At the same time, both alternative factors are highly correlated with the original time series (the correlations are 98% and 96%) and all results hold.47

The above shows that the credit factor is very robust to the rotation procedure but it does not provide any evidence as to how robust it is to the choice of observable macro time series. I therefore re-estimate the model with alternative macro factors, once using real-time time series of GDP growth and inflation and once using completely different observables altogether.

In the main estimation I use revised GDP and CPI numbers.48 However, GDP numbers are revised regularly, often substantially and sometimes with a long lag, while CPI numbers are less subject to revision. Accordingly, the correlation of the revised GDP data with real-time data is only about 67% while the inflation time series are virtually identical. Therefore, I re-estimate the model using real-time GDP data available from the Federal Reserve Bank of Philadelphia to gauge the impact on the credit factor. After going through the original rotations, it turns out the new $f_1$ factor is almost identical to the original credit factor, with the correlation between the two time series reaching 93% (the level and slope factors exhibit correlations of 79% and 95%, respectively). Thus, the results presented in section 6.3.3 still hold qualitatively and the credit factor estimated using real-time GDP growth data can be used to forecast the revised time series.

The macro-finance model presented in section 4 uses GDP growth and inflation as the observable macro variables. While the focus on these two variables can be justified by their importance in determining monetary policy in the context of a Taylor rule, there is no doubt that GDP growth and inflation alone are not able to fully capture the state of the economy. The credit factor is independent of the history of the two macro variables by construction. However, the preferred interpretation of the credit factor in the context of a transmission channel from credit markets to the real economy is that it is also exogenous to the whole macro economy. In order to capture more of the overall economy than is contained in GDP growth and inflation itself, I use two very different macro time series. Namely, I use the first two principal components of a large macro dataset with a total of 114 macro time series used in Boivin, Giannoni, and Mihov (2007).49 The correlations between the first two principal components and GDP growth and inflation are −57% and 13%, respectively. However, re-estimating the model and going through the

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47 It is also possible to rotate the latent factors such that the predictive power of $f_1$ is maximized, even though such an exercise does not provide a lot of insights as it does not help in interpreting the latent factors. This rotation results in a credit factor that has a correlation of about 90% with the original $f_1$, meaning that the agnostic procedure followed in the original rotation is very close to maximizing the predictive power of the first orthogonalized residuals.

48 See appendix A.1 for a discussion of the data choice.

49 The data includes various economic indicators, inflation indicators, money aggregates, equity returns and other financial indicators. I thank Marc Giannoni for providing me with the estimates of the principal components.
rotations, it turns out that the resulting credit factor has a correlation of 79% with the original $f_1$ factor and retains its predictive power for future real activity.\footnote{The correlation between the $f_2$ and $f_3$ factors is significantly lower with 60% and 48%, respectively.} This means that the credit factor is surprisingly robust to including additional information about the macro economy and is consistent with the existence of a transmission channel from credit conditions to the real economy.

### 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 conclusive insight as both components contribute to the predictive power of the credit spreads. Third, decomposing credit spreads into components based on the state variables in the model helps discovering the drivers of the predictive power. Finally, the credit factor is very robust to different rotation procedures and the use of alternative macro observables.

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 that ultimately affect the external finance premium. In recent work, Christiano, Motto, and Rostagno (2008) augment a dynamic stochastic general equilibrium model to include financial markets and find that a shock originating in the financial sector accounts for a significant portion of business cycle fluctuations. Cúrdia and Woodford (2008) develop a New Keynesian model of the monetary transmission mechanism and conclude that optimal monetary policy should take into account changes in credit spreads.

### 7 Out-of-Sample Forecasting and the Credit Crisis

The sample period from 1992:2–2006:1 over which the macro-finance model is estimated is too short to conduct a thorough investigation of the out-of-sample forecasting performance of the model. However, the ongoing credit crisis of 2007–2009 provides a challenging environment that allows to compare model-based forecasts with realized GDP growth and GDP growth forecasts from alternative sources.

The original model parameters are estimated over the 1992:2–2006:1 sample period, which does not include the current crisis and only contains a very short recession in 2001. For the out-of-sample period from 2006:1–2008:4, I only update the data—without re-estimating the model—and filter out the credit, level and slope factors. Panel A in Figure 8 shows the normalized 1-year $B$ spread and its normalized components. The credit factor has risen dramatically since 2007:2, indicating a strongly negative outlook based on the regression results presented in section 6.3.3 and the new information response functions reported in section 6.3.4.
GDP forecasts can directly be computed using the model parameters as the dynamics in equation (3) imply that the objective expectation, or $\mathbb{P}$-expectation, of the future state variables is a linear function of the current state variables:

$$E_t(z_{t+\tau}) = \Psi^\tau \mu + \Phi^\tau z_t,$$

where

$$\Psi^\tau \triangleq \sum_{k=0}^{\tau-1} \Phi^k = (I - \Phi)^{-1} (I - \Phi^\tau).$$

Panels B to D in Figure 8 show the $\mathbb{P}$-expectations of cumulative GDP growth for one, two and four quarters during the out-of-sample period. For the same horizons, I also plot realized GDP growth and survey forecasts taken from the “Survey of Professional Forecaster” (SPF), the “Livingston Survey” (LS), and “Blue Chip Economic Indicators” (BCEI).

The model performs surprisingly well and mostly in line with the survey forecasts. The model-based forecasts are slightly above the survey forecasts for most of 2006 and early 2007 but come back down sharply just before the start of the recession. As of the end of 2008, the model provides more pessimistic and—taking into account economic data releases up to July 2009—more accurate forecasts than any of the surveys, predicting a contraction of $-3.3\%$, $-3.0\%$ and $-2.0\%$ for the one, two and four quarter horizons, respectively.

As noted above, the model-based forecasts do not make use of all the available information since the parameters are not adjusted as additional information becomes available. This puts the model at a disadvantage to the survey forecasts that presumably use the full information set. At the same time, the out-of-sample results provide a further test for the relationships between the state variables discussed in section 6.3.3, which turn out to be very robust to the ongoing crisis.

Apart from re-estimating the model in real-time to use the new data fully and estimate updated parameters, the model could also be extended to incorporate the survey forecasts directly, which could increase the accuracy of the model-based forecasts even further.

8 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.

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51 Chernov and Mueller (2008), appendix C provides a description of the surveys in the context of inflation forecasts. Among others, GDP forecasts are also included in the surveys.

52 Note that these are truly out-of-sample forecasts. Per year-end 2008 GDP numbers for the fourth quarter are not available and hence are not used to make forecasts.

53 Chernov and Mueller (2008) show for inflation forecasts how a model that incorporates both, Treasury yields and inflation expectations, performs better than models that use only one source of information.
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 credit 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. 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 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 explains between 50% and 65% 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 almost 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.

During the time period 2006:1–2008:4, which includes the ongoing credit crisis and the beginning of a recession, the model generates annualized out-of-sample forecasts for GDP growth of $-3.3\%$, $-3.0\%$ and $-2.0\%$ for the one, two and four quarter horizons, respectively, numbers that are more pessimistic but roughly in line with survey forecasts from professional forecasters. This provides further confidence in the validity of the results as the estimation period ends before the start of the crisis.

The high predictive power of the credit factor and the dynamic reaction of GDP growth to a shock in the credit factor lend support to the existence of a transmission channel from borrowing conditions to real activity consistent with the financial accelerator theory and recent work on the transmission of shocks originating in the financial sector. This interpretation is further supported by results based on alternative macro data that capture a larger part of the overall economy than GDP growth and inflation alone.
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 $\pi_t$, 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.\(^{54}\) 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.\(^{55}\) 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, I implicitly 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.

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

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

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

(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

There are several potential sources for Treasury yields, all of which have some benefits and costs. I use the Guerkyanak, Sack, and Wright (2006) (GSW henceforth) quarterly time series of continuously

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\(^{54}\) More information can be found on the Bureau of Economic Analysis (BEA) website.

\(^{55}\) The real-time data is used for robustness checks and is available from the Federal Reserve Bank of Philadelphia website.
compounded zero coupon yields from 1971:3 to 2006:1 with maturities three and six months and one, two, three, five, seven and ten years.\textsuperscript{56} The starting point of the sample period for Treasury yields is determined by the first quarter in which the 10-year yield is available.

GSW employ the Svensson (1994) methodology for fitting the yield curve, therefore smoothing across maturities. Cochrane and Piazzesi (2008) point out that even small amounts of smoothing have the potential to lose a lot of information depending on the application. Accordingly, they mainly work with the well known Fama-Bliss dataset available from CRSP, which contains unsmoothed yields for maturities between one and five years. However, measuring the whole yield curve, i.e. using maturities longer than five years is 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.

The shortest yield maturity in the GSW dataset is one year but GSW also report the yield curve parameters, which allows calculating arbitrary maturities. However, they advise against using their curve for yields below six months maturity because they drop three month and lower maturity securities at the estimation stage for technical reasons. Comparing three month and six month GSW yields with interest rates from the Federal Reserve statistical release H15 (Treasury constant maturity and Treasury bill secondary market rates) reveals that the GSW series behave well even at these short maturities. Accordingly, I use GSW yields for all maturities.

Bikbov and Chernov (2008) use a proprietary dataset of unsmoothed Fama-Bliss approximation of the zero coupon bond prices, which has yields for all desired maturities, from three months up to ten years. Unfortunately, this dataset has not been updated since 2002:4 and furthermore, the limited distribution of the data would complicate a replication of findings based thereupon. As a robustness check however, all results in the paper are reproduced using the proprietary dataset augmented with data from CRSP from 2003:1 to 2005:4. The three month risk free rate is taken from the Fama Risk Free Rates file, the six month yield is taken from the Fama T-bill structure file and the other yields are taken from the Fama-Bliss dataset. The results are virtually unchanged and are available upon request.

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

\textsuperscript{56} The data is regularly updated and available from the Federal Reserve Board website (last accessed March 10, 2009, http://federalreserve.gov/econresdata/researchdata.htm).
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. Lehman Brothers also provides a high yield bond index but only starting in 1987:1. The high yield bond index with the longest history available through Datastream is the “Merill Lynch US High Yield 100,” which starts in 1980:1. For both high 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**

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:

\[
g_{t,k} = \alpha_k(1) + \gamma_k(1)g^T_t(1) + \Gamma'CON_t + u_{t+k},
\]

\[
g_{t,k} = \alpha_k(\tau) + \gamma_k(\tau)(y^T_t(\tau) - g^T_t(1)) + \Gamma'CON_t + u_{t+k},
\]

where \( CON_t \) is a vector of control variables containing current and lagged GDP growth and inflation. In the existing literature, the predictive regressions are usually run without control variables. However, adding the controls does not qualitatively change the results. In addition to the coefficient estimates \( \gamma_k(\tau) \) and the adjusted \( R^2 \) for the regressions including macro control variables, I also report the adjusted \( R^2 \) for the univariate term spread and short rate regressions (ignoring controls).

The \( \gamma_k(\tau) \) coefficients for the term spread regressions presented in Table 7, panels A and B, are significant for horizons between one and three years in the full and in the pre-1992:2 sample. Adjusted \( R^2 \) for the univariate regressions range between 20% and 30% in the full sample and go up to 40% in the early sample for the 5-year term spread. In the post-1992:2 sample period (Table 7, panel C), the term spread loses its predictive power. Coefficients are not significant anymore and the adjusted \( R^2 \) for the univariate regressions 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 not significant. 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. The online appendix contains 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 7, 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 1985:1–2006:1, 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.

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 dataset 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 not as rich, yields qualitatively similar results to the ones presented in section 3.2, I replicate Table 1, panel B (univariate credit spread regressions including the lagged macro variables, the short rate and the 5-year term spread as control variables) using the additional dataset. The results in Table 8, 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 adjusted $R^2$s, 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 (adjusted $R^2$s are decreasing for longer horizons). I also report the adjusted $R^2$s for the univariate regressions without controls (comparable to the results in Table 1, panel A).

The results for the extended sample periods are presented in Table 8, 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 1985:1–2006:1 (or 1987:1–2006:1 for the Lehman Brothers high yield index). Comparing results using all and only post-1985:1 data in Table 8, it is evident that spreads for investment grade credits become better predictors for real activity over time. It is also apparent that the relationship between real activity and the high yield spread becomes stronger in the late-1980s, consistent with the notion that the market for high yield debt did not really develop until after the mid-1980s. Before, most high yield bonds consisted of debt that was originally issued by former investment grade firms, so called “fallen angels.” Arguably, these bonds behave rather differently than bonds originally intended to be issued with a low rating, which might distort results in the early periods.

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 data only, respectively. The results are qualitatively similar to what is reported in Table 8. Investment grade and high yield spreads across the whole term structure significantly predict GDP growth for short and longer horizons, the results being particularly strong if all control variables are included. For high yield spreads, 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 very 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 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 and credit spreads 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. We 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, $O$, ensures that the three factors are orthogonal to each other. I define a rotation $O = Rx_1$, so that the variance-covariance matrix of $x$ becomes diagonal. The matrix $R$ is not unique; i.e., the rotation of type $O$ can generate many triplets of orthogonal factors $x$. The second proposed rotation, $M$, can be applied after any of the rotations from the class $O$ resolves this type of indeterminacy. Define $M = Ux_t$, where the matrix $U$ is the orthogonal matrix; i.e., $UU' = I$, that preserves the correlation structure between the factors. In the three-dimensional case, the matrix $U$ is determined by two parameters, which are established in the base model by maximizing the average of the loadings of the 3-month and 10-year credit spreads ($AAA$, $BBB$ and $B$) on $x_1$. After the second rotation, the first latent factor, $x_1$, is identified. Define $x^{(1)}_t = (x_{2,t}, x_{3,t})'$, the vector of latent variables excluding $x_{1,t}$. Further define the third rotation, $N = Sx^{(1)}_t$, where $S$ again is the orthogonal matrix. In the two-dimensional case the matrix $S$ is determined by a single parameter, which is established in the base model by maximizing the average of the factor loadings of the 3-month and 10-year Treasury yield on $x_2$. 
References


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.


Table 1. Credit Spread Regressions

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

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

Panel C reports the coefficients $\beta_k^i$ and $\beta_k^{i,SL}$, and the $R^2$ and $R^2_{adj}$ from the regression:

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

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, $r$, 5-year term spread, $T^5$, respectively. The sample period is 1992:2–2006:1. GDP data is included up to 2009:1. 

### Panel A: Univariate credit spread regressions with controls

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>AAA 1 yr $R^2$</th>
<th>AAA 10 yrs $R^2$</th>
<th>BBB 1 yr $R^2$</th>
<th>BBB 10 yrs $R^2$</th>
<th>B 1 yr $R^2$</th>
<th>B 10 yrs $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 qtr (56)</td>
<td>0.04</td>
<td>-0.21 (0.18)</td>
<td>-0.18 (0.09)</td>
<td>-1.75 (0.12)</td>
<td>-0.53*** (0.17)</td>
<td>-0.78*** (0.17)</td>
</tr>
<tr>
<td>1 yr (56)</td>
<td>-0.62</td>
<td>-0.32 (0.39)</td>
<td>-1.62*** (0.23)</td>
<td>-1.84*** (0.39)</td>
<td>-0.37*** (0.23)</td>
<td>-0.59*** (0.26)</td>
</tr>
<tr>
<td>3 yrs (56)</td>
<td>-0.44</td>
<td>-0.60 (0.55)</td>
<td>-0.67 (0.53)</td>
<td>0.07 (0.12)</td>
<td>-0.11 (0.12)</td>
<td>-0.26* (0.10)</td>
</tr>
</tbody>
</table>

### Panel B: Univariate credit spread regressions with controls

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>AAA 1 yr $R^2$</th>
<th>AAA 10 yrs $R^2$</th>
<th>BBB 1 yr $R^2$</th>
<th>BBB 10 yrs $R^2$</th>
<th>B 1 yr $R^2$</th>
<th>B 10 yrs $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 qtr (56)</td>
<td>-0.36</td>
<td>-0.13 (0.18)</td>
<td>-0.81*** (0.18)</td>
<td>-1.37*** (0.25)</td>
<td>-0.51*** (0.30)</td>
<td>-0.74*** (0.31)</td>
</tr>
<tr>
<td>1 yr (56)</td>
<td>-0.91</td>
<td>-0.46** (0.59)</td>
<td>-1.97*** (0.43)</td>
<td>-2.34*** (0.60)</td>
<td>-0.39*** (0.38)</td>
<td>-0.65*** (0.44)</td>
</tr>
<tr>
<td>3 yrs (56)</td>
<td>-2.38*** (0.36)</td>
<td>-2.83*** (0.59)</td>
<td>-1.55*** (0.50)</td>
<td>-1.74*** (0.67)</td>
<td>-0.13 (0.28)</td>
<td>-0.27** (0.32)</td>
</tr>
</tbody>
</table>

### Panel C: Bivariate credit spread regressions

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>AAA $\beta^{KL}$</th>
<th>BBB $\beta^{KL}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 qtr (56)</td>
<td>-0.81** (1.89)</td>
<td>-2.53** (0.73)</td>
</tr>
<tr>
<td>1 yr (56)</td>
<td>-3.25** (1.32)</td>
<td>-1.50** (0.69)</td>
</tr>
<tr>
<td>3 yrs (56)</td>
<td>-3.80** (0.89)</td>
<td>-1.57** (0.58)</td>
</tr>
</tbody>
</table>

### Panel D: Bivariate credit spread regressions with controls

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>AAA $\beta^{KL}$</th>
<th>BBB $\beta^{KL}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 qtr (56)</td>
<td>-0.53* (2.00)</td>
<td>-2.01** (0.93)</td>
</tr>
<tr>
<td>1 yr (56)</td>
<td>-3.12** (1.37)</td>
<td>-1.01 (0.78)</td>
</tr>
<tr>
<td>3 yrs (56)</td>
<td>-3.58*** (0.82)</td>
<td>-1.92*** (0.52)</td>
</tr>
</tbody>
</table>
### Table 2. Summary of $R^2$

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 $g$ itself and inflation $\pi$:

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

In panel B, the short rate $r_t$ or various measures of the term spread, $y^T_t(\tau) - y^{T(1)}_t(\tau)$, are added to the regression. Panel C adds the 5-year term spread and various credit spreads $CS^i_t(\tau)$. The sample period for all regressions is 1992:2–2006:1, GDP data is included up to 2009:1.

<table>
<thead>
<tr>
<th>Horizon</th>
<th>1 qrt</th>
<th>2 qrts</th>
<th>1 yr</th>
<th>2 yrs</th>
<th>3 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Macro</strong></td>
<td>0.17</td>
<td>0.20</td>
<td>0.22</td>
<td>0.18</td>
<td>0.10</td>
</tr>
<tr>
<td><strong>Panel B</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short rate $r_t$</td>
<td>0.26</td>
<td>0.23</td>
<td>0.23</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>Term spread 1 yr</td>
<td>0.26</td>
<td>0.23</td>
<td>0.23</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>Term spread 5 yrs</td>
<td>0.18</td>
<td>0.20</td>
<td>0.22</td>
<td>0.19</td>
<td>0.14</td>
</tr>
<tr>
<td>Term spread 10 yrs</td>
<td>0.18</td>
<td>0.20</td>
<td>0.22</td>
<td>0.18</td>
<td>0.13</td>
</tr>
<tr>
<td><strong>Panel C</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AAA 1 yr</td>
<td>0.22</td>
<td>0.26</td>
<td>0.30</td>
<td>0.28</td>
<td>0.21</td>
</tr>
<tr>
<td>BBB 1 yr</td>
<td>0.26</td>
<td>0.34</td>
<td>0.42</td>
<td>0.42</td>
<td>0.46</td>
</tr>
<tr>
<td>B 1 yr</td>
<td>0.30</td>
<td>0.37</td>
<td>0.37</td>
<td>0.29</td>
<td>0.21</td>
</tr>
<tr>
<td>AAA 10 yrs</td>
<td>0.28</td>
<td>0.38</td>
<td>0.57</td>
<td>0.71</td>
<td>0.57</td>
</tr>
<tr>
<td>BBB 10 yrs</td>
<td>0.25</td>
<td>0.36</td>
<td>0.54</td>
<td>0.64</td>
<td>0.67</td>
</tr>
<tr>
<td>B 10 yrs</td>
<td>0.29</td>
<td>0.34</td>
<td>0.44</td>
<td>0.34</td>
<td>0.23</td>
</tr>
</tbody>
</table>

### Table 3. Model Fit: $R^2$ for Implied Yields and Spreads

The table reports the $R^2$ of the implied yields and credit spreads. The sample period is 1992:2–2006:1.

<table>
<thead>
<tr>
<th>Maturity</th>
<th>1 qrt</th>
<th>1 yr</th>
<th>10 yrs</th>
<th>Slope</th>
<th>Curvature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treasuries</td>
<td>0.985</td>
<td>0.995</td>
<td>0.976</td>
<td>0.946</td>
<td>0.791</td>
</tr>
<tr>
<td>AAA</td>
<td>0.207</td>
<td>0.358</td>
<td>0.647</td>
<td>0.426</td>
<td>0.057</td>
</tr>
<tr>
<td>BBB</td>
<td>0.681</td>
<td>0.733</td>
<td>0.777</td>
<td>0.671</td>
<td>0.300</td>
</tr>
<tr>
<td>B</td>
<td>0.982</td>
<td>0.989</td>
<td>0.914</td>
<td>0.830</td>
<td>0.798</td>
</tr>
</tbody>
</table>
Table 4. Implied Credit Spread Regressions

Panel A reports the slope coefficient $\beta_i^k(\tau)$, and the adjusted $R^2$ ($\overline{R^2}$) from regressing future GDP growth $g_{t,k}$ for $k$ quarters on implied credit spreads, $CS_i^k(\tau)$, for rating class $i$ and maturity $\tau$, and a vector of control variables, $CON_i$:

$$g_{t,k} = \alpha_i^k(\tau) + \beta_i^k(\tau)CS_i^k(\tau) + \Gamma_kCON_i + \epsilon_{t+k,k},$$

where $CS_i^k(\tau) = y_{t}^i(\tau) - \hat{y}_{t}^i(\tau)$ and all the yields are model implied instead of actual yields. The vector $CON_i$ contains current and lagged GDP growth and inflation, the current short rate, $r_t = y_t^T(1)$, and the 5-year term spread, $y^T_5(20) - y^T_1(1)$. The yields used as control variables are actual instead of implied yields. The yields used as control variables are actual instead of implied yields. $\overline{R^2}$ is the adjusted $R^2$ from univariate regressions with implied credit spreads only, excluding the control variables.

Panel B reports the slope coefficient $\beta_i^k(\tau)$, and the $R^2$ and adjusted $R^2$ ($\overline{R^2}$) from regressing future GDP growth $g_{t,k}$ for $k$ quarters, on the estimation error given by $CS_i^k(\tau) - CS_i^k(\tau)$, the difference between the actual and the implied credit spread.

$$g_{t,k} = \alpha_i^k(\tau) + \beta_i^k(\tau)\left( CS_i^k(\tau) - \hat{CS_i}^k(\tau) \right) + \epsilon_{t+k,k}.$$

Hodrick (1992) (1B) standard errors are in parentheses. ***, ** and * denotes coefficient is significantly different from zero at 1%, 5% and 10% confidence level, respectively. The sample period is 1992:2–2006:1.

---

**Panel A: Implied credit spreads**

<table>
<thead>
<tr>
<th></th>
<th>AAA 1 yr</th>
<th>AAA 10 yrs</th>
<th>BBB 1 yr</th>
<th>BBB 10 yrs</th>
<th>B 1 yr</th>
<th>B 10 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon (Obs.)</td>
<td>$\beta$</td>
<td>$R^2$</td>
<td>$\overline{R^2}$</td>
<td>$\beta$</td>
<td>$R^2$</td>
<td>$\overline{R^2}$</td>
</tr>
<tr>
<td>1 qtr</td>
<td>-8.34***</td>
<td>0.21</td>
<td>-4.74**</td>
<td>0.19</td>
<td>-5.66***</td>
<td>0.21</td>
</tr>
<tr>
<td>(55)</td>
<td>(2.64)</td>
<td>0.13</td>
<td>(1.81)</td>
<td>0.12</td>
<td>(0.78)</td>
<td>0.15</td>
</tr>
<tr>
<td>1 yr</td>
<td>-9.92***</td>
<td>0.42</td>
<td>-6.78***</td>
<td>0.54</td>
<td>-2.78***</td>
<td>0.37</td>
</tr>
<tr>
<td>(52)</td>
<td>(2.16)</td>
<td>0.45</td>
<td>(1.39)</td>
<td>0.20</td>
<td>(0.65)</td>
<td>0.28</td>
</tr>
<tr>
<td>3 yrs</td>
<td>-8.39***</td>
<td>0.29</td>
<td>-4.46***</td>
<td>0.36</td>
<td>-2.55**</td>
<td>0.24</td>
</tr>
<tr>
<td>(44)</td>
<td>(3.00)</td>
<td>0.31</td>
<td>(1.24)</td>
<td>0.26</td>
<td>(1.06)</td>
<td>0.09</td>
</tr>
</tbody>
</table>

**Panel B: Estimation errors**

<table>
<thead>
<tr>
<th></th>
<th>AAA 1 yr</th>
<th>AAA 10 yrs</th>
<th>BBB 1 yr</th>
<th>BBB 10 yrs</th>
<th>B 1 yr</th>
<th>B 10 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon (Obs.)</td>
<td>$\beta$</td>
<td>$R^2$</td>
<td>$\overline{R^2}$</td>
<td>$\beta$</td>
<td>$R^2$</td>
<td>$\overline{R^2}$</td>
</tr>
<tr>
<td>1 qtr</td>
<td>-0.03</td>
<td>0.00</td>
<td>-1.72</td>
<td>0.01</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>(55)</td>
<td>(3.08)</td>
<td>-0.02</td>
<td>(1.92)</td>
<td>0.00</td>
<td>(1.48)</td>
<td>-0.02</td>
</tr>
<tr>
<td>1 yr</td>
<td>0.12</td>
<td>0.00</td>
<td>-3.03**</td>
<td>0.11</td>
<td>-0.73</td>
<td>0.01</td>
</tr>
<tr>
<td>(52)</td>
<td>(1.65)</td>
<td>-0.02</td>
<td>(1.37)</td>
<td>0.09</td>
<td>(1.11)</td>
<td>-0.01</td>
</tr>
<tr>
<td>3 yrs</td>
<td>-0.65</td>
<td>0.01</td>
<td>-2.55***</td>
<td>0.14</td>
<td>-1.74**</td>
<td>0.15</td>
</tr>
<tr>
<td>(44)</td>
<td>(0.47)</td>
<td>-0.02</td>
<td>(0.87)</td>
<td>0.12</td>
<td>(0.81)</td>
<td>0.13</td>
</tr>
</tbody>
</table>

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Table 5. Credit Spread Components

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

$$g_{t+k} = \alpha_k(\tau) + \beta_{i,M}^k(\tau)CS_{i,t}^M(\tau) + \beta_{i,f1}^k(\tau)CS_{i,t}^f(\tau) + \beta_{i,f2}^k(\tau)CS_{i,t}^{f2}(\tau) + \beta_{i,f3}^k(\tau)CS_{i,t}^{f3}(\tau) + u_{t+k},$$

where $CS_{i,t}^M(\tau)$ and $CS_{i,t}^f(\tau)$ 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, $\overline{CS}_i(\tau)$, is the sum of the four components. Hodrick (1992) (1B) standard errors are in parentheses. ***, ** and * denotes coefficient is significantly different from zero at 1%, 5% and 10% confidence level, respectively. The sample period is 1992:2–2006:1. GDP data is included up to 2009:1.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>AAA 1 yr</th>
<th>AAA 10 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon (Obs.)</td>
<td>Coeff.</td>
<td>S.E.</td>
</tr>
<tr>
<td>1 qrt</td>
<td>$\beta^M$</td>
<td>-15.14***</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-9.68***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>8.43</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-8.08</td>
</tr>
<tr>
<td>1 yr</td>
<td>$\beta^M$</td>
<td>-12.04***</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-8.75***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>-0.42</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-12.67</td>
</tr>
<tr>
<td>3 yrs</td>
<td>$\beta^M$</td>
<td>0.11</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-5.06***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>6.64*</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-9.65</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B</th>
<th>BBB 1 yr</th>
<th>BBB 10 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon (Obs.)</td>
<td>Coeff.</td>
<td>S.E.</td>
</tr>
<tr>
<td>1 qrt</td>
<td>$\beta^M$</td>
<td>-2.03**</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-2.91***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>10.36</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-1.41</td>
</tr>
<tr>
<td>1 yr</td>
<td>$\beta^M$</td>
<td>-1.36</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-2.55***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>-7.74</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-1.38</td>
</tr>
<tr>
<td>3 yrs</td>
<td>$\beta^M$</td>
<td>1.15</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-1.15**</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>22.80***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-0.38</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C</th>
<th>B 1 yr</th>
<th>B 10 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon (Obs.)</td>
<td>Coeff.</td>
<td>S.E.</td>
</tr>
<tr>
<td>1 qrt</td>
<td>$\beta^M$</td>
<td>-0.47**</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-0.62***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>-13.83</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-0.40</td>
</tr>
<tr>
<td>1 yr</td>
<td>$\beta^M$</td>
<td>-0.32</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-0.55***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>9.89</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-0.40</td>
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<tr>
<td>3 yrs</td>
<td>$\beta^M$</td>
<td>0.24</td>
</tr>
<tr>
<td>(56)</td>
<td>$\beta^f_1$</td>
<td>-0.26**</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_2$</td>
<td>-28.58***</td>
</tr>
<tr>
<td></td>
<td>$\beta^f_3$</td>
<td>-0.12</td>
</tr>
</tbody>
</table>
Table 6. Contribution to Forecasting Power

The table reports the per cent contribution of the respective credit spread components to the overall forecasting power measured by the $R^2$ of the following regression:

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

where $CS_{M,\tau}$ and $CS_{f,\tau}$ denote the components of the credit spreads that can be attributed to the observable macro variables and its lags $M$, and the projection residuals $f_1$, $f_2$ and $f_3$, respectively. Theoretically, the residuals $f$ are orthogonal to the history of the macro variables and consequently, the decomposition of the $R^2$ is straightforward. In the sample, the contribution of the macro variables $M$ is first separated from the contribution of the projection residuals $f$. Then, the residuals are ordered as given, i.e. $f_1$ first, $f_2$ second and $f_3$ last. The qualitative results are unaffected by alternative orderings. The fractions reported in the table are calculated from the average $R^2$ for forecast horizons one and two quarters and one, two and three years, respectively. The sample period is 1992:2–2006:1. GDP data is included up to 2009:1.

<table>
<thead>
<tr>
<th></th>
<th>$M$</th>
<th>$f_1$</th>
<th>$f_2$</th>
<th>$f_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA 1 yr</td>
<td>0.40</td>
<td>0.49</td>
<td>0.08</td>
<td>0.02</td>
</tr>
<tr>
<td>AAA 10 yrs</td>
<td>0.43</td>
<td>0.47</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>BBB 1 yr</td>
<td>0.25</td>
<td>0.64</td>
<td>0.08</td>
<td>0.03</td>
</tr>
<tr>
<td>BBB 10 yrs</td>
<td>0.40</td>
<td>0.50</td>
<td>0.08</td>
<td>0.02</td>
</tr>
<tr>
<td>B 1 yr</td>
<td>0.25</td>
<td>0.63</td>
<td>0.08</td>
<td>0.03</td>
</tr>
<tr>
<td>B 10 yrs</td>
<td>0.36</td>
<td>0.53</td>
<td>0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>
Table 7. Term Spread and Short Rate Regressions

The table reports the slope coefficient $\gamma_k(\tau)$ and the adjusted $R^2$ ($R^2_n$) from regressing future GDP growth, $g_{t+k}$, for $k$ quarters on the short rate, $y_t^r(1)$ (first column), and various term spreads, $y_t^r(\tau) - y_t^r(1)$, respectively. In addition, I include a vector of macro control variables, $CON_t$, containing current and lagged GDP growth and inflation:

$$ g_{t+k} = \alpha_k + \gamma_k(\tau) \left(y_t^r(\tau) - y_t^r(1)\right) + \Gamma_k CON_t + u_{t+k} $$

The table also reports the adjusted $R^2$ ($R^2_n$) from univariate short rate and term spread regressions, excluding the macro variables. The last column reports the $R^2$ ($R^2_m$) and adjusted $R^2$ ($R^2_n$) from regressing future GDP growth on the macro control variables only:

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

Hodrick (1992) (1B) standard errors are in parentheses. *** and * denotes coefficient is significantly different from zero at 1%, 5% and 10% confidence level, respectively. The sample period is 1992:2–2006:1. GDP data is included up to 2009:1.

<table>
<thead>
<tr>
<th>Panel A: 1971:3–2006:1</th>
<th>Short rate $r_t$</th>
<th>Term spread 1 yr</th>
<th>Term spread 5 yrs</th>
<th>Term spread 10 yrs</th>
<th>Macro</th>
</tr>
</thead>
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<tr>
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<td>$R^2_n$</td>
<td>$\gamma$</td>
<td>$R^2$</td>
</tr>
<tr>
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<td>0.18</td>
<td>0.45</td>
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<tr>
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<td>0.09</td>
<td>0.29</td>
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<td>0.43***</td>
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<th>Term spread 5 yrs</th>
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<td>$R^2_n$</td>
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<td>0.39</td>
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<td>(0.31)</td>
<td>0.12</td>
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<th>Term spread 5 yrs</th>
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<th>Macro</th>
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<td>$R^2_n$</td>
<td>$\gamma$</td>
<td>$R^2$</td>
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<td>(0.54)</td>
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<td>(0.22)</td>
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<td>-0.01</td>
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<td>-0.01</td>
<td>(0.48)</td>
<td>0.00</td>
<td>(0.20)</td>
</tr>
<tr>
<td>3 yrs</td>
<td>0.07</td>
<td>0.03</td>
<td>0.64*</td>
<td>0.09</td>
<td>0.18</td>
</tr>
<tr>
<td>(56)</td>
<td>(0.09)</td>
<td>-0.01</td>
<td>(0.32)</td>
<td>0.05</td>
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<th>Term spread 1 yr</th>
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<th>Macro</th>
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<td>$R^2_n$</td>
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<td>$R^2$</td>
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<td>0.32</td>
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<td>0.12</td>
<td>(0.19)</td>
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<tr>
<td>1 yr</td>
<td>0.01</td>
<td>0.19</td>
<td>1.00**</td>
<td>0.26</td>
<td>0.25</td>
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<td>(85)</td>
<td>(0.08)</td>
<td>0.00</td>
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<td>0.29**</td>
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<td>(0.07)</td>
<td>0.02</td>
<td>0.26</td>
<td>0.08</td>
<td>(0.13)</td>
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Table 8. Lehman Brothers and Merrill Lynch Bond Indices

The table reports the slope coefficient $\beta_i(\tau)$ and the adjusted $R^2$s ($\bar{R}^2$) from regressing future GDP growth $g_{t+k}$ for $k$ quarters on credit spreads, $CS_i(\tau)$, for rating class $i$ and maturity $\tau$, and a vector of control variables, $CON_i$:

$$g_{t+k} = \alpha_i(\tau) + \beta_i(\tau)CS_i(\tau) + \Gamma_i CON + \nu_{t+k},$$

where $CS_i(\tau) = y_i^T(\tau) - y_i^T(\tau)$ and $y_i^T(\tau)$ and $y_i^T(\tau)$ denote the respective corporate bond and Treasury yields. AAA and BBB spreads are calculated using the redemption yields for the respective Lehman Brothers corporate bond and Treasury indices. The maturities $\tau$ are either “intermediate” (IM, between 1 and 10 years) or “long” (L, above 10 years). Data for the Lehman Brothers high yield bond index (LB HY) is available starting in 1987:1, the “Merill Lynch US High Yield 100” (ML HY) starts in 1980:1. Both high yield spreads are calculated using the Lehman Brothers Treasury index (all maturities). The vector $CON_i$ contains current and lagged GDP growth and inflation, the current short rate, $r_1 = y_i(1)$, and the 5-year term spread, $y_i(20) - y_i(1)$. The table also reports the adjusted $R^2$ from regressing future GDP growth on the credit spreads only, excluding the control variables ($\bar{R}^2$). Hodrick (1992) (1B) standard errors are in parentheses. ***, ** and * denotes coefficient is significantly different from zero at 1%, 5% and 10% confidence level, respectively. The sample period is 1992:2–2006:1. GDP data is included up to 2009:1.

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>AAA IM</th>
<th>AAA L</th>
<th>BBB IM</th>
<th>BBB L</th>
<th>ML HY</th>
<th>LB HY</th>
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<td>1 qrt</td>
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<td>-1.37</td>
<td>0.11</td>
<td>-1.07**</td>
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<td>(0.87)</td>
<td>0.11</td>
<td>(1.07)</td>
<td>0.04</td>
<td>(0.46)</td>
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<tr>
<td>1 yr</td>
<td>-2.44***</td>
<td>0.51</td>
<td>-2.18**</td>
<td>0.25</td>
<td>-1.53***</td>
<td>0.53</td>
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<tr>
<td>(56)</td>
<td>(0.65)</td>
<td>0.32</td>
<td>(0.92)</td>
<td>0.10</td>
<td>(0.38)</td>
<td>0.40</td>
</tr>
<tr>
<td>3 yrs</td>
<td>-1.54***</td>
<td>0.45</td>
<td>-1.12**</td>
<td>0.21</td>
<td>-0.86***</td>
<td>0.40</td>
</tr>
<tr>
<td>(56)</td>
<td>(0.46)</td>
<td>0.44</td>
<td>(0.59)</td>
<td>0.05</td>
<td>(0.30)</td>
<td>0.34</td>
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Panel A: 1992:2–2006:1

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<th>BBB IM</th>
<th>BBB L</th>
<th>ML HY</th>
<th>LB HY</th>
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</thead>
<tbody>
<tr>
<td>1 qrt</td>
<td>-2.37***</td>
<td>0.81</td>
<td>-2.45***</td>
<td>0.28</td>
<td>-1.50**</td>
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<tr>
<td>(133)</td>
<td>(0.83)</td>
<td>0.09</td>
<td>(0.91)</td>
<td>0.01</td>
<td>(0.51)</td>
<td>0.16</td>
</tr>
<tr>
<td>1 yr</td>
<td>-2.09***</td>
<td>0.35</td>
<td>-1.57**</td>
<td>0.30</td>
<td>-1.04***</td>
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<td>(0.61)</td>
<td>0.12</td>
<td>(0.59)</td>
<td>-0.01</td>
<td>(0.37)</td>
<td>0.17</td>
</tr>
<tr>
<td>3 yrs</td>
<td>-0.16</td>
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<td>-0.13**</td>
<td>0.39</td>
<td>0.14**</td>
<td>0.39</td>
</tr>
<tr>
<td>(133)</td>
<td>(0.46)</td>
<td>0.09</td>
<td>(0.34)</td>
<td>0.02</td>
<td>(0.24)</td>
<td>-0.01</td>
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Panel B: all available data

<table>
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<th>Horizon (Obs.)</th>
<th>AAA IM</th>
<th>AAA L</th>
<th>BBB IM</th>
<th>BBB L</th>
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<th>LB HY</th>
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Panel C: post-1985:1

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<th>Horizon (Obs.)</th>
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<th>AAA L</th>
<th>BBB IM</th>
<th>BBB L</th>
<th>ML HY</th>
<th>LB HY</th>
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<tbody>
<tr>
<td>1985:1–2006:1</td>
<td>AAA IM</td>
<td>AAA L</td>
<td>BBB IM</td>
<td>BBB L</td>
<td>ML HY</td>
<td>LB HY</td>
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</tbody>
</table>
The figure shows the actual and model implied slope and curvature of the Treasury yields (row one) and the actual and model implied 1- and 10-year credit spreads for AAA, BBB and B credits, respectively (rows two through four). The model estimation period is 1992:2–2006:1. The implied quantities for the out-of-sample period 2006:2–2008:3 are calculated using the original parameters and updated data (dash-dotted lines). The shaded regions show the NBER recessions.
Figure 2. Credit Spreads and Treasury Yields: Expectations and Term Premia

The figure shows the decomposition of the implied credit spreads and Treasury yields into a part based on expectations about the future short rate and a term premium. The model estimation period is 1992:2–2006:1. The quantities for the out-of-sample period 2006:2–2008:3 are calculated using the original parameters and updated data (dashed lines).
Figure 3. 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. Panel A also contains a plot of the factor $f_1$ that is estimated by maximizing the correlation with the prewithened index of tighter loan standards, denoted $f_1 \text{ (corr)}$. Correlations between $f_1$ and the credit spreads are 67% and 60%, respectively, the correlation between the two $f_1$ time series is 98%. Panel B plots the factor $f_1$ against the prewithened index of tighter loan standards from the Senior Loan Officer Opinion Survey. The correlation between the two series is 64%. The prewithened series are residuals from regressing the original series on eight lags of inflation and real activity. All series are normalized to facilitate comparison. The model estimation period is 1992:2–2006:1. The factors and residuals up to 2008:3 are calculated using the original parameters and updated data (dotted and dash-dotted lines). The shaded regions show the NBER recessions.
Figure 4. Factor $f_2$, Treasury Yields and Federal Funds Target Rate

Panel A plots quarterly time series of the estimated factor $f_2$ from the base model against 3-month and 10-year Treasury yields. Panel A also contains a plot of the factor $f_2$ that is estimated by maximizing the correlation with the prewhitened Fed funds target rate, denoted $f_2$ (corr). Correlations between $f_2$ and the Treasury yields are 77% and 85%, respectively, the correlation between the two $f_2$ time series is 96%. Panel B plots the factor $f_2$ against the prewhitened Federal funds target rate. The correlation between the two series is 70%. The prewhitened series are residuals from regressing the original series on eight lags of inflation and real activity. All series are normalized to facilitate comparison. The model estimation period is 1992:2–2006:1. The factors and residuals up to 2008:3 are calculated using the original parameters and updated data (dotted and dash-dotted lines). The shaded regions show the NBER recessions.
Figure 5. Normalized Factor Loadings

The figure shows how Treasury yields and credit spreads change in response to a one standard deviation change in the state variables $g$, $\pi$, $f_1$, $f_2$ and $f_3$. Panel A shows the reactions to a one standard deviation change in the credit factor $f_1$, panels B and C show the reactions to a one standard deviation change in the level and slope factors $f_1$ and $f_2$ and panels D and E show the reactions to a one standard deviation change in the macro variables $g$ and $\pi$. The responses are all expressed in standard deviations to facilitate comparison, the maturities are expressed in quarters on the x-axis.
Figure 6. 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. The model estimation period is 1992:2–2006:1. The decomposition up to 2008:3 is calculated using the original parameters and updated data (dashed and dotted lines).
Figure 7. New Information Response Functions for Real Activity

The figure plots responses of quarterly GDP growth to one standard deviation shocks in the credit ($f_1$, panel A), level ($f_2$, panel B) and slope ($f_3$, panel C) factors, respectively. The 95% confidence bounds are calculated via parametric bootstrap. The time horizon for all new information response functions is 12 quarters.
Figure 8. Out-of-Sample Credit Factor and Forecasting GDP Growth

Panel A shows the evolution of the 1-year $B$ spread, the corresponding macro component and the credit, level and slope factor over the 2005:4–2008:4 time period. All time series are standardized to facilitate comparison. Panels B to D compare model based GDP growth forecasts with realized average GDP growth and survey forecasts for the one quarter, two quarters and one year horizons, respectively. Model based forecasts are generated using the estimated parameters per 2006:1 and updating the data subsequently, i.e. without re-estimating the model. The survey forecasts are taken from the Survey of Professional Forecasters (SPF), the Livingston survey (LS) and Blue Chip Economic Indicators (BCEI). Realized GDP growth includes data up to 2009:2. The shaded region shows the current NBER recession.
Figure 9. Treasury Yields and Credit Spreads

Panel A shows the 3-month, 1-year and 10-year Treasury yields, and 10-year corporate bond yields for AAA, BBB and B credits, respectively. Panels B and C show the 1-year and 10-year spreads for AAA, BBB and B credits, respectively. The time period is 1971:3–2008:3 although corporate bond data are only available starting in the 1990s. The shaded regions show the NBER recessions.